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

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Abstract

Deposits are the foundation of bank funding and financial stability. We investigate how Brazil's instant payment system, Pix, reshapes deposit dynamics. Pix, launched by the Central Bank of Brazil in November 2020, enables real-time transfers 24/7 at minimal cost. Using monthly bank-municipality panel data from 2010-2025, we examine how Pix changes bank deposit levels and their volatility. We take advantage of three important features of Pix that facilitate identification. First, participation in Pix was mandatory for large banks, making the reform exogenous to bank characteristics and eliminating selection bias. Second, adoption and usage decisions were made by consumers and firms after launch, generating variation in Pix intensity across banks and municipalities. Third, the shift from traditional payment instruments to instant transfers was unanticipated, creating a quasi-natural experiment in deposit dynamics. First, we find that Pix significantly increases bank deposits, consistent with greater financial inclusion and faster money circulation. Second, Pix increases deposit volatility locally, reflecting faster reallocation of funds across institutions. Third, Pix reduces deposit volatility at the national bank level, suggesting banks benefit from geographic diversification of deposit flows. We validate these findings by analyzing a large temporary shock to public trust in Pix in January 2025 triggered by fake news regarding taxation. During that episode, deposit levels temporarily dropped and their volatility spiked. Overall, our study demonstrates that fast payment innovations significantly transform the way how banks attract and retain deposit funding.

This version: March 13, 2026

Keywords: Banks, Payment Systems, Fintech, Deposits, Brazil

JEL classification: E42, G21, G23, G28

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Disclaimer: The views expressed in this paper are those of the authors and do not necessarily reflect those of the Getulio Vargas Foundation.

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 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). At the end of 2024, it was used by more than 93% of Brazilians 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 stability within the financial system. 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 altering depositor 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 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 payments, and due to the higher speed at which money circulates 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, effectively 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 and payment 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 clients (both new and existing)

[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.

create exogenous variation in deposits across municipalities and banks. Third, the substitution effects of Pix with 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 assess 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 various Pix intensity measures, using monthly data from the BCB at the bank-municipality level for the period January 2010 to August 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 shock to public trust in Pix that occurred in January 2025.

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.

Concerning our second hypothesis, we find a significant increase in deposit volatility at the bank-municipality (and municipality) level after the introduction of Pix. A wavelet decomposition and bandpass filter analysis confirm that Pix increased the deposit volatility at the bank-municipality level, especially at longer-term horizons. Interestingly, we also 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 validate these findings analyzing the effects of a large temporary shock to public trust in Pix 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 their volatility spiked temporarily. The government shortly afterwards denied any plans for Pix taxation. As a result, the Pix 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. Digital payments, 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, 2025; Silva et al., 2023). While prior studies focus on payment efficiency and financial inclusion, we analyze how the introduction of Pix influences how 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 traditionally 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 run risk during tightening cycles (Blickle et al., 2025). 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 are linked to higher deposits, lending, and productivity, albeit heterogeneous distributional effects (Fonseca and Matray, 2024). Recent research shows 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 deposit dynamics at the bank level. Our study fills 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. In Section 4, we present our main results on the impact of Pix on deposits and their volatility. In Section 5, we provide evidence on the effects of an exogenous shock to public trust in Pix. In Section 6, we summarize the findings of further checks and robustness tests. Section 7 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 after the start of the COVID-19 crisis, similar to many other countries and mainly due to suppressed consumption expenses during the pandemic (first dashed vertical line), and later an additional significant increase after the introduction of Pix (second dashed vertical line).

(Insert Figure 2 here)

2.2. Hypotheses

The introduction of Pix might have reshaped deposit dynamics for several reasons. First, individuals have progressively replaced 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 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 physical 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 August 2025. In our main analysis, we investigate monthly data at the bank-municipality level (main sample, ESTBAN from the Central Bank of

Brazil). In additional analyses, we investigate data aggregated at the municipality level, national bank level, and country level.

Brazilian banks' balance sheets items are classified as "verbete" (items) 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 1,816,831 observations, with 148 unique bank institutions across 3,724 municipalities in Brazil. In the aggregate municipality-time dataset, there are 631,353 observations. In the bank-time dataset, there are 20,450 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 heterogeneous effects across banks and municipalities. These complementary datasets and measurement strategies capture the impact of the Pix launch and the cross-sectional variation in 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 volume* in the post-period. Equation (1) shows the regression model:

$$\begin{aligned}\text{Ln}(Deposits)_{i,m,t} = {} & \beta_1 Pix_t \text{ (or } Pix\ volume_{m,t}\text{)} + Bank\ controls_{i,m,t} \\ & + IP_{s,t} + \alpha_i + \delta_m + \varepsilon_{i,m,t} \qquad (1)\end{aligned}$$

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

[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.

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:

$$\begin{aligned} \textit{Deposit volatility}_{i,m,t} = {} & \beta_1 \textit{Pix}_t \text{ (or } \textit{Pix volume}_{m,t}\text{)} + \textit{Bank controls}_{i,m,t} \\ & + IP_{s,t} + \alpha_i + \delta_m + \varepsilon_{i,m,t} \qquad (2) \end{aligned}$$

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 in the future (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 evidences 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 qualitative 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 sudden and large exogenous shock to trust in Pix that we can date precisely and that is strong enough to generate measurable variation in deposits and deposit volatility.

3.4 Summary statistics

Table 1 provides summary statistics for the main variables. In the post-Pix period, there is a noticeable increase in both the mean and median values of bank deposits. 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. Regarding the Pix variables, the data indicate a rapid increase of usage.

(Insert Table 1 here)

4. Results

4.1. The impact of Pix on deposits

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 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. Again, 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. The impact of Pix on deposit volatility

Our analysis so far indicates that the introduction of Pix as well as the Pix volumes have had a significantly 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 the remainder, we conduct three tests of our Hypothesis H2 to provide evidence on these questions.

4.2.1. 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 3 shows the corresponding results.

(Insert Table 3 here)

[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.

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. Again, all Pix intensity variables show a positive and significant coefficient at the 1% level.

4.2.2 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 2–4 months (high-frequency, short-term variations); *D2*: Fluctuations with periods of 4–8 months; *D3*: Fluctuations with periods of 8–16 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:

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

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

We then estimate panel data regressions using the reconstructed detail components – the alternative measure of deposit volatility over different time 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 panel fixed effects for banks 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 (2–4 month) fluctuations, while a significant β_{14} indicates an impact on longer-term (16–32 month) dynamics. In all regressions, we employ robust standard errors.

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 4, Panel A presents the results.

(Insert Table 4 here)

One 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 scales (D1 and D3). 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.

4.2.3. Bandpass filter analysis

We further conduct a 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 4, 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 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.

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

We validate the previous evidence on deposit dynamics in an analysis of a large temporary 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 3.

(Insert Figure 3 here)

We exploit the exogenous variation in Pix usage due to this negative shock and analyze its impact on bank deposit dynamics. Figure 4 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 4 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 5 here)

Table 5, Panel A reports the results for deposits using the Pix indicator. While Pix itself continues to have a significantly positive effect on bank deposits in all models, we find a significantly negative effect of the shock only at the municipality (column 2) and country level (column 4). The contrast between the significantly negative effects at the aggregate levels and the non-significant effects at granular levels suggests that the shock affected depositor behavior at a systemic level.

Table 5, Panel B reports the corresponding results using the Pix intensity measures and their interactions with Shock to trust in Pix. Again, the Pix volume and Pix quantify continue to 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 effect in Column (3) and (4) are significantly positive, indicating that users made smaller Pix payments but in greater numbers.

Table 5, 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.

Table 5, 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.

Overall, this analysis complements our previous findings from panel data regressions and strengthens the identification. We show that Pix has a positive baseline effect on both deposits and deposit volatility. These effects were not just dampened but temporarily reversed following the shock to public trust in Pix.

6. Further checks and robustness tests

We conduct further checks and several robustness tests. Specifically, we perform tests for different aggregation levels, time trend specifications, and alternative sample restrictions.

In Table 6, we re-estimate the deposit regressions at the municipality and bank levels. 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.

In Table 7, we report the corresponding tests for deposit volatility. 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.

In Table 8, we conduct robustness tests including a linear time trend in the baseline deposit regressions to control for underlying trends in deposit growth. 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, in Table 9, we estimate our baseline model on subsamples to examine the potential heterogeneity of our main findings. We perform sample splits based on bank size, deposits per capita, and GDP per capita. We find that the coefficient on the Pix indicator remains significantly positive in all subsamples, indicating that the positive effect of Pix on deposits holds 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.

7. 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 large temporary shock to public trust in Pix triggered by fake news regarding payment system taxation.

Our findings are clear and consistent. The introduction of Pix significantly increases both bank deposits and deposit volatility. These findings hold across models controlling for bank characteristics, macroeconomic conditions, and fixed effects. We extend and complement this analysis of deposit volatility with a wavelet decomposition and bandpass filter analysis. We find that 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 national bank level, pointing at geographic diversification benefits within banks. We validate these findings by analyzing the temporary shock to public trust in Pix in January 2025. During that episode, deposit levels temporarily dropped and their volatility spiked. Once, the government publicly denied any plans about taxation, Pix usage and deposits returned to their pre-shock levels.

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

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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.

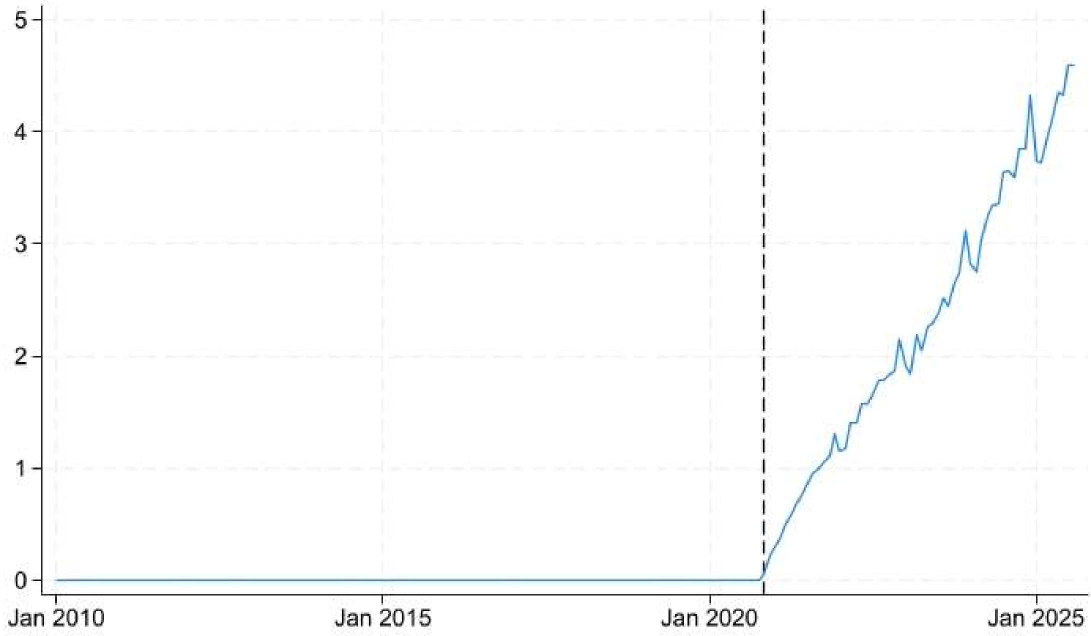

Figure 2: Total deposits at Brazilian banks

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: 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 August 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.

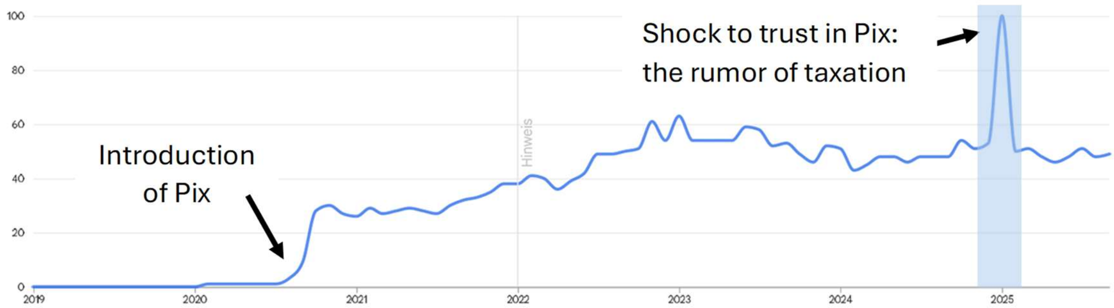

Figure 4: Pix and deposits volumes around the shock to trust in Pix

This figure displays the total absolute Pix volume and the total absolute deposit volume at Brazilian banks around the shock to trust in Pix. The broken 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.

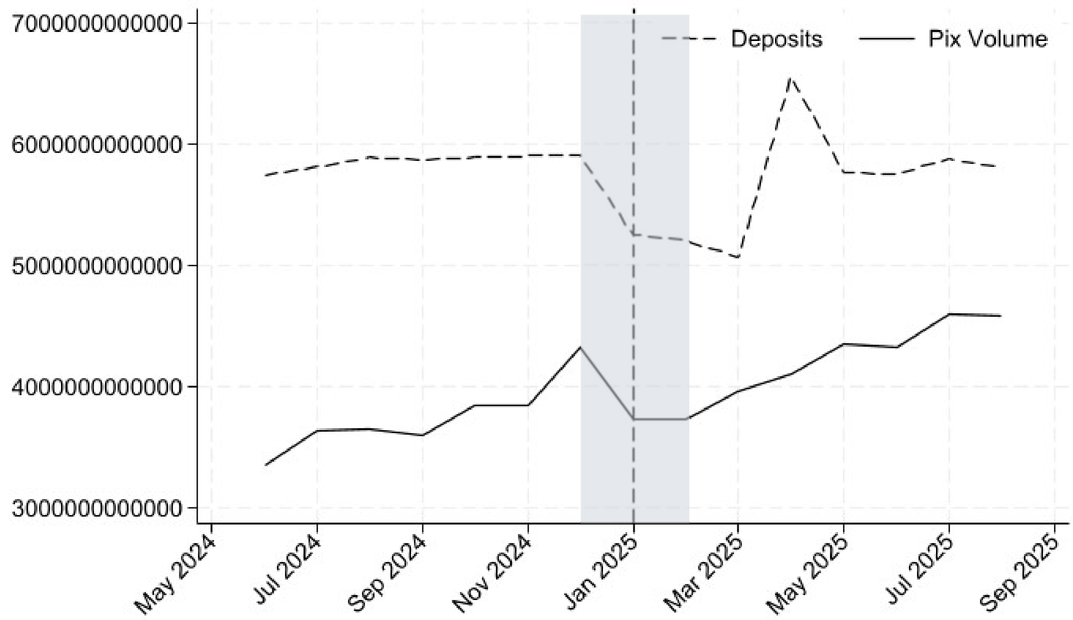

Table 1: Summary statistics

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 August 2025. The Post Pix period is November 2020 to August 2025; the Pre Pix period is January 2010 – October 2020.

Variable	Period	Mean	Median	Std. dev.	Number of obs.
Pix variables					
Pix volume	Post Pix	4,875,493,436	262,189,536	34,896,119,000	500,020
Pix quantity	Post Pix	11,349,282	619,630	83,793,027	500,020
Bank variables					
Deposits	Pre Pix	297,469,281	22,185,046	7,030,358,438	1,316,814
Ln(Deposits)	Pre Pix	16.619	16.915	3.019	1,316,814
Deposit volatility	Pre Pix	19,990,184	1,387,858	444,811,081	1,316,800
ROA	Pre Pix	0.017	0.012	0.017	1,309,573
Total Assets	Pre Pix	323,851,378	72,375,779	828,348,303	1,316,814
Deposits	Post Pix	588,747,884	56,179,084	10,033,300,455	500,073
Ln(Deposits)	Post Pix	17.645	17.844	2.887	500,017
Deposit volatility	Post Pix	130,595,550	3,518,265	3,835,540,466	499,991
ROA	Post Pix	0.018	0.012	0.019	496,695
Total Assets	Post Pix	408,035,719	115,759,025	900,482,350	500,073
Macro-economic conditions					
IP (Industrial production index)	Full	103.843	102.923	16.777	1,650,016

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 August 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$_t$	1.026***	0.424***	0.79450***	0.475***	0.655***	0.586***
	(0.158)	(0.133)	(0.126)	(0.100)	(0.177)	(0.139)
Controls						
Ln(Total Assets$_{t-1}$)		1.072***		0.982***		0.995***
		(0.114)		(0.094)		(0.093)
ROA$_{t-1}$		18.430***		4.677**		3.947**
		(6.576)		(2.144)		(1.910)
IP$_t$				0.003***		0.002***
				(0.001)		(0.001)
COVID-19$_t$					0.293**	-0.243***
					(0.138)	(0.092)
Bank fixed effects	No	No	Yes	Yes	Yes	Yes
Municipality fixed effects	No	No	Yes	Yes	Yes	Yes
Number of observations	1,816,831	1,790,678	1,816,830	1,626,414	1,816,830	1,626,414
Adj. R^2	0.023	0.381	0.705	0.831	0.706	0.832

Panel B: Pix intensity

Dep. var.: Ln($Deposits_t$)	(1)	(2)	(3)	(4)	(5)	(6)
Pix $volume_t$	0.073**					
	(0.030)					
Pix $quantity_t$		0.076**				
		(0.031)				
Pix volume $received_t$			0.075**			
			(0.031)			
Pix volume $paid_t$				0.070**		
				(0.029)		
Pix volume $individuals_t$					0.076**	
					(0.032)	
Pix volume $firms_t$						0.058**
						(0.024)
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	1,626,375	1,626,375	1,626,375	1,626,375	1,626,375	1,626,375
Adj. R^2	0.839	0.839	0.839	0.839	0.839	0.839

Table 3: 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 August 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$_t$	0.111***	0.117***	0.112***	0.135***	0.233***	0.234***
	(0.036)	(0.014)	(0.033)	(0.014)	(0.053)	(0.019)
Controls						
Ln(Total Assets$_{t-1}$)		-0.031**		-0.094***		-0.084***
		(0.012)		(0.017)		(0.016)
ROA$_{t-1}$		-1.566***		-1.747***		-2.313***
		(0.434)		(0.589)		(0.574)
IP$_t$				-0.000**		-0.001***
				(0.000)		(0.000)
COVID-19$_t$					-0.231***	-0.195***
					(0.044)	(0.018)
Bank fixed effects	No	No	Yes	Yes	Yes	Yes
Municipality fixed effects	No	No	Yes	Yes	Yes	Yes
Number of observations	1,712,760	1,700,039	1,712,760	1,541,601	1,712,760	1,541,601
Adj. R^2	0.006	0.012	0.065	0.087	0.079	0.098

Panel B: Pix intensity

Dep. var.: Deposit volatility$_t$	(1)	(2)	(3)	(4)	(5)	(6)
Pix volume$_t$	0.02***					
	(0.01)					
Pix quantity$_t$		0.02***				
		(0.01)				
Pix volume received$_t$			0.02***			
			(0.01)			
Pix volume paid$_t$				0.02***		
				(0.01)		
Pix volume individual$_t$					0.02***	
					(0.01)	
Pix volume firms$_t$						0.02***
						(0.01)
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	1,541,563	1,541,563	1,541,563	1,541,563	1,541,563	1,541,563
Adj. R^2	0.199	0.199	0.199	0.199	0.199	0.199

Table 4: Wavelet decomposition of 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 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 2-4 months, 4-8 months, 8-16 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)
Pix$_t$	-0.00	0.01***	-0.01	0.03**
	(0.01)	(0.00)	(0.01)	(0.01)
Controls				
Ln(Total Assets$_{t-1}$)	0.00	-0.01***	0.00	-0.02*
	(0.01)	(0.00)	(0.01)	(0.01)
ROA$_{t-1}$	-0.01***	0.00*	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
IP$_t$	-0.16	0.21***	-0.60***	-0.23**
	(0.15)	(0.07)	(0.17)	(0.11)
COVID-19$_t$	-0.00	-0.00***	0.00***	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Bank fixed effects	Yes	Yes	Yes	Yes
Municipality fixed effects	Yes	Yes	Yes	Yes
Number of observations	1,207,052	1,207,052	1,207,052	1,207,052
Adj. R^2	0.001	0.005	0.004	0.010

Panel B: Butterworth bandpass analysis

Dep. var.: Deposit volatility$_t$	(1)	(2)	(3)
Pix$_t$	-0.001	0.014**	0.557***
	(0.007)	(0.006)	(0.122)
Controls			
Ln(Total Assets$_{t-1}$)	-0.005***	0.002**	0.895***
	(0.001)	(0.001)	(0.109)
ROA$_{t-1}$	-0.109	-0.281***	3.267
	(0.101)	(0.095)	(2.478)
IP$_t$	-0.000	0.000	0.002***
	(0.000)	(0.000)	(0.001)
COVID-19$_t$	0.003	-0.014***	-0.181**
	(0.006)	(0.005)	(0.079)
Bank fixed effects	Yes	Yes	Yes
Municipality fixed effects	Yes	Yes	Yes
Number of observations	1,207,052	1,207,052	1,207,052
Adj. R^2	0.001	0.000	0.842

Table 5: 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	0.616***	0.543***	1.367***	0.467***
	(0.148)	(0.006)	(0.117)	(0.046)
Shock to trust in Pix_t	-1.657	-0.215***	0.095	-0.105***
	(1.705)	(0.033)	(0.108)	(0.032)
Controls				
Ln(Total $Assets_{t-1}$)	0.997***	0.491***	0.735***	0.135***
	(0.094)	(0.010)	(0.081)	(0.041)
ROA_{t-1}	4.265**	3.377***	7.941	53.323***
	(1.938)	(0.324)	(6.966)	(13.416)
IP_t	0.002**	-0.001***	-0.002	-0.004***
	(0.001)	(0.000)	(0.003)	(0.001)
COVID-19_t	-0.26977***	-0.07186***	-0.43561***	-0.05124
	(0.096)	(0.004)	(0.078)	(0.057)
Bank fixed effects	Yes	No	Yes	No
Municipality fixed effects	Yes	Yes	No	No
Number of observations	1,626,414	557,528	20,307	187
Adj. R^2	0.833	0.936	0.873	0.820

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	0.072**		0.027***		0.049***		0.017***	
	(0.030)		(0.000)		(0.004)		(0.001)	
Pix quantity		0.075**		0.038***		0.062***		0.021***
		(0.031)		(0.004)		(0.005)		(0.001)
Shock to trust in Pix ×Pix intensity	0.141	0.182	0.115***	0.135***	0.002	0.002	-0.004***	-0.005***
	(0.316)	(0.283)	(0.002)	(0.026)	(0.004)	(0.005)	(0.001)	(0.001)
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	1,626,375	1,626,375	557,528	557,528	20,307	20,307	187	187
Adj. R^2	0.839	0.839	0.937	0.937	0.874	0.874	0.828	0.833

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$_t$	0.263***	0.029***	-0.104**	0.002
	(0.056)	(0.004)	(0.040)	(0.010)
Shock to trust in Pix$_t$	1.413**	0.111***	0.078*	0.029***
	(0.697)	(0.013)	(0.041)	(0.008)
Controls				
Ln(Total Assets$_{t-1}$)	-0.082***	-0.035***	-0.100***	-0.003
	(0.014)	(0.003)	(0.025)	(0.006)
ROA$_{t-1}$	-1.580	-1.133***	-0.808	3.870
	(1.185)	(0.142)	(2.378)	(2.828)
IP$_t$	-0.001**	-0.000***	-0.002***	-0.000
	(0.000)	(0.000)	(0.001)	(0.000)
COVID-19$_t$	-0.214***	-0.003	0.075**	0.007
	(0.043)	(0.003)	(0.029)	(0.011)
Bank fixed effects	Yes	No	Yes	No
Municipality fixed effects	Yes	Yes	No	No
Number of observations	1,626,443	557,528	20,580	187
Adj. R^2	0.103	0.152	0.344	0.049

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	0.032***		0.027***		-0.004**		0.0001	
	(0.009)		(0.004)		(0.001)		(0.000)	
Pix quantity		0.032***		0.038***		-0.005**		0.0002
		(0.009)		(0.000)		(0.002)		(0.000)
Shock to trust in Pix ×Pix intensity	0.322***	0.293***	0.115***	0.135***	0.003*	0.003*	0.001***	0.001***
	(0.116)	(0.103)	(0.103)	(0.026)	(0.001)	(0.002)	(0.000)	(0.000)
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	1626404	1626404	557528	557528	20580	20580	187	187
Adj. R^2	0.173	0.173	0.165	0.165	0.344	0.344	0.045	0.047

Table 6: 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 August 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	0.933***	0.538***	1.264***	1.351***
	(0.015)	(0.006)	(0.158)	(0.109)
Controls				
Ln(Total $Assets_{t-1}$)		0.490***		0.743***
		(0.010)		(0.080)
ROA_{t-1}		3.233***		8.738
		(0.321)		(7.713)
IP_t		-0.001***		-0.002
		(0.000)		(0.003)
COVID-19_t		-0.067***		-0.435***
		(0.004)		(0.070)
Municipality fixed effects	No	Yes	No	No
Bank fixed effects	No	No	No	Yes
Number of observations	631353	557528	20450	19480
Adj. R^2	0.049	0.936	0.036	0.878

Panel B: Pix intensity

Dep. var.: Ln(Deposits$_t$)	(1)	(2)	(3)	(4)
Data aggregation level	Municipality	Municipality	Bank	Bank
Pix volume$_t$	0.029***		0.041***	
	(0.004)		(0.004)	
Pix quantity$_t$		0.040***		0.054***
		(0.004)		(0.005)
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	Yes	Yes
Number of observations	557528	557528	19480	19480
Adj. R^2	0.942	0.942	0.877	0.878

Table 7: 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 August 2025. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Panel A: Pix indicator

Dep. var.: Deposit volatility Data aggregation level	(1) Municipality	(2) Municipality	(3) Bank	(4) Bank
Pix_t	0.003	0.02714***	-0.047	-0.110***
	(0.004)	(0.004)	(0.031)	(0.038)
Controls				
Ln(Total $Assets_{t-1}$)		-0.00000***		-0.108***
		(0.000)		(0.025)
ROA_{t-1}		-0.83323***		-1.727
		(0.131)		(2.773)
IP_t		-0.00020***		-0.002***
		(0.000)		(0.001)
COVID-19_t		-0.01478***		0.084***
		(0.003)		(0.028)
Municipality fixed effects	No	Yes	No	No
Bank fixed effects	No	No	No	Yes
Number of observations	631330	557528	20731	19744
Adj. R^2	0.000	0.149	0.002	0.364

Panel B: Pix intensity

Dep. var.: Deposit volatility$_t$	(1)	(2)	(3)	(4)
Data aggregation level	Municipality	Municipality	Bank	Bank
Pix volume$_t$	-0.002		-0.003**	
	(0.002)		(0.001)	
Pix quantity$_t$		-0.003**		-0.003**
		(0.002)		(0.002)
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	Yes	Yes
Number of observations	557528	557528	19744	19744
Adj. R^2	0.161	0.161	0.362	0.362

Table 8: 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 August 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)
Pix_t	0.196	0.429***	0.167*	0.490***	0.614***
	(0.151)	(0.065)	(0.087)	(0.062)	(0.097)
Controls					
Time $trend_t$	0.009***	-0.000	0.007***	-0.000	-0.000
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Ln(Total $Assets_{t-1}$)		1.073***		0.984***	0.998***
		(0.117)		(0.100)	(0.099)
ROA_{t-1}		18.433***		4.687**	3.962**
		(6.572)		(2.147)	(1.923)
IP_t				0.003***	0.002***
				(0.001)	(0.001)
COVID-19_t					-0.244***
					(0.089)
Number of observations	1816831	1790678	1816830	1626414	1626414
Adj. R^2	0.032	0.381	0.710	0.831	0.832

Table 9: 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)
Sample split variables	Total assets		Deposits per capita		GDP per capita	
	Low	High	Low	High	Low	High
Pix$_t$	1.581***	0.555***	0.624***	0.589***	0.666***	0.563***
	(0.382)	(0.130)	(0.150)	(0.136)	(0.141)	(0.142)
Controls						
Ln(Total Assets$_{t-1}$)	1.327***	0.915***	0.748***	1.063***	0.745***	1.094***
	(0.219)	(0.089)	(0.066)	(0.119)	(0.075)	(0.127)
ROA$_{t-1}$	15.714***	1.882	4.069***	3.844	2.937*	3.966
	(5.587)	(1.499)	(1.263)	(2.525)	(1.548)	(2.503)
IP$_t$	0.006	0.001***	0.000	0.003***	0.000	0.003***
	(0.005)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
COVID-19$_t$	-0.948***	-0.194**	-0.157**	-0.265***	-0.200***	-0.250**
	(0.228)	(0.083)	(0.070)	(0.095)	(0.072)	(0.096)
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Municipality fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	75609	1507371	454157	1149315	580809	1022663
Adj. R^2	0.842	0.808	0.776	0.838	0.814	0.840