Fast Payment Systems and Deposit Dynamics: Evidence from Brazil's Pix

Philipe Balan[a,*], Marcelo Cabús Klötzle[b], Lars Norden[a,c]

[a] *Brazilian School of Public and Business Administration, Getulio Vargas Foundation, Brazil*

[b] *PUC-Rio, Brazil*

[c] *EPGE Brazilian School of Economics and Finance, Getulio Vargas Foundation, Brazil*

Abstract

Deposits constitute the foundation of bank funding and financial stability. This paper investigates the impact of Pix, Brazil's fast payment system, on bank deposit levels and deposit volatility. Pix significantly expands bank deposits because of heightened financial inclusion, cash substitution, and accelerated velocity of money. Furthermore, Pix elevates local deposit volatility but reduces volatility at the national bank level, indicating geographic diversification benefits. We corroborate these results by exploiting a large temporary exogenous shock to public trust caused by taxation-related misinformation regarding Pix. Our findings demonstrate that fast payment innovations fundamentally transform how banks attract and retain deposit funding.

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[*] Corresponding author: P. Balan, Brazilian School of Public and Business Administration, Getulio Vargas Foundation, Rua Jornalista Orlando Dantas 30, 22231-010 Rio de Janeiro, RJ, Brazil. E-mail: philipe.sousa@fgv.edu.br.

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1. Introduction

The rise of instant payment systems represents a transformative shift in the landscape of financial transactions, enabling real-time, seamless transfers that enhance efficiency, reduce costs, and promote broader economic participation. Among these financial innovations, Brazil's Pix, launched by the Central Bank of Brazil (*Banco Central do Brasil*, BCB) in November 2020, stands out as a pioneering fast payment system (FPS). Pix allows users to execute payments 24/7 through mobile interfaces, utilizing simple identifiers. Importantly, the introduction of Pix was mandatory for large banks in Brazil (Duarte et al., 2022; Corredor et al., 2020).

This system has rapidly gained traction, with over 67% of Brazilian adults adopting it within its first year, surpassing traditional card transactions and contributing to the digitalization of payments (Trombini, 2023; Fiserv, 2023). At the end of 2024, it was used by more than 93% of Brazilian adults. By facilitating immediate fund availability at low or no cost, Pix illustrates how public-sector-led digital infrastructures can democratize access to financial services in emerging markets where cash dominates and financial exclusion persists (Aurazo et al., 2024; Cornelli et al., 2024).

In this paper, we investigate a critical question: What is the impact of Pix on deposit dynamics? We focus on the level and volatility of bank deposits. Deposits constitute the primary funding source for banks, underpinning their liquidity, lending capacity, and overall financial stability. In traditional banking models, deposits provide a stable, low-cost base for intermediation, enabling credit extension and supporting economic growth. However, the rise of instant payments like Pix introduces potential disruptions by potentially altering depositor preferences and behavior, enhancing payment convenience, and intensifying competition among banks. If depositors can transfer funds instantly across institutions without friction, this could erode the stickiness of deposits at banks with large nationwide branch networks and benefit smaller or local banks, including online banks. Such dynamics are especially pertinent in Brazil, where concentration in the banking system is high, and deposits fuel a significant portion of credit to households and firms. Understanding these effects is vital for policymakers, as shifts in deposit volumes and volatility could amplify monetary policy transmission, influence financial stability, and affect inclusive growth amid declining cash usage.

Based on this context, we develop and test two hypotheses. Our first hypothesis is that Pix increased deposits at Brazilian financial institutions. This effect can be due to higher financial inclusion, substitution of cash and traditional non-cash means of payment, and due to the higher velocity of money in the economy. Our second hypothesis is that Pix increased the volatility of deposits at Brazilian financial institutions. Because Pix serves as an effective substitute for cash, individuals no longer need to withdraw cash from banks. This reduces the need for depositors to maintain large precautionary balances at their main bank for daily transactions, as funds can be instantly reallocated across banks, leading to heightened in- and outflows and thus greater deposit volatility.

To test these hypotheses, we take advantage of three important features of Pix that facilitate identification. First, participation was mandatory for all large Brazilian financial institutions authorized by the Central Bank of Brazil.[1] Pix was exogenous to banks, eliminating selection bias and ensuring coverage across the banking system. Second, bank customers could choose whether and how intensively to use Pix after the system started. These adoption and usage choices by customers (both new and existing) create exogenous variation in deposits across municipalities and banks. Third, the substitution effects of Pix

[1] In Brazil, financial or payment institutions licensed by the BCB with more than 500,000 active customer accounts - including checking, savings, and prepaid accounts - are required to offer Pix. Institutions below this threshold can voluntarily offer Pix if they adhere to the BCB's technical and operational rules. If institutions pass the threshold, they have to offer Pix to their customers after 90 days. For comparison, India's Unified Payment Interface (UPI), relied on voluntary participation and a competitive market structure.

with cash and other traditional payment instruments were largely unanticipated, as the technology had no prior equivalent. The sudden availability of instant payments likely induced structural changes in deposit dynamics. The combination of these three features provides a clean identification setting to investigate how a mandatory, public sector-led payment system affected banks' deposits and their volatility.

In our main analysis, we estimate panel data models with a Pix indicator and, alternatively, various Pix intensity measures, using monthly data from the BCB at the bank-municipality level for the period January 2010 to December 2025. These data make it possible for us to exploit quasi-experimental variation in Pix adoption and usage across municipalities, driven by pre-existing banking infrastructure, digital access, and demographic factors. We further analyze the impact of a large temporary exogenous shock to public trust in Pix that occurred in January 2025 on bank deposits and their volatility.

We find the following results. Concerning our first hypothesis, we find a significant increase in deposit levels of Brazilian financial institutions after the launch of Pix. We confirm this effect across various Pix intensity measures and at different data aggregation levels, including the bank-municipality, municipality, and (countrywide) bank levels. The effect is robust when we control for bank characteristics, the COVID-19 crisis, economic activity (industrial production index), and bank, municipality and time fixed effects. The main mechanisms that explain the increase of bank deposits due to Pix are financial inclusion of households and informal workers, substitution of cash, and the higher velocity of money.

Concerning our second hypothesis, we find a significant increase in deposit volatility at the bank-municipality (and municipality) level after the introduction of Pix. We also find that this adverse effect of Pix on deposit volatility is smaller in municipalities where economic informality is relatively high. A wavelet decomposition and bandpass filter analysis shows that Pix increased the deposit volatility at the bank-municipality level, especially at longer-term horizons. Interestingly, we find that deposit volatility significantly decreases at the (national) bank level after the introduction of Pix, pointing to the geographic diversification benefits of fast payment systems within banks.

We complement this analysis with further evidence, exploiting a sudden exogenous shock to public trust in Pix that occurred in January 2025. This shock led to a significant temporary decline in Pix usage, triggered by a viral video post that created the rumor that the Brazilian federal government planned to tax Pix payments. Strikingly, after the rumor spread, Pix received more attention than at the time of its launch. We show that deposit levels significantly dropped and deposit volatility spiked temporarily. The government shortly afterwards denied any plans for Pix taxation, and its usage volume, deposits, and deposit volatility returned to their previous levels.

Our study contributes to two strands of the literature in financial economics: fintech and digital fast payment systems, and bank deposits and financial stability. Fintech, and fast payment systems in particular, improve payment efficiency, reduce transaction costs, and foster financial inclusion, especially with public-sector support (Aurazo et al., 2024). Prior research shows that such systems accelerate digital finance adoption and intensify competition through fintech and big-tech entry, particularly when combined with central bank engagement, real-time settlement, and open access (Cornelli et al., 2024). Research on central bank digital currencies points to similar competitive effects on deposits and intermediation, while highlighting risks of bank disintermediation (Chiu et al., 2023; Berg et al., 2023; Infante et al., 2022). Evidence from payment shocks confirms real economic effects: India's demonetization accelerated adoption of alternative payment instruments, affected credit provision, and generated persistent shifts in payment behavior through network effects (Chodorow-Reich et al., 2020; Cruze et al., 2022), while debit card rollouts in Mexico reveal strong network externalities reshaping merchant and consumer behavior (Higgins, 2022). More broadly, fintech innovations are associated with financial inclusion and resilience, though they may pose risks to vulnerable populations and financial stability (Sant'Anna & Figueiredo, 2024; Silva et al., 2023). Related work links instant payments to economic activity: instant digital payments foster entrepreneurship and new firm creation (Leite et al., 2025), and the strategic digitization of money reshapes competition in currency and payments (Cong and Mayer, 2025). While prior studies focus on payment efficiency and financial inclusion, we analyze how Pix influences the way banks attract and retain deposit funding.

Deposits are fundamental for bank funding, money creation, payments, and financial stability. Access to deposits provides banks with relatively inexpensive and stable funding. Higher deposit volatility, however, raises funding costs and shortens loan maturities, with effects shaped by diversification and liquidity conditions (Choudhary and Limodio, 2017), while recent work shows that deposit flightiness varies with monetary conditions, amplifying bank run risk during tightening cycles (Blickle et al., 2025; Schliephake and Hakenes, 2026). Egan et al. (2017) show that competition for deposits and the sensitivity of uninsured depositors to bank distress can generate fragile equilibria and amplify systemic risk in the banking sector. Their analysis highlights how depositor behavior creates feedback effects between bank risk and funding stability. Moreover, Egan et al. (2025) document that depositors rarely switch accounts. This depositor inertia creates dynamic competition in which banks balance attracting new depositors with extracting rents from inactive ones. The resulting inertia increases banks' franchise value and can influence financial stability.

In Brazil, financial inclusion policies and digital payments are linked to higher deposits, lending, and productivity, albeit heterogeneous distributional effects (Fonseca and Matray, 2024; Trombini, 2023). Existing studies show that Pix intensifies competition for deposits, increases deposit elasticity, strengthens monetary policy transmission, and affects banks' liquidity transformation (Sarkisyan, 2025; Liang et al., 2025; Gonzalez et al., 2025). However, research has not systematically analyzed the direct effects of Pix on deposits and deposit volatility at the bank level. Our study helps to fill this gap by examining how the introduction and usage of Pix affect deposit levels and deposit volatility using granular bank–municipality data from Brazil.

The remainder of the paper is organized as follows. In Section 2, we present the institutional background and develop our hypotheses. In Section 3, we describe the data and empirical strategy. We report our results for the impact of Pix on deposits in Section 4 and those for deposit volatility in Section 5. In Section 6, we provide evidence on the effects of a large exogenous shock to public trust in Pix. In Section 7, we summarize the findings of further checks and robustness tests. Section 8 concludes.

2. Institutional background and hypotheses

2.1. Institutional background

The development of Brazil's instant payment system began internally at the BCB in 2018, during the administration of President Michel Temer. The first public presentation, including the unveiling of its official name "Pix", occurred in February 2020.

The operational rollout of Pix proceeded in structured phases to ensure system stability and participant readiness. Key registration for Pix keys began on October 5, 2020, allowing users to link identifiers, such as email addresses or phone numbers, to their accounts in anticipation of full functionality. A limited operational phase began on November 3, 2020, during which a subgroup comprising 1% to 5% of bank clients could conduct transactions under controlled conditions to test the infrastructure. The full launch, enabling unrestricted access for all eligible users, occurred on November 16, 2020. Figure 1 plots the total Pix volume over time.

(Insert Figure 1 here)

Figure 2 shows the natural logarithm of total deposits at Brazilian banks over time. We see a significant increase in deposits in the first six months of the COVID-19 crisis, similar to other countries and mainly due to suppressed consumption expenses during COVID-19 (first dashed vertical line), and later an additional significant increase after the introduction of Pix (second dashed vertical line). Importantly, Figure 2 shows that the average growth in deposits after the launch of Pix is higher than during the pre-Pix years.

(Insert Figure 2 here)

2.2. Hypotheses

The introduction of Pix may have reshaped deposit dynamics for several reasons. First, individuals have progressively replaced cash and other traditional means of payments by Pix. Prior to the start of Pix, making payments was often cumbersome and time-consuming. Individuals typically needed to visit a bank or an ATM to withdraw cash for transactions, a practice that required physical presence and adherence to banking hours. Once the cash was handed over, the recipient had to deposit the money to his or her bank account, a step that could be delayed or, in some cases, never completed due to convenience or other factors. This reliance on cash introduced significant frictions, including transaction time and fees, delays in fund availability, and risks associated with carrying and handling cash.

Second, Pix's technological features revolutionized the way payments are made, enabling instant, direct transfers between bank accounts. Pix payments are executed electronically in real time (guaranteed execution in up to seven seconds), eliminating the need for cash withdrawals or deposits. Senders can transfer funds directly to the recipient's bank account using simple identifiers such as an ID number, phone number, e-mail address, or a QR code, with transactions processed in seconds and available 24/7 at minimal or no cost.

Third, Pix – because of its various technological and practical benefits like mobile access (rather than online banking from computers) that became clear to the broader public very quickly - has promoted financial inclusion. Many "unbanked" Brazilians opened bank accounts for the first time to be able to use Pix. The money circulating in these new accounts was largely money that circulated as cash previously. Hence, considering these three factors, we hypothesize:

> **HYPOTHESIS H1:** *Pix increases the level of deposits at Brazilian financial institutions.*

Furthermore, Pix may have affected the volatility of deposits at financial institutions, mainly because of its speed and fast adoption. The Pix system, now used by nearly all individuals with bank accounts, facilitates significantly faster transactions, and a higher daily volume of payments, driven by its convenience and absence of transaction fees and slow execution times. These effects might have increased the deposit volatility at the bank level and made deposits "flightier". Because of individuals' reduced reliance on cash, Pix has increased the competitiveness of smaller and digital banks, making them more attractive to users. Hence, we hypothesize:

> **HYPOTHESIS H2:** *Pix increases the deposit volatility at Brazilian financial institutions.*

3. Data and methodology

3.1. Data

Our study is based on detailed data from Central Bank of Brazil (BCB), spanning the period from January 2010 to December 2025. In our main analysis, we investigate monthly data at the bank-municipality level (main sample). In additional analyses, we investigate data at the municipality level, national bank level, and country level.

Brazilian banks' balance sheets items are classified as "verbete" by BCB. We create the variable *Deposits* as the sum of the items 401, 420 and 431. In the bank-municipality-time dataset, there are 1,847,093 observations, with 148 banks from 3,724 municipalities in Brazil. In the aggregate municipality-time dataset, there are 642,767 observations. In the bank-time dataset, there are 22,774 observations and 148 unique banks.

We analyze data at different aggregation levels combined with different identification strategies to capture both cross-sectional and within-bank variation in deposits. The bank–municipality-time panel allows us to study within-bank differences across municipalities, while the aggregated municipality dataset captures local heterogeneity in Pix usage and deposit responses. The bank-time level dataset allows us to study the countrywide impact on banks including possible diversification effects, and the aggregate country-time level dataset allows us to study the impact of Pix on the whole financial system.

We first use a Pix indicator variable during the 2010–2025 period to estimate the average treatment effect of its introduction as a nationwide quasi-natural experiment. We then analyze various Pix intensity measures (transaction volumes and transaction numbers during the post-Pix period) to capture the effects across banks and municipalities. These complementary datasets and measurement strategies capture the impact of Pix's launch and the cross-sectional variation in its adoption and usage intensity.

3.2. Empirical strategy: Baseline models

We perform multivariate panel data analysis to estimate the effect of Pix on deposits and the deposit volatility for bank *i* in municipality *m* and time (year-month) *t*, respectively.

First, we analyze the impact of Pix on Ln(*Deposits*). We take the natural logarithm of deposits because the variable is highly skewed. Our main explanatory variable is the indicator Pix_t, which equals one in November 2020 and afterwards, and zero before. Note that Pix switches to one at the same time for all banks and municipalities in Brazil. We saturate the model with time-varying bank controls, a COVID-19 indicator to account for special effects during the pandemic, an index of industrial production (*IP*) at the state level to control for macro-economic conditions,[2] and bank and municipality fixed effects α_i and δ_m, respectively.

We also examine the effects of the Pix intensity on deposits in the post-Pix period. We replace the dummy variable *Pix* by various time-varying municipality-specific measures of the *Pix intensity* (*Pix volume* or *Pix quantity*) in the post-period. Equation (1) shows the regression model:

$$\begin{aligned} \text{Ln}(Deposits)_{\text{i,m,t}} = {} & \beta_1 Pix_{\text{t}} \text{ (or } Pix\ intensity_{m,t}) + Bank\ controls_{i,m,t} \\ & + IP_{\text{s,t}} + \alpha_{\text{i}} + \delta_{\text{m}} + \varepsilon_{\text{i,m,t}} \end{aligned} \tag{1}$$

[2] Two remarks are in order. First, we cannot use GDP per municipality as control because this variable is only available at a yearly frequency, while our data are monthly. Second, missing IP values are imputed based on the following assumptions: Acre aligns with Amazonas; Alagoas is the average of Pernambuco and Bahia; Amapá aligns with Pará; Distrito Federal aligns with Goiás; Paraíba is the average of Rio Grande do Norte, Ceará, and Pernambuco; Piauí is the average of Maranhão, Ceará, Pernambuco, and Bahia; Rondônia is the average of Amazonas and Mato Grosso; Roraima is the average of Amazonas and Pará; Sergipe aligns with Bahia; and Tocantins is the average of Goiás, Mato Grosso, Pará, Maranhão, and Bahia. Data was collected from IBGE’s PIM-PF dataset.

Furthermore, we analyze the impact of Pix on *Deposit volatility*. Unlike the level of deposits, which is reported by banks every month, the deposit volatility is unobservable and has to be estimated. To do so, we follow three strategies. First, estimate the standard deviation of *Deposits* on a rolling window of 13 months (from t-6 to t+6) for each bank and municipality over time. Then, we assign that standard deviation to the midpoint of the same rolling window and repeat this procedure for the whole sample period to build a volatility time series for each bank and municipality. Second, we conduct a wavelet decomposition analysis, which has several advantages over the rolling window approach. The wavelet approach makes it possible to directly compute monthly volatilities and differentiate between the effects on short- and long-term volatility. Third, we apply bandpass filtering to decompose the log deposit series into three frequency bands (1-6 months, 7-12 months, and 12+ months) using Butterworth filters after detrending, then regressing the raw filtered components directly on Pix to estimate its impact on the amplitude of cyclical fluctuations at each horizon. The bandpass approach makes it possible to isolate monthly cyclical components and to differentiate between the effects on short-, medium-, and long-term deposit fluctuations. Equation (2) shows the corresponding regression model:

$$\textit{Deposit volatility}_{i,m,t} = \beta_1 \textit{Pix}_t \text{ (or } \textit{Pix intensity}_{m,t}\text{)} + \textit{Bank controls}_{i,m,t} + \textit{IP}_{s,t} + \alpha_i + \delta_m + \varepsilon_{i,m,t} \tag{2}$$

3.3. Empirical strategy: Negative shock to public trust in Pix

We complement the previous panel data analysis with a quasi-natural experiment to strengthen our identification.

In early January 2025, a viral video posted by the politician Nikolas Ferreira triggered a sudden and large negative shock to public trust in Pix, which resulted in a decline in Pix usage. He stated that "*the Pix will not be taxed, but I do not doubt that it could be*," intentionally linking the Brazilian tax authorities' new monitoring rules under *Instrução Normativa* RFB 2219/2024 to a supposed plan to tax Pix transactions (InfoMoney, 2025). His framing suggested the new rules were only a first step towards future taxation, especially harming low-income informal workers, and this narrative quickly spread across social media (Gazeta do Povo, 2025; Poder360, 2025; Luciano and Fleck, 2025).

This episode had two key characteristics. First, its impact was unprecedented: press reports indicate that Ferreira's video accumulated around 200-300 million views on Instagram and other platforms within 24 hours, surpassing the Brazilian population and making it one of the most-viewed political videos in the country's history (Gazeta do Povo, 2025; Revista Oeste, 2025; Poder360, 2025). Second, the content directly attacked a central pillar of Pix – that it is a free, public, and widely accessible payment infrastructure – by casting doubt on the government's commitment not to tax small-value, day-to-day transfers. Shortly afterwards, the Brazilian federal government revoked the controversial monitoring rule and officially denied any plan to tax Pix. Bankers' associations and the Ministry of Finance publicly reiterated that Pix remained free of taxation or any fees (InfoMoney, 2025; CNN Brasil, 2025; Luciano and Fleck, 2025).

Despite the formal revocation and official clarifications, survey and usage evidence document a material erosion of public trust in Pix. Survey evidence shows that 87% of Brazilians were exposed to misinformation about a Pix tax and around 67% believed that the federal government would in fact impose a fee on Pix transactions (Luciano and Fleck, 2025). At the same time, Pix transaction numbers in early 2025 declined relative to previous years, and reports suggest that some users temporarily reverted to cash due to fear of taxation and increased monitoring (Luciano and Fleck, 2025; DISA, 2025). This episode represents a large temporary exogenous shock to trust in Pix that we can date precisely and that is strong enough to generate variation in deposits and deposit volatility.

3.4. Summary statistics

Table 1 provides summary statistics for the main variables. There is a noticeable increase in the mean and median values of bank deposits from the pre-Pix to the post-Pix period. The deposit volatility also increased substantially. Banks' return on assets (ROA) shows no material change from the pre-Pix to the post-Pix period. Total assets exhibit an increase in the post-Pix period.

(Insert Table 1 here)

4. The impact of Pix on deposits

4.1. Baseline results

We estimate multivariate panel data regression models with the natural logarithm of bank deposits as the dependent variable, as shown in Equation (1). Table 2 reports the regression results for the indicator *Pix*. We employ robust standard errors clustered at the bank level in all models.

(Insert Table 2 here)

The estimated coefficient of *Pix* is positive and statistically significant at the 1% level for all models, consistent with our Hypothesis H1. In Models 5 and 6, we include a *COVID-19* indicator to control for the special effects of the pandemic on deposits. The

Pix coefficient remains positive and significant at the 1% level. Overall, the results are robust and consistent, demonstrating that Pix has had a significantly positive impact on bank deposits at Brazilian financial institutions.

Moreover, Panel B shows the impact of the Pix intensity measures. We examine whether banks in municipalities with higher Pix volumes exhibit higher levels of deposits on their balance sheets. We estimate a regression model with Ln(*Deposits*) as the dependent variable on various Pix intensity measures,[3] bank controls, and bank and municipality fixed effects. The coefficients of all Pix intensity variables are positive and significant at the 5% level. We additionally show that all of our main results are robust to controlling for the Selic policy rate and disaggregated continuous COVID-19 measures (cases per capita and deaths); these results are reported in Table OA1 of the Online Appendix.

These results are in line with our Hypothesis H1 and robust, demonstrating that Pix transaction volumes and quantities, particularly those involving individuals, have a significantly positive effect on deposits of Brazilian financial institutions.

4.2. Mechanisms

4.2.1. Financial inclusion of households and informal workers

To rationalize our previous findings on the impact of Pix on deposits, we present evidence on several mechanisms. The plausibly most pertinent mechanism is financial inclusion. To participate in Pix, it is necessary to have a cell phone *and* a bank account. Hence, previously unbanked households and informal workers, who relied on cash to make or receive payments, opened for the first time bank accounts to use Pix.

[3] We divide the Pix intensity variables by one trillion and the variable Pix quantity by one billion for ease of exposition. All Pix intensity variables are zero in the pre-Pix period.

First, according to the Banco Central do Brasil (BCB), by December 2022, 71.5 million people had been financially included through Pix, defined as individuals who had made no electronic transfer in the twelve months before its launch and became active users afterwards (BCB, 2023). By the same date, 133 million Brazilians (77% of the adult population) and 11.8 million firms held Pix keys, linked to around 400 million checking accounts (BCB, 2023). Consistent with new account openings, account ownership among Brazilians increased from about 70% in 2017 to 84% in 2021 (World Bank, 2022).

Second, Pix also helped to include cash payments in the informal economy into the formal financial system, which is another channel how fast payment systems foster financial inclusion (Fonseca and Matray, 2024). We investigate this channel empirically by interacting our Pix measures with an exogenous municipality-level measure of informality following Ulyssea (2018) and re-estimate the deposit and deposit volatility regressions.[4] The variable *Informality* - as single term - is fully absorbed by the municipality fixed effects. Table 3 reports the results.

(Insert Table 3 here)

We find a significantly positive coefficient on the interaction term *Pix* × *Informality* at the municipality level, indicating that the deposit-increasing effect of Pix we documented previously is concentrated in municipalities with a larger informal economy. This finding is consistent with the channel that Pix drew cash-based transactions from the informal economy into the formal financial system.

[4] Specifically, we measure informality as follows: $Informality_{m,2019} = 1 - (Formal\ workers_{m,2019}/Total\ population_{m,2019})$ following Ulyssea (2018). The measure varies across municipalities, but it is fixed for all years using 2019 data.

Overall, these results indicate that Pix raises deposit levels most strongly where the scope for formalizing economic activity is greatest, confirming that financial inclusion is a first-order mechanism behind our finding.

4.2.2. Substitution of cash and other traditional means of payments

The effects of Pix on deposits likely go beyond those of financial inclusion. Cash substitution of the already banked population - for convenience reasons - is another potential mechanism. Although cash substitution cannot be measured directly (as cash payments leave no electronic record), the evidence based on indirect measures indicates a substantial shift. The share of cash in transactions fell from 42% in 2020 to 22% in 2023, while currency in circulation declined by about 10% over the same period (Sampaio and Ornelas, 2024). A complementary counterfactual analysis estimates cash in circulation at R$ 47.6 billion in 2020-23, which corresponds to around 14% (de Andrade and da Cruz, 2025). This substitution was large for cash, while Pix complemented – rather than replaced - other electronic payments such as TED, payment orders, and payment cards (Sampaio and Ornelas, 2024). Funds that were moved as cash by the banked population were increasingly deposited into existing bank accounts (and not only into new accounts by the previously unbanked population) to participate in Pix, consistent with the increase in bank deposits we document.

4.2.3. Increased velocity of money

Another potentially important mechanism through which Pix may have raised the level of bank deposits is its significant impact on the velocity of money. Following the Fisher's seminal equation of exchange, MV = PT, we measure monetary velocity V as the value of payments in period T divided by the quantity of money M, so that V corresponds to the turnover of the stock of money due to payments. We construct the numerator from the BCB Statistics on Payment Instruments (*Estatísticas de Meios de Pagamento*), summing the value of all payment instruments (Pix, TED, TEC, check, payment orders (boleto), DOC, intrabank transfers, debit agreements, direct debit, cash withdrawals, and credit, debit, and prepaid cards) and the denominator from two measures of the money stock: the stock of bank deposits, and the standard monetary aggregate M1 (BCB series 27791) (https://www.bcb.gov.br/estatisticas/panoramaosd). This revised measure is computed at quarterly frequency and uses the broader BCB quarterly payments table; the wider instrument coverage raises the level of measured velocity but leaves the decomposition below unchanged. Figure 3 provides evidence on the velocity of money mechanism.

(Insert Figure 3 here)

Panel A of Figure 3 plots the quarterly monetary velocity relative to the deposit stock, decomposed into Pix and all other instruments. Two patterns stand out. First, velocity rose after the launch of Pix: payments turned over the deposit base about 1.34 times per quarter in the two years before the launch and about 1.83 times per quarter in 2025 (1.64 in 2024), which is an increase of around 37%, even though the deposit base itself grew over the period. Second, this acceleration is entirely due to Pix. The velocity of all other payment instruments together remained flat, moving from 1.34 to 1.33 turnovers per quarter, while Pix alone added 0.38 turnovers per quarter in 2024 and 0.50 in 2025. This additional velocity originates from money that was previously idle as cash rather than from funds already used for electronic payments. Panel B of Figure 3, where we take the M1 money aggregate as denominator of the turnover measure, confirms this view. The velocity of money, reflected by a turnover of 11.2 in 2019 and 16.9 in 2025, increased by around

51%. Pix accounts for the entire acceleration in money velocity, with cards making up only about 3% of total payment value, confirming that the trend is driven by Pix rather than by cards.

Overall, the evidence shows an acceleration in the velocity of money, which provides another explanation of our panel data regression results above.

5. The impact of Pix on deposit volatility

Our analysis indicates that the introduction of Pix and the Pix volumes have had a positive effect on deposits of Brazilian banks. However, what happened to the volatility of deposits after the launch of Pix? Did it change, and if yes, did it increase (flighty deposits) or decrease (sticky deposits)? In this section, we conduct three tests of our Hypothesis H2 to provide evidence on these questions.

5.1. Rolling-window analysis

First, we calculate the standard deviation of deposit volumes at the bank-municipality-time level in a rolling window setting. We define the window as a 13-month period and assign the resulting standard deviation to the window mid-point. We then estimate a regression of the deposit volatility on Pix, bank controls, and municipality and bank fixed effects, as shown in Equation (2). Table 4 shows the corresponding results.

(Insert Table 4 here)

The *Pix* coefficient is positive and highly significant in all models, indicating that Pix increased deposit volatility at the bank level. Panel B shows the impact of Pix intensity variables, controlling for bank and municipality fixed effects. All Pix intensity variables show a positive and significant coefficient at the 1% level. The corresponding robustness tests with alternative controls are reported in Table OA2 of the Online Appendix.

In the next step, we examine whether the level of informal economic activity in a municipality affects the impact of Pix on deposit volatility. We re-estimate the augmented model from Table 3, where we interact Pix with *Informality*, for deposit volatility. Table 5 reports the results.

(Insert Table 5 here)

Table 5 shows two important results. First, the significantly positive impact of Pix on deposit volatility is confirmed. Second, we find in all models a significantly negative coefficient of the interaction term, indicating that the increase in volatility of deposits is smaller when the level of informality is relatively high. This finding complements the results from Table 3. When informality in a municipality is relatively high, we see a stronger positive impact of Pix on bank deposits and a reduced increase in deposit volatility compared to other municipalities. Hence, the favorable effects of Pix are stronger when informality is relatively high, consistent with the financial inclusion effect of informal workers.

5.2. Wavelet decomposition

We further perform a wavelet decomposition, which is a multi-resolution method used in many fields of research. This method enables the direct computation of monthly volatility, the construction of continuous volatility series, and the separation of short- and long-term dynamics through different frequency bands.

Because of the unbalanced structure of our dataset, in which some units exhibit missing observations, we restrict the sample to complete panels with at least 64 contiguous observations to ensure sufficient length for a meaningful wavelet decomposition (supporting up to four scales). For panels with minor gaps, we apply linear interpolation, and sensitivity analyses confirm the robustness of this procedure. The treatment variable is the Pix indicator (equal to one in the post-Pix period, and zero before), while controls include the lagged Return on Assets (ROA), log of Total Assets, the Industrial Production Index (IP), and the COVID-19 indicator.

For each panel unit, we apply the Maximal Overlap Discrete Wavelet Transform (MODWT) to the time series of ln(Deposits). We use the least asymmetric Daubechies filter to achieve an optimal balance between smoothness and compactness, a configuration well suited for financial time series. MODWT is selected because it is shift-invariant and can accommodate non-dyadic series lengths, making it appropriate for our panel structure. The decomposition is performed at four levels (j = 1–4), given that most panels include approximately 180 monthly observations. This yields detailed components at the following scales: *D1*: Fluctuations with periods of 2–3 months (high-frequency, short-term variations);[5] *D2*: Fluctuations with periods of 4–7 months; *D3*: Fluctuations with periods of 8–15 months; and *D4*: Fluctuations with periods of 16–32 months. Multi-Resolution Analysis (MRA) reconstructs the detail components $D_j(t)$ for scales j=1,2,3,4, each representing the time-aligned contribution of scale-specific fluctuations to the original series:

$$Ln(Deposits) \approx \sum_{j=1}^{4} D_j(t) + S_4(t) \tag{3}$$

[5] Due to the Nyquist limit the D1 component has to start with month 2 (and not with month 1).

where S4(t) is the smooth component capturing the residual trend at the coarsest scale.

We estimate panel data regressions using the reconstructed components – the alternative measure of deposit volatility over different horizons – as dependent variables:

$$D_{jit} = \beta_{0j} + \beta_{1j}Pix_t + \beta_{2j}Covid_t + \gamma_j X_{it-1} + \alpha_i + \delta_{mt} + \epsilon_{it} \tag{4}$$

where i denotes panels, t denotes time, X_{it-1} includes the lagged control variables, α_i absorbs fixed effects for bank i, and δ_{mt} captures a full vector of interacted municipality-time fixed effects. The coefficient β_{1j} measures the impact of Pix on the amplitude of fluctuations at scale j. For instance, a significant β_{11} indicates that Pix affects short-term (2–3 months) fluctuations, while a significant β_{14} indicates an impact on longer-term (16–32 months) dynamics.

This multi-scale approach uncovers frequency-dependent effects of Pix on deposit fluctuations, offering nuanced insights into its short- and long-term impacts compared to aggregate analyses. Results are robust to alternative wavelet filters and level specifications. Table 6, Panel A presents the results.

(Insert Table 6 here)

On the one hand, we find a strong positive effect of Pix on both D2 and D4 scales. This evidence indicates that Pix exerts a middle and long-term increase on deposit volatility. On the other hand, we do not find a significant effect on the short-term scale (D1) or the medium-term scale (D3). Hence, the significant increase in deposit volatility is concentrated at specific horizons rather than being uniform across all horizons. Overall, the findings of the wavelet decomposition are broadly consistent with the results of our rolling window analysis, indicating that Pix increased the deposit volatility. The corresponding robustness tests with alternative controls are reported in Table OA3 of the Online Appendix.

5.3. Bandpass filter analysis

We further conduct a Butterworth bandpass filter analysis, which is a frequency-domain method widely used in macroeconomics and time series analysis. This approach enables the direct isolation of monthly cyclical components, the construction of continuous fluctuation series, and the separation of short-, medium-, and long-term dynamics through distinct frequency bands.

For each panel unit, we first detrend the time series of ln(Deposits) using a linear time trend to isolate cyclical fluctuations. We then apply Butterworth bandpass filters (order 3) with zero-phase implementation to decompose the detrended series into three frequency bands, 1-6 months, 7-12 months and 12+ months. Table 6, Panel B shows the results of the regression of Pix on these bands. Pix had no effect on the short term but had a significantly positive impact over the mid- and long-term horizon on deposit volatility. The corresponding robustness tests with alternative controls are reported in Table OA4 of the Online Appendix. The Butterworth bandpass filter analysis corroborates the wavelet decomposition results, indicating that Pix primarily increases medium- and long-term fluctuations in deposits, while having no statistically significant effect at short horizons.

6. The impact of a sudden negative shock to public trust in Pix

We complement the previous evidence on deposit dynamics with an analysis of the sudden negative shock to public trust in Pix in January 2025, triggered by a viral video that created the rumor about taxation. This shock was exogenous, unexpected and large.

Strikingly, it caused more attention to Pix on Google trends in Brazil than the Pix launch itself, as shown in Figure 4.

(Insert Figure 4 here)

We exploit the exogenous variation in Pix usage due to this negative shock and analyze its impact on bank deposits and deposit volatility. Figure 5 displays the aggregate time series of the Pix volume and deposits in Brazil in the months surrounding the shock. In January 2025, the Pix volume sharply declined as did the total volume of deposits.

(Insert Figure 5 here)

To analyze these effects formally, we estimate our baseline model, including an indicator variable that equals one in January 2025 and zero otherwise, to capture the immediate effect of the negative shock to public trust in Pix. We also consider the Pix volumes and quantities and the corresponding interaction terms with the shock indicator. We estimate these models at different aggregation levels, i.e. at the bank-municipality, municipality, bank, and country level.

(Insert Table 7 here)

Table 7, Panel A-B report the results for deposits and Panel C-D for deposit volatility. In Panel A, Pix continues to have a significantly positive effect on bank deposits in all models. However, there is a significantly negative effect of the shock at the municipality (column 2) and country level (column 4). The difference in the results at the aggregate levels (municipality and country level) and the non-significant effects at granular levels (bank-municipality and bank level) suggests that the shock affected depositor behavior at a systemic level. Panel B reports the corresponding results for deposits using the Pix intensity measures and their interactions with Shock to trust in Pix. In Panel B, the eight columns are grouped by aggregation level - bank-municipality (Columns 1-2), municipality (Columns 3-4), bank (Columns 5-6), and country (Columns 7-8) - where the first column in each pair reports the effect of the Pix volume and the second the effect of the Pix quantity. The Pix volume and Pix quantity have a significantly positive effect on bank deposits in all models, the interaction term of Pix and the Shock to trust in Pix is significantly negative at the country level for the Pix volume and quantity (Columns 7-8). The interaction effects in Columns (3) and (4) are significantly positive, indicating that users made smaller Pix payments but in greater numbers.

Table 7, Panel C reports the impact of the trust shock on deposit volatility using the Pix indicator. The results show that the trust shock consistently increased deposit volatility across all levels of analysis, while the effect of Pix itself varies: positive at granular levels (bank-municipality and municipality), negative at the bank level, and null at the country level. Panel D reports the corresponding results using Pix intensity measures and their interactions with the Shock to trust in Pix. The baseline effects of Pix on deposit volatility are similar to those in Panel C. Moreover, the effects of the interaction terms with the shock are significantly positive in the eight models, consistent with Panel C.

In addition, the results on the impact of the shock on deposit levels and deposit volatility are upheld in further (unreported) analyses where we control for the interest rate Selic and COVID-19 intensity measures.

Overall, this analysis complements and confirms our previous findings from panel data regressions and strengthens the identification.

7. Further checks and robustness tests

We conduct further checks and several robustness tests. Specifically, we perform tests for different aggregation levels, with a time trend, and subsamples. We also add further control variables.

First, we estimate the deposit regressions at the municipality and bank levels instead of the bank-municipality level. Table 8 reports the results.

(Insert Table 8 here)

The coefficient on the Pix indicator remains positive and statistically significant, confirming that the introduction of Pix increased deposits across different aggregation levels. Similarly, the Pix intensity measures are positive and significant. These results confirm that the positive relationship between Pix adoption and deposits is robust at different aggregation levels. Table OA5 reports the corresponding analyses, controlling for Selic and COVID-19 intensity measures.

Second, we perform similar tests for deposit volatility. Table 9 reports the results.

(Insert Table 9)

At the municipality level, the coefficient on Pix becomes positive and statistically significant once controls are included, suggesting that Pix increases deposit volatility locally. In contrast, the coefficient is significantly negative at the bank level, consistent with the idea that banks can smooth deposit fluctuations across municipalities through geographic diversification. For the Pix intensity, the coefficients are also negative and significant, indicating that higher Pix usage is associated with lower volatility at more aggregated levels. These nuanced results complement our main findings at the bank-municipality level. Table OA6 reports the corresponding analyses, controlling for Selic and COVID-19 intensity measures.

Third, we conduct robustness tests including a linear time trend in the baseline deposit regressions to control for underlying trends in deposit growth. Table OA7 of the Online Appendix reports the results. The coefficient on the Pix indicator remains positive and statistically significant, confirming that general time trends do not drive the increase in deposits after the introduction of Pix.

Finally, we estimate our baseline model on subsamples to examine the potential heterogeneity in the marginal effects of Pix. Specifically, we perform sample splits based on bank size, deposits per capita, and GDP per capita. Table 10 reports the results.

(Insert Table 10 here)

We find that the coefficient on the Pix indicator remains significantly positive in all subsamples, indicating that the positive effect of Pix on deposits is robust across different bank characteristics and socio-economic environments. Interestingly, the effect of Pix on deposits is three times larger at smaller banks than at larger banks. As discussed earlier, one explanation for this finding is the increased attractiveness of having deposits at small, local and/or digital banks that have no nationwide branch network.

8. Conclusion

We investigate the impact of Brazil's instant payment system Pix on bank deposit dynamics. Pix was mandatory and exogenous for all large banks in Brazil, while its adoption and usage intensity were a choice of banks' customers. To identify the causal impact of Pix on banks, we analyze monthly panel data from the Central Bank of Brazil across varying levels of aggregation, such as bank-municipality, municipality, and bank levels, during the period 2010-2025. Our identification strategy further leverages exogenous variation in Pix volumes, stemming from a sudden negative shock to public trust in Pix triggered by rumors regarding payment system taxation.

Our findings are clear and consistent. The introduction of Pix significantly increased the level of bank deposits in Brazil. This result is robust across models controlling for bank characteristics, macroeconomic conditions, and fixed effects. The main mechanisms that explain these results are financial inclusion of households and informal workers, substitution of cash, and higher velocity of money. Furthermore, the start of Pix increased the volatility of deposits at the local level. This adverse effect is smaller in municipalities where informality is relatively high. We complement this analysis of deposit volatility with a wavelet decomposition and bandpass filter analysis for different time horizons. Pix significantly increases the longer-term volatility of deposits, while it has no effects on the short-term volatility. We also find that Pix reduced deposit volatility at the (countrywide) bank level, pointing at geographic diversification benefits within banks.

Overall, our study demonstrates that fast payment innovations fundamentally transform the way banks attract and retain funding. The evidence is novel and offers valuable insights for bankers, regulators and policymakers, navigating the evolving landscape of instant payment systems.

References

Aurazo, J., Cantú, C., Frost, J., Kosse, A., Velasquez, J., 2024. A revolution in digital payments: Faster, user-friendlier and cheaper. BIS Papers, no. 152, December.

Banco Central do Brasil, 2023. Pix Management Report: Conception and First Years of Operation 2020–2022. Brasília: BCB.

Berg, T., Keil, J., Martini, J., Puri, M., 2023. Payment firms, cryptocurrencies, and CBDCs. Mimeo.

Blickle, K., Li, Z., Lu, J., Ma, Y., 2025. The dynamics of deposit flightiness and its impact on financial stability. Mimeo.

Chiu, J., Davoodalhosseini, M., Jiang, J., Zhu, Y., 2023. Bank market power and central bank digital currency: Theory and quantitative assessment. *Journal of Political Economy*, forthcoming.

Chodorow-Reich, G., Gopinath, G., Mishra, P., & Narayana, R., 2020. Cash and the economy: Evidence from India's demonetization. *Quarterly Journal of Economics* 135, 57-103.

Choudhary, M., Limodio, N., 2017. Deposit volatility, liquidity and long-term investment: Evidence from a natural experiment in Pakistan. Mimeo.

CNN Brasil, 2025. Demonstração de que pessoas estão indignadas, diz Nikolas à CNN sobre vídeo. January 14, 2025.

Cong, L., Mayer, S., 2025. Strategic digitization in currency and payment competition. *Journal of Financial Economics* 168, 104055.

Cornelli, G., Frost, J., Warren, J., Yang, F., Velasquez, J., 2024. Retail fast payment systems as a catalyst for digital finance. BIS Working Papers, no. 1228, July.

Corredor, E., Trombini, A., Zampolli, F., 2020. CoDi and Pix. BIS Quarterly Review, December, 15–22.

Cruze, R., Gupta, A., Mezzanotti, F., 2022. Shocks and technology adoption: Evidence from electronic payment systems. Working Paper.

De Andrade, J. V. M., da Cruz, L. S., 2025. Impact of the pandemic on currency circulation in Brazil: Projections using the SARIMA model. Working paper, arXiv:2503.07876.

DISA, 2025. Disinformation's eroding influence on trust in Brazil's primary digital public infrastructure. Digital Influence and Security Alliance (DISA), March 10, 2025.

Duarte, A., Frost, J., Gambacorta, L., Koo Wilkens, P., Shin, H., 2022. Central banks, the monetary system and public payment infrastructures: Lessons from Brazil's Pix. BIS Bulletin, no. 52, March.

Egan, M., Hortaçsu, A., Kaplan, N., Sunderam, A., Yao, V., 2025. Dynamic Competition for Sleepy Deposits. NBER Working Paper 34267.

Egan, M., Hortaçsu, A., Matvos, G., 2017. Deposit competition and financial fragility: Evidence from the US banking sector. *American Economic Review* 107, 169-216.

Fiserv, 2023. An instant payments revolution started in Brazil. Fiserv Insights.

Fonseca, J., Matray, A., 2024. Financial inclusion, economic development, and inequality: Evidence from Brazil. *Journal of Financial Economics* 156, 103854.

Gazeta do Povo, 2025. Vídeo de Nikolas Ferreira contra fiscalização do PIX viraliza. *Gazeta do Povo*, January 14, 2025.

Gonzalez, R., Ma, Y., Zeng, Y., 2025. The effect of instant payments on the banking system. Central Bank of Brazil, Working Paper no. 619.

Higgins, S., 2022. Financial technology adoption: Network externalities of cashless payments in Mexico. Mimeo.

Infante, S., Kim, K., Orlik, A., Silva, A. F., Tetlow, R., 2022. The macroeconomic implications of CBDC: A review of the literature. Federal Reserve Board Working Paper no. 2022-076.

InfoMoney, 2025. Vídeo de Nikolas Ferreira sobre Pix viraliza nas redes sociais; governo nega mudanças. *InfoMoney*, January 14, 2025.

Leite, R., Mendes, L., Moura, M., 2025. The real effects of fintech: Instant digital payments and entrepreneurship. Working Paper.

Liang, A., Sampaio, A., Sarkisyan, A., 2025. Digital payments and monetary policy transmission. Mimeo.

Luciano, M., Fleck, G., 2025. How disinformation is undermining trust in Brazil's most used digital public infrastructure. *TechPolicy Press*, March 9, 2025.

Poder360, 2025. Vídeo de Nikolas sobre o Pix chega a 300 mi de visualizações. *Poder360*, January 15, 2025.

Revista Oeste, 2025. Vídeo de Nikolas Ferreira sobre fiscalização do Pix alcança 300 milhões de visualizações. *Revista Oeste*, January 15, 2025.

Sampaio, A., Ornelas, J., 2024. Payment technology complementarities and their consequences in the banking sector: Evidence from Brazil's Pix. Central Bank of Brazil, Working Paper no. 600.

Sant'Anna, D., Figueiredo, P., 2024. Fintech innovation: Is it beneficial or detrimental to financial inclusion and financial stability? A systematic literature review and research directions. *Emerging Markets Review* 60, 101140.

Sarkisyan, A., 2025. Instant Payment Systems and Competition for Deposits. Mimeo.

Schliephake, E., Hakenes, H., 2026. The Deposit Base – Multibanking and Bank Stability. Working Paper, June 2026.

Silva, T., de Souza, S., Guerra, S., Tabak, B., 2023. COVID-19 and bank branch lending: The moderating effect of digitalization. *Journal of Banking and Finance* 146, 106684.

Trombini, A., 2023. Digital payments as a boon to financial inclusion. BIS Speech, International Finance Forum (IFF) 20th Anniversary, Guangzhou, 27–29 October.

Ulyssea, G., 2018. Firms, Informality, and Development: Theory and Evidence from Brazil. *American Economic Review* 108, 2015–2047.

World Bank, 2022. The Global Findex Database 2021: Financial Inclusion, Digital Payments, and Resilience in the Age of COVID-19. Washington, DC: World Bank.

Figure 1: Total Pix volume

This figure displays the total absolute usage volume of Pix (in BRL), divided by 1 trillion, over time. The broken vertical line indicates the introduction of Pix in November 2020.

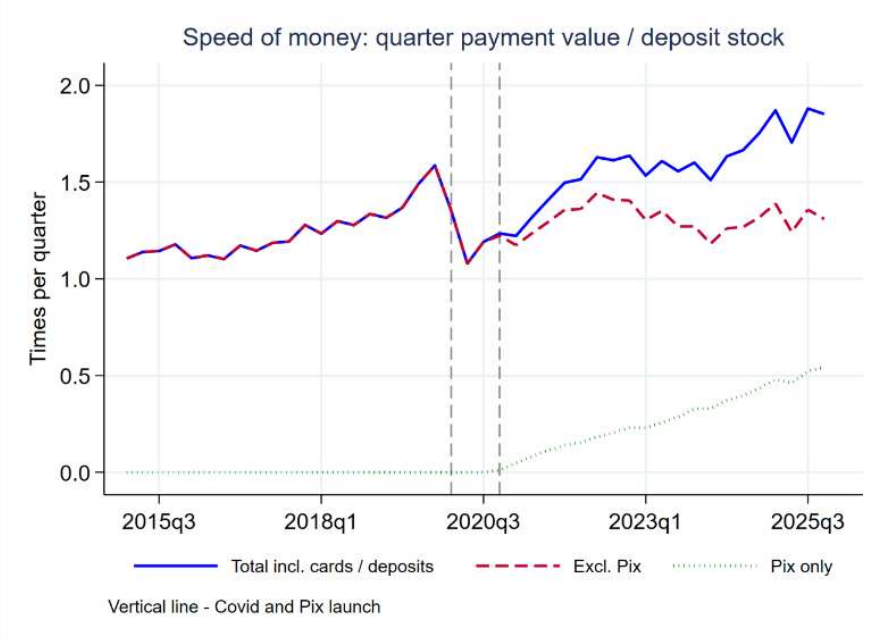
Figure 2: Total deposits at Brazilian banks

This figure displays the total deposits at Brazilian banks (in BRL), divided by 1 trillion, over time. The broken vertical line indicates the introduction of Pix in November 2020.

Figure 3: Velocity of money

This figure shows how the launch of Pix affected the velocity of money in Brazil during 2015-2025. Panel A plots the turnover due to payments relative to the stock of bank deposits. Panel B plots the turnover due to payments relative to the M1 monetary aggregate. The vertical lines indicate the start of the COVID-19 pandemic in March 2020 and the launch of Pix in November 2020.

Panel A: Turnover of the stock of deposits



Panel B: Turnover relative to the M1 monetary aggregate

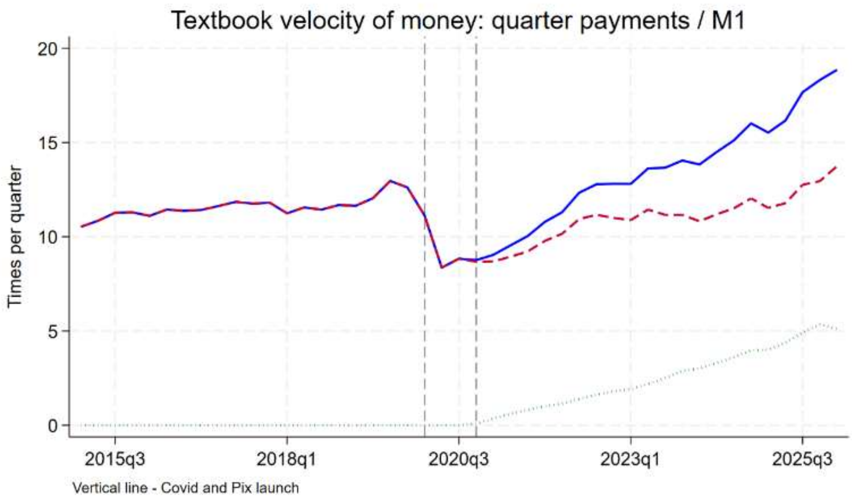


Figure 4: Pix in Google trends in Brazil

This figure displays the Google trends results for web searches for the term "Pix" in Brazil during the period from January 1, 1999 to December 31, 2025. The shock to trust in Pix occurred in early January 2025 due to the fake news (intentionally launched rumor related to the *Instrução Normativa RFB 2219/2024*) that the Brazilian Federal Government intended to tax Pix transactions. The Brazilian Federal Government officially refuted the rumor on January 15, 2025.

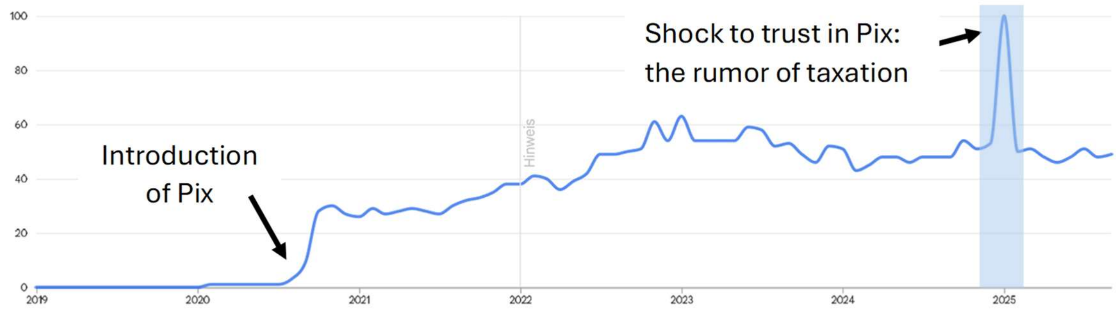


Figure 5: Pix and deposits volumes around the negative shock to trust in Pix

This figure displays the Pix volume and the deposit volume at Brazilian banks divided by 1 trillion, around the shock to trust in Pix. The vertical line indicates the shock that occurred in early January 2025 due to the fake news (intentionally launched rumor related to the *Instrução Normativa RFB 2219/2024*) that the Brazilian Federal Government intended to tax Pix transactions. The Brazilian Federal Government officially refuted the rumor on January 15, 2025.

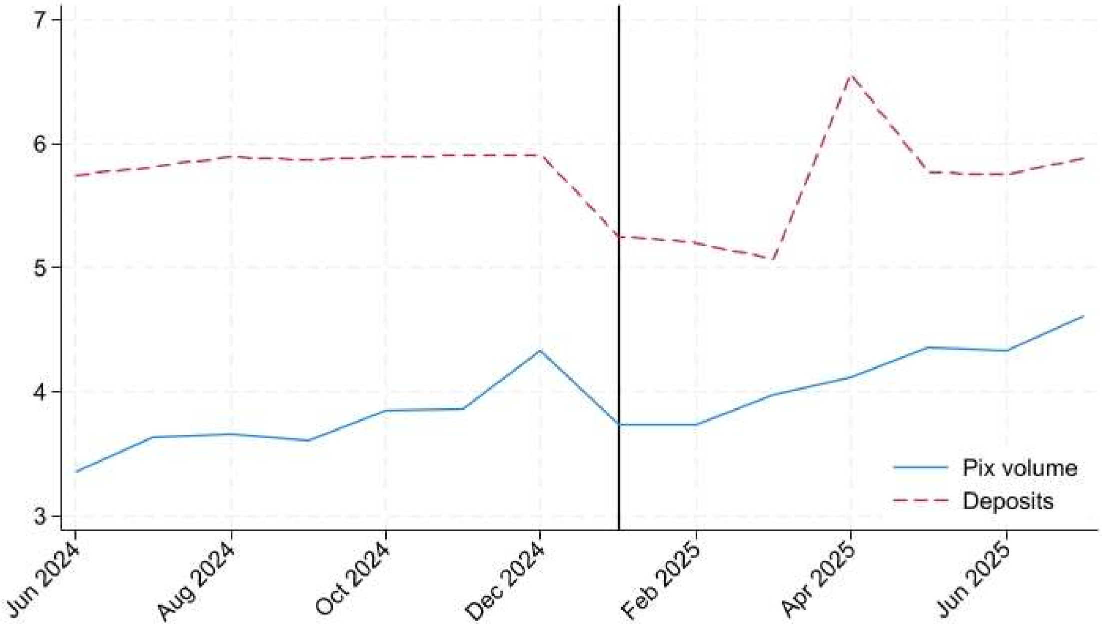


Table 1: Summary statistics

This table presents summary statistics for the main variables at the bank-municipality-time level. The data frequency is monthly. The sample spans the period from January 2010 to December 2025. The Post Pix period is November 2020 to December 2025; the Pre Pix period is January 2010 – October 2020. The statistics for the Pix dummy refer to the full period, those for the Pix volume and Pix quantity to the post-pix period. The latter variables are set to zero during the pre-Pix period in the regression analyses.

Variable	Period	Mean	Median	Std. dev.	Number of obs.
Pix variables					
Pix	Full	0.287	0.000	0..452	1,847,165
Pix volume	Post Pix	5,267,302,049	280,064,832	38,450,352,128	530,298
Pix quantity	Post Pix	12,248,855	670,640	90,857,224	530,298
Bank variables					
Deposits	Pre Pix	297,469,280	22,185,046	7,030,358,528	1,316,814
Ln(Deposits)	Pre Pix	16.619	16.915	3.019	1,316,814
Deposit volatility	Pre Pix	20,832,870	1,447,013	460,762,304	1,316,800
ROA	Pre Pix	0.017	0.012	0.017	1,309,573
Total Assets	Pre Pix	3,548,317,835	72,375,776	111,252,185,088	1,316,814
Deposits	Post Pix	602,074,611	57,193,596	10,256,972,800	530,351
Ln(Deposits)	Post Pix	17.666	17.862	2.871	530,279
Deposit volatility	Post Pix	131,283,729	3,724,961	3,726,300,416	530,278
ROA	Post Pix	0.019	0.012	0.017	526,957
Total Assets	Post Pix	4,749,693,542	116,484,600	144,844,013,568	530,351
Macro-economic conditions					
IP (Industrial production index)	Full	103.911	103.211	16.241	1,628,380

Table 2: Pix and deposits

This table reports the panel data regression results on the impact of Pix on deposits at the bank-municipality level. The dependent variable is Ln(Deposits). In Panel A, Pix is an indicator variable that switches to one after the introduction of Pix in November 2020. In Panel B, the Pix intensity is a hybrid variable, being zero before the Pix introduction and the natural log of the Pix volume or quantity after the Pix introduction. The sample period is January 2010 to December 2025. Robust standard errors clustered at the bank level are shown in parentheses. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Panel A: Pix indicator

Dep. var.: Ln($Deposits_t$)	(1)	(2)	(3)	(4)	(5)	(6)
Pix_t	1.0473***	0.4337***	0.8108***	0.4817***	0.6956***	0.5898***
	(0.1552)	(0.1372)	(0.1218)	(0.1020)	(0.1639)	(0.1402)
Controls						
Ln(Total $Assets_{t-1}$)		1.0745***		0.9881***		1.0014***
		(0.1151)		(0.0977)		(0.0970)
ROA_{t-1}		17.9656***		4.5454**		3.7717*
		(6.4684)		(2.1851)		(1.9280)
IP_t				0.0029***		0.0020***
				(0.0007)		(0.0007)
COVID-19_t					0.2610**	-0.2541***
					(0.1255)	(0.0953)
Bank fixed effects	No	No	Yes	Yes	Yes	Yes
Municipality fixed effects	No	No	Yes	Yes	Yes	Yes
Number of observations	1,847,093	1,820,586	1,847,092	1,605,140	1,847,092	1,605,140
Adj. R^2	0.025	0.383	0.706	0.831	0.707	0.832

Panel B: Pix intensity

Dep. var.: Ln($Deposits_t$)	(1)	(2)	(3)	(4)	(5)	(6)
Pix $volume_t$	0.0757**					
	(0.0297)					
Pix $quantity_t$		0.0778**				
		(0.0308)				
Pix volume $received_t$			0.0772**			
			(0.0308)			
Pix volume $paid_t$				0.0728**		
				(0.0283)		
Pix volume $individuals_t$					0.0781**	
					(0.0309)	
Pix volume $firms_t$						0.0605**
						(0.0240)
Bank $controls_{t-1}$	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Municipality fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	1,605,102	1,605,102	1,605,102	1,605,102	1,605,102	1,605,102
Adj. R^2	0.839	0.839	0.839	0.839	0.839	0.839

Table 3: Pix, informality, and deposits

This table reports the panel data regression results on the impact of Pix interacted with the informality indicator on deposits at the bank-municipality level. Pix is an indicator variable that switches to one after the introduction of Pix in November 2020. The sample period is January 2010 to December 2025. Robust standard errors clustered at the bank level are shown in parentheses. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Dep. var.: Ln($Deposits_t$)	(1)	(2)	(3)	(4)	(5)	(6)
Data aggregation level	Bank-Municipality	Bank-Municipality	Bank-Municipality	Municipality	Municipality	Municipality
Pix	0.2805	0.8638**	0.9850***	-0.1295**	0.2364***	0.3354***
	(0.4527)	(0.3651)	(0.3074)	(0.0659)	(0.0413)	(0.0442)
Informality x Pix	0.6584	-0.4571	-0.4984	0.9888***	0.3438***	0.2538***
	(0.4741)	(0.4814)	(0.4038)	(0.0795)	(0.0500)	(0.0544)
Controls						
Ln(Total $Assets_{t-1}$)		0.9682***	1.0027***		0.5083***	0.4808***
		(0.0857)	(0.0973)		(0.0082)	(0.0100)
ROA_{t-1}		4.7599**	3.8005**		3.7354***	2.7279***
		(2.0960)	(1.9133)		(0.2875)	(0.3171)
IP			0.0020***			-0.0009***
			(0.0007)			(0.0001)
COVID-19			-0.2544***			-0.0769***
			(0.0952)			(0.0042)
Bank fixed effects	Yes	Yes	Yes	No	No	No
Municipality fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	1,847,092	1,820,586	1,605,140	642,767	637,922	547,931
Adj. R^2	0.706	0.835	0.832	0.880	0.933	0.940

Table 4: Pix and deposit volatility

This table reports the results on the impact of Pix on deposit volatility at the bank-municipality level. The dependent variable is the deposit volatility (standard deviation) in a 13-month rolling window. In Panel A, Pix is an indicator variable that switches to one after the introduction of Pix in November 2020. In Panel B, the Pix intensity is a hybrid variable, being zero before Pix introduction and the natural log of the Pix volume or quantity after the Pix introduction. The sample period is January 2010 to December 2025. Robust standard errors clustered at the bank level are shown in parentheses. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Panel A: Pix indicator

Dep. var.: Deposit volatility$_t$	(1)	(2)	(3)	(4)	(5)	(6)
Pix$_t$	0.1854*	0.1600***	0.1829*	0.1855***	0.3178**	0.2844***
	(0.1062)	(0.0502)	(0.1003)	(0.0546)	(0.1579)	(0.0815)
Controls						
Ln(Total Assets$_{t-1}$)		-0.0313**		-0.1015***		-0.0893***
		(0.0131)		(0.0154)		(0.0139)
ROA$_{t-1}$		-1.4787**		-1.2269		-1.9345**
		(0.6290)		(1.0674)		(0.9383)
IP$_t$				0.0001		-0.0007**
				(0.0005)		(0.0003)
COVID-19$_t$					-0.3056**	-0.2325***
					(0.1311)	(0.0630)
Bank fixed effects	No	No	Yes	Yes	Yes	Yes
Municipality fixed effects	No	No	Yes	Yes	Yes	Yes
Number of observations	1,847,061	1,820,642	1,847,061	1,605,196	1,847,061	1,605,196
Adj. R^2	0.011	0.014	0.069	0.081	0.086	0.093

Panel B: Pix intensity

Dep. var.: Deposit volatility$_t$	(1)	(2)	(3)	(4)	(5)	(6)
Pix volume$_t$	0.0353***					
	(0.0111)					
Pix quantity$_t$		0.0348***				
		(0.0106)				
Pix volume received$_t$			0.0363***			
			(0.0113)			
Pix volume paid$_t$				0.0337***		
				(0.0108)		
Pix volume individual$_t$					0.0363***	
					(0.0113)	
Pix volume firms$_t$						0.0284***
						(0.0098)
Bank controls$_{t-1}$	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Municipality fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	1,605,158	1,605,158	1,605,158	1,605,158	1,605,158	1,605,158
Adj. R^2	0.176	0.176	0.176	0.176	0.176	0.176

Table 5: Pix, informality, and deposit volatility

This table reports the panel data regression results on the impact of Pix interacted with the informality indicator on deposit volatility at the bank-municipality level. Pix is an indicator variable that switches to one after the introduction of Pix in November 2020. The sample period is January 2010 to December 2025. Robust standard errors clustered at the bank level are shown in parentheses. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Dep. var.: Deposit volatility	(1)	(2)	(3)	(4)	(5)	(6)
Data aggregation level	Bank-Municipality	Bank-Municipality	Bank-Municipality	Municipality	Municipality	Municipality
Pix	0.7163**	0.4744**	0.5509***	0.1665***	0.1242***	0.1026***
	(0.3211)	(0.1853)	(0.1935)	(0.0280)	(0.0211)	(0.0241)
Informality x Pix	-0.6622**	-0.3588*	-0.3361**	-0.1825***	-0.1154***	-0.0856***
	(0.2827)	(0.1826)	(0.1524)	(0.0329)	(0.0250)	(0.0288)
Controls						
Ln(Total Assets t-1)		-0.1144***	-0.0884***		-0.0401***	-0.0391***
		(0.0174)	(0.0139)		(0.0035)	(0.0037)
ROA t-1		-1.7278*	-1.9150**		-1.4290***	-1.1465***
		(1.0221)	(0.9492)		(0.1403)	(0.1442)
IP			-0.0007**			-0.0004***
			(0.0003)			(0.0001)
COVID-19			-0.2326***			-0.0033
			(0.0631)			(0.0030)
Bank fixed effects	Yes	Yes	Yes	No	No	No
Municipality fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	1,847,061	1,820,642	1,605,196	642,742	637,922	547,931
Adj. R2	0.071	0.088	0.093	0.168	0.164	0.166

Table 6: Decomposition of deposit volatility over different time horizons

This table reports the results on the impact of Pix on deposit volatility at the bank-municipality level. The dependent variable is the levels of Wavelets. Pix is an indicator variable that switches to one after the introduction of Pix in November 2020. Robust standard errors clustered at the bank level are shown in parentheses. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively. In Panel A, regressions (1), (2), (3) and (4) correspond to the deposit volatility over 2-3 months, 4-7 months, 8-15 months and 16-32 months, respectively. In Panel B, the dependent variables are the rolling standard deviations of the bandpass-filtered components of ln(deposits) over 1-6 months, 7-12 months, and 12+ months, respectively.

Panel A: Wavelet analysis

Dep. var.: Deposit volatility$_t$	(1)	(2)	(3)	(4)
Horizon	2-3 months	4-7 months	8-15 months	16-32 months
Pix$_t$	0.0095	0.0248***	0.0598***	0.0620***
	(0.0108)	(0.0038)	(0.0161)	(0.0156)
Controls				
Ln(Total Assets$_{t-1}$)	-0.0099***	0.0021	0.0159***	0.0399***
	(0.0025)	(0.0033)	(0.0022)	(0.0049)
ROA$_{t-1}$	-0.2204	0.7220**	-0.1679	-0.3943
	(0.2831)	(0.3499)	(0.1075)	(0.6345)
IP$_t$	-0.0003***	-0.0002***	0.0013***	0.0005***
	(0.0001)	(0.0000)	(0.0002)	(0.0001)
COVID-19$_t$	-0.0078	-0.0214***	-0.0481***	-0.0607***
	(0.0083)	(0.0029)	(0.0114)	(0.0125)
Bank fixed effects	Yes	Yes	Yes	Yes
Municipality fixed effects	Yes	Yes	Yes	Yes
Number of observations	1,186,378	1,186,378	1,186,378	1,186,378
Adj. R^2	0.003	0.006	0.017	0.044

Panel B: Butterworth bandpass analysis

Dep. var.: Deposit volatility$_t$	(1)	(2)	(3)
Horizon	1-6 months	7-12 months	> 12 months
Pix$_t$	0.1916***	0.3321***	20.9068***
	(0.0568)	(0.1224)	(3.8178)
Controls			
Ln(Total Assets$_{t-1}$)	-0.0220	-0.0363***	25.4556***
	(0.0138)	(0.0070)	(2.3503)
ROA$_{t-1}$	0.9252	0.5728	21.7553
	(1.0217)	(1.6418)	(67.7202)
IP$_t$	-0.0024***	-0.0001	0.0243
	(0.0007)	(0.0002)	(0.0165)
COVID-19$_t$	-0.1717***	-0.2726***	-5.8727**
	(0.0516)	(0.0950)	(2.6263)
Bank fixed effects	Yes	Yes	Yes
Municipality fixed effects	Yes	Yes	Yes
Number of observations	1,186,378	1,186,378	1,186,378
Adj. R^2	0.017	0.042	0.850

Table 7: Negative shock to public trust in Pix

This table reports the results of the negative shock to public trust in Pix on deposits in Panel A with Pix indicator, in Panel B we use Pix intensity, in Panel C we show the results on deposits volatility using Pix indicator and in Panel D we use Pix intensity. The columns refer to different aggregation levels of the data: (1) bank-municipality, (2) municipality, (3) bank, and (4) country. *Pix* is an indicator variable that switches to one after the introduction of Pix in November 2020. The variable *Shock to trust in Pix* equals one in January 2025, and zero otherwise. Robust standard errors clustered at the bank level are shown in parentheses. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Panel A: Deposits and Pix indicator

Dep. var.: Ln($Deposits_t$) Data aggregation level	(1) Bank-municipality	(2) Municipality	(3) Bank	(4) Country
Pix_t	0.6169***	0.5475***	1.3722***	0.4866***
	(0.1488)	(0.0060)	(0.1216)	(0.0451)
Shock to trust in Pix_t	-1.6675	-0.2204***	0.0800	-0.1409***
	(1.6809)	(0.0331)	(0.1032)	(0.0311)
Controls				
Ln(Total $Assets_{t-1}$)	1.0031***	0.4838***	0.7301***	0.1416***
	(0.0978)	(0.0100)	(0.0819)	(0.0415)
ROA_{t-1}	4.0873**	2.8818***	8.9267	52.8935***
	(1.9523)	(0.3206)	(6.8883)	(13.4440)
IP_t	0.0017**	-0.0010***	-0.0023	-0.0040***
	(0.0007)	(0.0002)	(0.0028)	(0.0012)
COVID-19_t	-0.2790***	-0.0818***	-0.4534***	-0.0868
	(0.1004)	(0.0042)	(0.0793)	(0.0575)
Bank fixed effects	Yes	No	Yes	No
Municipality fixed effects	Yes	Yes	No	No
Number of observations	1,605,140	547,931	20,708	191
Adj. R^2	0.833	0.940	0.871	0.827

Panel B: Deposits and Pix intensity

Dep. var.: Ln(Deposits)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Data aggregation level	Bank-municipality		Municipality		Bank		Country	
Pix volume	0.0743**		0.0309***		0.0486***		0.0173***	
	(0.0298)		(0.0037)		(0.0043)		(0.0015)	
Pix quantity		0.0761**		0.0414***		0.0620***		0.0221***
		(0.0308)		(0.0037)		(0.0055)		(0.0018)
Shock to trust in Pix ×Pix intensity	0.1512	0.1863	0.1130***	0.1323***	0.0021	0.0020	-0.0049***	-0.0062***
	(0.3050)	(0.2725)	(0.0257)	(0.0255)	(0.0035)	(0.0045)	(0.0010)	(0.0013)
Bank controls$_{t-1}$	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Bank fixed effects	Yes	Yes	No	No	Yes	Yes	No	No
Time fixed effects	Yes	Yes	Yes	Yes	No	No	No	No
Municipality fixed effects	Yes	Yes	Yes	Yes	No	No	No	No
Number of observations	1,605,102	1,605,102	547,931	547,931	20,708	20,708	191	191
Adj. R^2	0.839	0.839	0.946	0.946	0.871	0.872	0.836	0.841

Panel C: Deposit volatility and Pix indicator

Dep. var.: Deposit volatility$_t$	(1)	(2)	(3)	(4)
Data aggregation level	Bank-municipality	Municipality	Bank	Country
Pix$_t$	0.2619***	0.0304***	-0.1022**	0.0020
	(0.0709)	(0.0037)	(0.0393)	(0.0100)
Shock to trust in Pix$_t$	1.3867**	0.1090***	0.0804*	0.0255***
	(0.6554)	(0.0132)	(0.0417)	(0.0067)
Controls				
Ln(Total Assets$_{t-1}$)	-0.0907***	-0.0402***	-0.0992***	-0.0032
	(0.0138)	(0.0037)	(0.0245)	(0.0060)
ROA$_{t-1}$	-2.1973**	-1.2219***	-1.0870	3.6008
	(0.8521)	(0.1463)	(2.3102)	(2.7092)
IP$_t$	-0.0005	-0.0004***	-0.0023***	0.0001
	(0.0004)	(0.0001)	(0.0008)	(0.0003)
COVID-19$_t$	-0.2117***	-0.0010	0.0748**	0.0094
	(0.0531)	(0.0028)	(0.0289)	(0.0112)
Bank fixed effects	Yes	No	Yes	No
Municipality fixed effects	Yes	Yes	No	No
Number of observations	1,605,196	547,931	20,985	192
Adj. R^2	0.107	0.167	0.341	0.045

Panel D: Deposit volatility and Pix intensity

Dep. var.: Deposit volatility	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Data aggregation level	Bank-municipality		Municipality		Bank		Country	
Pix volume	0.0324***		-0.0019		-0.0036**		0.0001	
	(0.0103)		(0.0017)		(0.0014)		(0.0003)	
Pix quantity		0.0321***		-0.0029*		-0.0046**		0.0002
		(0.0099)		(0.0016)		(0.0018)		(0.0004)
Shock to trust in Pix ×Pix intensity	0.3093***	0.2829***	-0.0456***	-0.0486***	0.0028*	0.0036**	0.0009***	0.0011***
	(0.1074)	(0.0959)	(0.0111)	(0.0110)	(0.0014)	(0.0018)	(0.0002)	(0.0003)
Bank controls$_{t-1}$	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Bank fixed effects	Yes	Yes	No	No	Yes	Yes	No	No
Time fixed effects	Yes	Yes	Yes	Yes	No	No	No	No
Municipality fixed effects	Yes	Yes	Yes	Yes	No	No	No	No
Number of observations	1,605,158	1,605,158	547,931	547,931	20,985	20,985	192	192
Adj. R^2	0.178	0.178	0.180	0.180	0.341	0.341	0.046	0.047

Table 8: Effects of Pix on deposits at the municipality and bank level

This table reports the results on the impact of Pix on deposits at the municipality level and the (country-wide) bank level. The dependent variable is ln(Deposits). In Panel A, Pix is an indicator variable that switches to one after the introduction of Pix in November 2020. In Panel B, we use time-varying Pix intensity measures at the municipality level with bank controls and time fixed effects. Pix intensity is a hybrid variable, being zero before Pix launch. Pix intensity is the natural log of their volume or quantity. The sample period is January 2010 to December 2025. Robust standard errors clustered at the municipality or bank level, respectively, are shown in parentheses. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Panel A: Pix indicator

Dep. var.: Ln($Deposits_t$)	(1)	(2)	(3)	(4)
Data aggregation level	Municipality	Municipality	Bank	Bank
Pix	0.9460***	0.5431***	1.2762***	1.3738***
	(0.0153)	(0.0061)	(0.1584)	(0.1220)
Controls				
Ln(Total $Assets_{t-1}$)		0.4829***		0.7301***
		(0.0100)		(0.0819)
ROA_{t-1}		2.7322***		8.9826
		(0.3175)		(6.8795)
IP_t		-0.0009***		-0.0023
		(0.0002)		(0.0028)
COVID-19_t		-0.0776***		-0.4552***
		(0.0042)		(0.0799)
Municipality fixed effects	No	Yes	No	No
Bank fixed effects	No	No	No	Yes
Number of observations	642,767	547,931	20,853	20,708
Adj. R^2	0.052	0.940	0.038	0.871

Panel B: Pix intensity

Dep. var.: Ln(Deposits$_t$) Data aggregation level	(1) Municipality	(2) Municipality	(3) Bank	(4) Bank
Pix volume$_t$	0.0325***		0.0486***	
	(0.0037)		(0.0043)	
Pix quantity$_t$		0.0432***		0.0620***
		(0.0037)		(0.0055)
Bank controls$_{t-1}$	Yes	Yes	Yes	Yes
Municipality fixed effects	Yes	Yes	No	No
Bank fixed effects	No	No	Yes	Yes
Time fixed effects	Yes	Yes	No	No
Number of observations	547,931	547,931	20,708	20,708
Adj. R^2	0.946	0.946	0.871	0.872

Table 9: Effects of Pix on deposit volatility at the municipality and bank level

This table reports the results on the impact of Pix on deposit volatility at the municipality level and (country-wide) bank level. The dependent variable is the deposit volatility (standard deviation) in a 13-month rolling window. In Panel A, Pix is an indicator variable that switches to one after the introduction of Pix in November 2020. In Panel B, the Pix intensity is a hybrid variable, being zero before Pix introduction and the natural log of the Pix volume or quantity after the Pix introduction. Robust standard errors clustered at the municipality or bank level, respectively, are shown in parentheses. The sample period is January 2010 to December 2025. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Panel A: Pix indicator

Dep. var.: Deposit volatility	(1)	(2)	(3)	(4)
Data aggregation level	Municipality	Municipality	Bank	Bank
Pix_t	0.0013	0.0326***	-0.0485	-0.1005**
	(0.0035)	(0.0040)	(0.0304)	(0.0396)
Controls				
Ln(Total $Assets_{t-1}$)		-0.0398***		-0.0992***
		(0.0037)		(0.0244)
ROA_{t-1}		-1.1480***		-1.0336
		(0.1443)		(2.3057)
IP_t		-0.0004***		-0.0023***
		(0.0001)		(0.0008)
COVID-19_t		-0.0031		0.0729**
		(0.0030)		(0.0293)
Municipality fixed effects	No	Yes	No	No
Bank fixed effects	No	No	No	Yes
Number of observations	642,742	547,931	21,138	20,985
Adj. R^2	0.000	0.166	0.002	0.341

Panel B: Pix intensity

Dep. var.: Deposit volatility$_t$	(1)	(2)	(3)	(4)
Data aggregation level	Municipality	Municipality	Bank	Bank
Pix volume$_t$	-0.0026		-0.0035**	
	(0.0018)		(0.0014)	
Pix quantity$_t$		-0.0036**		-0.0045**
		(0.0017)		(0.0018)
Bank controls$_{t-1}$	Yes	Yes	Yes	Yes
Municipality fixed effects	Yes	Yes	No	No
Bank fixed effects	No	No	Yes	Yes
Time fixed effects	Yes	Yes	No	Yes
Number of observations	547,931	547,931	20,985	20,985
Adj. R^2	0.179	0.179	0.341	0.341

Table 10: Heterogenous results by bank size, deposits per capita, and GDP per capita

This table reports the results of the regression using the division of high and low percentile banks on deposits with Pix indicator. The dependent variable is Ln(Deposits). We perform sample splits by bank size (Total assets) in columns (1)-(2), Deposits per capita in columns (3)-(4), and GDP per capital in columns (5)-(6). Pix is an indicator variable that switches to one after the introduction of Pix in November 2020. Robust standard errors clustered at the bank level are shown in parentheses. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Dep. var.: Ln($Deposits_t$)	(1)	(2)	(3)	(4)	(5)	(6)
Split variables	Total assets		Deposits per capita		GDP per capita	
	Low	High	Low	High	Low	High
Pix	1.4899***	0.5458***	0.6295***	0.5595***	0.6679***	0.5352***
	(0.4017)	(0.1242)	(0.1560)	(0.1247)	(0.1393)	(0.1333)
Controls						
IP_t	0.0056	0.0016***	0.0005	0.0027***	0.0002	0.0029***
	(0.0061)	(0.0006)	(0.0007)	(0.0009)	(0.0008)	(0.0009)
Selic	0.4435**	0.0710	0.0232	0.1172*	0.0251	0.1209*
	(0.1996)	(0.0478)	(0.0248)	(0.0704)	(0.0306)	(0.0696)
COVID-19_t	-0.8695***	-0.1787**	-0.1606*	-0.2339***	-0.2065***	-0.2150***
	(0.2109)	(0.0746)	(0.0788)	(0.0785)	(0.0731)	(0.0800)
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Municipality fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	72,120	1,490,449	444,781	1,140,028	559,090	1,025,719
Adj. R^2	0.841	0.806	0.781	0.837	0.818	0.839

Online Appendix

Fast Payment Systems and Deposit Dynamics: Evidence from Brazil's Pix

Table OA1: Pix and deposits with alternative controls

This table reports the panel data regression results on the impact of Pix on deposits at the bank-municipality level. The dependent variable is Ln(Deposits). In Panel A, Pix is an indicator variable that switches to one after the introduction of Pix in November 2020. In Panel B, the Pix intensity is a hybrid variable, being zero before the Pix introduction and the natural log of the Pix volume or quantity after the Pix introduction. The sample period is January 2010 to December 2025. Robust standard errors clustered at the bank level are shown in parentheses. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Panel A: Pix indicator

Dep. var.: Ln(Deposits$_t$)	(1)	(2)	(3)
Pix$_t$	0.5639***	0.5188***	0.4815***
	(0.1310)	(0.1142)	(0.1021)
Selic	0.0990*		
	(0.0553)		
COVID-19 cases (per pop.)		-23.6549***	
		(8.0505)	
COVID-19 deaths			0.0000
			(0.0001)
Bank controls$_{t-1}$	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes
Municipality fixed effects	Yes	Yes	Yes
Number of observations	1,605,140	1,605,140	1,605,140
Adj. R^2	0.832	0.831	0.831

Panel B: Pix intensity

Dep. var.: Ln($Deposits_t$)	(1)	(2)	(3)
Pix volume	0.0297***	0.0758**	0.0740**
	(0.0065)	(0.0297)	(0.0297)
Selic	0.0673		
	(0.0533)		
COVID-19 cases (per pop.)		1.5890*	
		(0.9442)	
COVID-19 deaths			0.0001
			(0.0001)
Bank $controls_{t-1}$	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes
Municipality fixed effects	Yes	Yes	Yes
Number of observations	1,605,102	1,605,102	1,605,102
Adj. R^2	0.832	0.839	0.839

Table OA2: Pix and deposit volatility with alternative controls

This table reports the results on the impact of Pix on deposit volatility at the bank-municipality level. The dependent variable is the deposit volatility (standard deviation) in a 13-month rolling window. In Panel A, Pix is an indicator variable that switches to one after the introduction of Pix in November 2020. In Panel B, the Pix intensity is a hybrid variable, being zero before Pix introduction and the natural log of the Pix volume or quantity after the Pix introduction. The sample period is January 2010 to December 2025. Robust standard errors clustered at the bank level are shown in parentheses. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Panel A: Pix indicator

Dep. var.: Deposit volatility$_t$	(1)	(2)	(3)
Pix$_t$	0.3087***	0.1984***	0.1868***
	(0.0726)	(0.0586)	(0.0548)
Selic	-0.0931**		
	(0.0378)		
COVID-19 cases (per pop.)		-8.2467***	
		(2.6401)	
COVID-19 deaths			-0.0002***
			(0.0000)
Bank controls$_{t-1}$	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes
Municipality fixed effects	Yes	Yes	Yes
Number of observations	1,605,196	1,605,196	1,605,196
Adj. R^2	0.094	0.082	0.081

Panel B: Pix intensity

Dep. var.: Ln($Deposits_t$)	(1)	(2)	(3)
Pix volume	0.0163***	0.0354***	0.0374***
	(0.0038)	(0.0111)	(0.0113)
Selic	-0.1112***		
	(0.0338)		
COVID-19 cases (per pop.)		1.2215***	
		(0.2781)	
COVID-19 deaths			-0.0001***
			(0.0000)
Bank $controls_{t-1}$	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes
Municipality fixed effects	Yes	Yes	Yes
Number of observations	1,605,158	1,605,158	1,605,158
Adj. R^2	0.097	0.177	0.177

Table OA3: Wavelet decomposition of deposit volatility with alternative controls

This table reports the results on the impact of Pix on deposit volatility at the bank-municipality level. The dependent variable is the levels of Wavelets. Pix is an indicator variable that switches to one after the introduction of Pix in November 2020. Robust standard errors clustered at the bank level are shown in parentheses. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively. The regressions (1), (2), (3) and (4) correspond to the deposit volatility over 2-3 months, 4-7 months, 8-15 months and 16-32 months, respectively.

Panel A: Wavelet analysis with Selic

Dep. var.: Deposit volatility$_t$	(1)	(2)	(3)	(4)
Pix$_t$	0.0093	0.0265***	0.0528***	0.0583***
	(0.0107)	(0.0041)	(0.0130)	(0.0152)
Controls				
Ln(Total Assets$_{t-1}$)	-0.0098***	0.0018	0.0170***	0.0405***
	(0.0025)	(0.0034)	(0.0024)	(0.0050)
ROA$_{t-1}$	-0.2210	0.7277**	-0.1911*	-0.4067
	(0.2830)	(0.3479)	(0.1010)	(0.6352)
IP$_t$	-0.0003***	-0.0002***	0.0013***	0.0005***
	(0.0001)	(0.0000)	(0.0002)	(0.0001)
COVID-19$_t$	-0.0076	-0.0237***	-0.0387***	-0.0556***
	(0.0083)	(0.0035)	(0.0073)	(0.0128)
Selic	0.0006	-0.0068***	0.0279**	0.0149
	(0.0022)	(0.0025)	(0.0138)	(0.0122)
Bank fixed effects	Yes	Yes	Yes	Yes
Municipality fixed effects	Yes	Yes	Yes	Yes
Number of observations	1,186,378	1,186,378	1,186,378	1,186,378
Adj. R^2	0.003	0.006	0.017	0.044

Panel B: Wavelet analysis with COVID-19 cases (per pop.)

Dep. var.: Deposit volatility$_t$	(1)	(2)	(3)	(4)
Pix$_t$	0.0062	0.0164***	0.0425***	0.0386***
	(0.0076)	(0.0031)	(0.0119)	(0.0110)
Controls				
Ln(Total Assets$_{t-1}$)	-0.0104***	0.0009	0.0136***	0.0366***
	(0.0027)	(0.0034)	(0.0023)	(0.0053)
ROA$_{t-1}$	-0.1948	0.7866**	-0.0378	-0.2142
	(0.3085)	(0.3465)	(0.0926)	(0.6408)
IP$_t$	-0.0003***	-0.0002***	0.0014***	0.0007***
	(0.0001)	(0.0000)	(0.0003)	(0.0001)
COVID-19 cases (per pop.)	-0.1093	-0.6650***	-2.4076***	-2.0646***
	(0.2913)	(0.1544)	(0.6253)	(0.7031)
Bank fixed effects	Yes	Yes	Yes	Yes
Municipality fixed effects	Yes	Yes	Yes	Yes
Number of observations	1,186,378	1,186,378	1,186,378	1,186,378
Adj. R^2	0.003	0.005	0.014	0.041

Panel C: Wavelet analysis with COVID-19 deaths

Dep. var.: Deposit volatility$_t$	(1)	(2)	(3)	(4)
Pix$_t$	0.0061	0.0154***	0.0386***	0.0353***
	(0.0072)	(0.0029)	(0.0109)	(0.0100)
Controls				
Ln(Total Assets$_{t-1}$)	-0.0104***	0.0006	0.0125***	0.0357***
	(0.0027)	(0.0035)	(0.0024)	(0.0054)
ROA$_{t-1}$	-0.1931	0.7973**	0.0018	-0.1802
	(0.3128)	(0.3451)	(0.0934)	(0.6434)
IP$_t$	-0.0003***	-0.0002***	0.0014***	0.0007***
	(0.0001)	(0.0000)	(0.0003)	(0.0001)
COVID-19 deaths	-0.0000	-0.0000**	-0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Bank fixed effects	Yes	Yes	Yes	Yes
Municipality fixed effects	Yes	Yes	Yes	Yes
Number of observations	1,186,378	1,186,378	1,186,378	1,186,378
Adj. R^2	0.003	0.005	0.014	0.041

Table OA4: Butterworth bandpass analysis with alternative controls

This table reports the results on the impact of Pix on deposit volatility at the bank-municipality level. The dependent variables are the rolling standard deviations of the Butterworth bandpass-filtered components of ln(deposits) over 1-6 months, 7-12 months, and 12+ months, respectively. Pix is an indicator variable that switches to one after the introduction of Pix in November 2020. Robust standard errors clustered at the bank level are shown in parentheses. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Panel A: Butterworth bandpass analysis with Selic

Dep. var.: Deposit volatility$_t$	(1)	(2)	(3)
Pix$_t$	0.2005***	0.3450***	20.6604***
	(0.0560)	(0.1095)	(3.5620)
Controls			
Ln(Total Assets$_{t-1}$)	-0.0234	-0.0384***	25.4959***
	(0.0142)	(0.0074)	(2.3682)
ROA$_{t-1}$	0.9548	0.6158	20.9327
	(1.0123)	(1.5938)	(66.7521)
IP$_t$	-0.0024***	-0.0001	0.0239
	(0.0007)	(0.0002)	(0.0165)
COVID-19$_t$	-0.1838***	-0.2901***	-5.5384**
	(0.0505)	(0.0775)	(2.2234)
Selic	-0.0355***	-0.0516	0.9856
	(0.0087)	(0.0532)	(1.3763)
Bank fixed effects	Yes	Yes	Yes
Municipality fixed effects	Yes	Yes	Yes
Number of observations	1,186,378	1,186,378	1,186,378
Adj. R^2	0.017	0.042	0.850

Panel B: Butterworth bandpass analysis with COVID-19 cases (per pop.)

Dep. var.: Deposit volatility$_t$	(1)	(2)	(3)
Pix$_t$	0.1255***	0.2284***	19.3101***
	(0.0379)	(0.0867)	(3.0845)
Controls			
Ln(Total Assets$_{t-1}$)	-0.0313**	-0.0508***	25.3132***
	(0.0133)	(0.0103)	(2.3131)
ROA$_{t-1}$	1.4335	1.3685	32.5133
	(1.1274)	(1.8485)	(72.1981)
IP$_t$	-0.0018***	0.0008	0.0439**
	(0.0005)	(0.0005)	(0.0172)
COVID-19 cases (per pop.)	-5.9231***	-10.0895***	-601.5845***
	(2.0709)	(3.8270)	(226.7084)
Bank fixed effects	Yes	Yes	Yes
Municipality fixed effects	Yes	Yes	Yes
Number of observations	1,186,378	1,186,378	1,186,378
Adj. R^2	0.015	0.035	0.850

Panel C: Butterworth bandpass analysis with COVID-19 deaths

Dep. var.: Deposit volatility$_t$	(1)	(2)	(3)
Pix$_t$	0.1174***	0.2130***	18.2972***
	(0.0350)	(0.0809)	(2.7174)
Controls			
Ln(Total Assets$_{t-1}$)	-0.0337**	-0.0551***	25.0434***
	(0.0133)	(0.0119)	(2.2934)
ROA$_{t-1}$	1.5208	1.5271	42.6013
	(1.1496)	(1.8920)	(76.6419)
IP$_t$	-0.0018***	0.0008	0.0440**
	(0.0005)	(0.0005)	(0.0171)
COVID-19 deaths	-0.0002***	-0.0001***	0.0016
	(0.0000)	(0.0000)	(0.0029)
Bank fixed effects	Yes	Yes	Yes
Municipality fixed effects	Yes	Yes	Yes
Number of observations	1,186,378	1,186,378	1,186,378
Adj. R^2	0.015	0.034	0.849

Table OA5: Effects of Pix on deposits at the municipality and bank level

This table reports the results on the impact of Pix on deposits at the municipality level and the (country-wide) bank level. The dependent variable is ln(Deposits). In Panel A, Pix is an indicator variable that switches to one after the introduction of Pix in November 2020. In Panel B, we use time-varying Pix intensity measures at the municipality level with bank controls and time fixed effects. Pix intensity is a hybrid variable, being zero before Pix launch. Pix intensity is the natural log of their volume or quantity. The sample period is January 2010 to December 2025. Robust standard errors clustered at the municipality or bank level, respectively, are shown in parentheses. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Panel A: Pix indicator

Dep. var.: Ln($Deposits_t$)	(1)	(2)	(3)	(4)	(5)	(6)
Data aggregation level	Municipality	Municipality	Municipality	Bank	Bank	Bank
Pix	0.5559***	0.5247***	0.5118***	1.3320***	1.3128***	1.2757***
	(0.0066)	(0.0059)	(0.0059)	(0.1172)	(0.1194)	(0.1173)
Controls						
Selic	-0.0486***			0.1577		
	(0.0069)			(0.1167)		
COVID-19_t	-0.0938***	0.4829***		-0.4004***		
	(0.0041)	(0.0100)		(0.0723)		
COVID-19 cases (per pop.)		-8.9974***			-101.4008***	
		(0.3442)			(14.9512)	
COVID-19 deaths			-0.0001			-0.0000***
			(0.0001)			(0.0000)
Bank controls (t-1)	Yes	Yes	Yes	Yes	Yes	Yes
Municipality fixed effects	No	Yes	No	No	No	No
Bank fixed effects	No	No	No	Yes	Yes	Yes
Number of observations	547,931	547,931	547,931	20,708	20,708	20,708
Adj. R^2	0.940	0.940	0.940	0.871	0.871	0.871

Panel B: Pix intensity

Dep. var.: Ln($Deposits_t$)	(1)	(2)	(3)	(4)	(5)	(6)
Data aggregation level	Municipality	Municipality	Municipality	Bank	Bank	Bank
Pix $volume_t$	0.0301***	0.0325***	0.0325***	0.0475***	0.0465***	0.0454***
	(0.0003)	(0.0037)	(0.0037)	(0.0042)	(0.0042)	(0.0042)
Controls						
Selic	-0.0759***			0.1203		
	(0.0070)			(0.1166)		
COVID-19_t	-0.0821***			-0.3824***		
	(0.0041)			(0.0720)		
COVID-19 cases (per pop.)		0.0590			-93.7815***	
		(0.2804)			(14.5762)	
COVID-19 deaths			0.0000			-0.0000***
			(0.0000)			(0.0000)
Bank $controls_{t-1}$	Yes	Yes	Yes	Yes	Yes	Yes
Municipality fixed effects	Yes	Yes	Yes	No	No	No
Bank fixed effects	No	No	No	Yes	Yes	Yes
Time fixed effects	No	Yes	Yes	No	No	No
Number of observations	547,931	547,931	547,931	20,708	20,708	20,708
Adj. R^2	0.941	0.946	0.946	0.872	0.872	0.871

Table OA6: Effects of Pix on deposit volatility at the municipality and bank level

This table reports the results on the impact of Pix on deposit volatility at the municipality level and (country-wide) bank level. The dependent variable is the deposit volatility (standard deviation) in a 13-month rolling window. In Panel A, Pix is an indicator variable that switches to one after the introduction of Pix in November 2020. In Panel B, the Pix intensity is a hybrid variable, being zero before Pix introduction and the natural log of the Pix volume or quantity after the Pix introduction. Robust standard errors clustered at the municipality or bank level, respectively, are shown in parentheses. The sample period is January 2010 to December 2025. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Panel A: Pix indicator

Dep. var.: Deposit volatility	(1)	(2)	(3)	(4)	(5)	(6)
Data aggregation level	Municipality	Municipality	Municipality	Bank	Bank	Bank
Pix_t	0.0456***	0.0309***	0.0313***	-0.0815**	-0.0887**	-0.0841**
	(0.0043)	(0.0032)	(0.0031)	(0.0408)	(0.0372)	(0.0365)
Controls						
Selic	-0.0496***			-0.0711		
	(0.0036)			(0.0439)		
COVID-19_t	-0.0197***			0.0481*		
	(0.0035)			(0.0277)		
COVID-19 cases (per pop.)		0.2871*			14.5681***	
		(0.1476)			(4.5064)	
COVID-19 deaths			-0.0000			0.0000***
			(0.0000)			(0.0000)
Bank $controls_{t-1}$	Yes	Yes	Yes	Yes	Yes	Yes
Municipality fixed effects	Yes	Yes	Yes	No	No	No
Bank fixed effects	No	No	No	Yes	Yes	Yes
Number of observations	547,931	547,931	547,931	20,985	20,985	20,985
Adj. R^2	0.168	0.166	0.166	0.342	0.341	0.340

Panel B: Pix intensity

Dep. var.: Deposit volatility$_t$	(1)	(2)	(3)	(4)	(5)	(6)
Data aggregation level	Municipality	Municipality	Municipality	Bank	Bank	Bank
Pix volume$_t$	0.0025***	-0.0026	-0.0025	-0.0029*	-0.0031**	-0.0030**
	(0.0002)	(0.0018)	(0.0018)	(0.0015)	(0.0013)	(0.0013)
Controls						
Selic	-0.0517***				-0.0696	
	(0.0037)				(0.0444)	
COVID-19$_t$	-0.0185***			0.0462*		
	(0.0033)			(0.0273)		
COVID-19 cases (per pop.)		0.0807			14.0150***	
		(0.1538)			(4.3974)	
COVID-19 deaths			-0.0000			0.0000***
			(0.0000)			(0.0000)
Bank controls$_{t-1}$	Yes	Yes	Yes	Yes	Yes	Yes
Municipality fixed effects	Yes	Yes	No	No	No	No
Bank fixed effects	No	No	Yes	Yes	Yes	Yes
Time fixed effects	No	Yes	Yes	No	No	No
Number of observations	547,931	547,931	547,931	20,985	20,985	20,985
Adj. R^2	0.168	0.179	0.179	0.342	0.341	0.340

Table OA7: Time trend analysis

This table reports the panel data regression results on the impact of Pix on deposits at the bank-municipality level, as in Table 2, except that we additionally include a linear Time trend (year-month number in the sample period). The dependent variable is Ln(Deposits). Pix is an indicator variable that switches to one after the introduction of Pix in November 2020. The sample period is January 2010 to December 2025. Robust standard errors clustered at the bank level are shown in parentheses. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Dep. var.: Ln(Deposits$_t$)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pix	0.1975	0.4317***	0.1674*	0.4852***	0.6181***	0.5803***	0.5427***	0.4850***
	(0.1510)	(0.0663)	(0.0870)	(0.0633)	(0.1007)	(0.0826)	(0.0772)	(0.0633)
Time trend	0.0089***	0.0000	0.0069***	-0.0000	-0.0003	-0.0002	-0.0003	-0.0000
	(0.0018)	(0.0015)	(0.0012)	(0.0011)	(0.0010)	(0.0011)	(0.0011)	(0.0011)
Controls								
IP$_t$				0.0029***	0.0018***			
				(0.0008)	(0.0006)			
Selic						0.0953		
						(0.0641)		
COVID-19$_t$					-0.2566***	-0.2211***		
					(0.0915)	(0.0722)		
COVID-19 cases (per pop.)							-23.9071***	
							(7.5660)	
COVID-19 deaths								0.0000
								(0.0001)
Bank controls$_{t-1}$	No	Yes	No	No	Yes	Yes	Yes	Yes
Municipality fixed effects	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed effects	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	1,847,093	1,820,586	1,847,092	1,605,140	1,605,140	1,605,140	1,605,140	1,605,140
Adj. R^2	0.034	0.383	0.711	0.831	0.832	0.832	0.831	0.831