

Digital Transformation and Financial Inclusion: The Case of Instant Payments in Brazil

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Abstract

Pix represented one of the most profound recent transformations in Brazil's payment system by introducing a low-cost, interoperable, and public instant payment infrastructure available throughout the country in November 2020. This paper investigates how Pix diffusion is associated with changes in local banking markets. The results indicate that Pix expansion is associated with faster growth in total deposits and with shifts in deposit composition toward more liquid accounts in municipalities with lower initial digital infrastructure. These municipalities also experience stronger credit expansion, particularly in rural credit, while real estate credit responds little to the diffusion of instant payments. Bank balance sheets adjust with increases in total assets and liquidity and a relative decline in securities holdings and equity, suggesting an expansion of intermediation funded by deposits. Taken together, the findings suggest that a public and interoperable instant payment infrastructure can foster financial deepening and broaden access to formal banking services, especially in municipalities that were initially more digitally constrained.

Keywords: Pix, instant payments, financial inclusion, banking markets, deposits, credit expansion, digital infrastructure, Brazil.

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1. Introduction

The rapid diffusion of digital financial technologies has transformed the way households and firms interact with the banking system. Innovations in payment systems reduce transaction costs, increase speed and reliability, and expand access to electronic transactions, with potentially far-reaching consequences for financial inclusion and local financial intermediation. These effects are especially relevant in emerging economies, where cash reliance, limited physical banking infrastructure, and large unbanked populations have historically constrained participation in the formal financial system.

In Brazil, the introduction of Pix by the Central Bank in November 2020 marked a structural turning point in the national payment landscape. By enabling instant, low-cost, and continuously available account-to-account transfers, Pix rapidly became one of the dominant electronic payment instruments in the country within only a few years. Unlike traditional payment methods such as TED and DOC, Pix eliminated fixed fees for individuals and substantially reduced operational and intermediation costs for merchants and financial institutions.

Pix was implemented simultaneously across the country and immediately became available to all regulated institutions. Thus, this centralized and uniform rollout, combined with a heterogeneous diffusion in usage intensity among municipalities, provides a suitable setting to study how reductions in payment frictions affect local banking outcomes.

By lowering the cost and increasing the speed and reliability of transfers, Pix changes how households and firms manage liquidity, receive income, and make payments. These changes can increase the demand for transaction balances, facilitate the formalization of economic activity, and improve the ability of borrowers to pay debt. In this sense, instant payments can influence both deposit mobilization and credit provision, particularly in areas where the digital infrastructure was previously limited and payment frictions were more binding. Based on these mechanisms, we formulate two testable hypotheses. First, the diffusion of Pix increases the level of bank deposits and affects their composition, potentially expanding more liquid balances held within the banking system, with stronger effects in municipalities characterized by lower pre-existing levels of digital readiness. Second, Pix adoption is associated with higher credit provision, reflecting improved liquidity management, reduced transaction costs, and enhanced repayment capacity, again with more pronounced effects in municipalities with less digital connectivity.

To do this, we analyze changes in the level and composition of bank deposits, including check-

ing, savings, time, and total deposits. Second, we examine variations in credit outcomes, both in aggregate and in specific modalities such as mortgage and rural credit. By analyzing deposits and credit together, the paper provides an integrated view of how innovations in instant payment spread through local financial systems.

A central feature of the analysis is the exploration of heterogeneity between municipalities with different levels of digital readiness prior to the introduction of Pix, proxied by penetration of mobile phones. This dimension allows us to assess whether the effects of instant payments are stronger in areas initially more constrained by limited digital infrastructure and higher transaction costs, where the reduction in payment frictions may represent a larger shock to local financial intermediation.

Our empirical strategy combines a municipality–month panel covering the period from 2016 to 2024 with an event-study design that exploits the nationwide rollout of Pix in November 2020 and the cross-sectional variation in pre-Pix mobile penetration. In addition, we estimate panel regressions that relate the continuous variation in Pix usage intensity to financial outcomes. All specifications include municipality and time fixed effects, as well as a rich set of socioeconomic controls, allowing us to isolate within-municipality changes over time while accounting for common macroeconomic and institutional shocks.

This study contributes to the literature on financial innovation and payment systems in several ways. First, it provides new evidence on the local effects of an instant payment system in a large emerging economy using detailed administrative data at the municipality level. Second, it highlights the role of digital infrastructure as a key mediator in shaping the impact of payment technologies on financial intermediation. Third, by jointly examining deposits and credit outcomes, the paper offers a comprehensive perspective on how reductions in payment frictions translate into changes in liquidity management and lending activity. More broadly, the results inform policy discussions on the design of public digital payment infrastructures and their potential to foster financial deepening in emerging markets.

This paper is organized into six sections. Section 2 provides the institutional and financial background of Pix and the Brazilian banking system. Section 3 discusses the related literature. Section 4 describes the data sources and the empirical strategy. Section 5 presents the main results on the composition of deposits and credit outcomes. Section 6 concludes.

2. Institutional and Financial Background in Brazil

The introduction of a new payment technology does not necessarily imply a proportional increase in total transaction volume. In payment markets, innovations typically operate through substitution mechanisms across existing instruments. When a new instrument reduces transaction costs, increases convenience, improves interoperability, or accelerates settlement, users tend to reallocate transactions away from less efficient methods toward the new alternative. The magnitude and direction of substitution depend on the functional overlap between instruments. Payment methods that perform similar roles in day to day transactions are more likely to be displaced, whereas instruments that provide additional services, such as embedded credit or liquidity smoothing, may experience more limited direct substitution.

In this context, the economic impact of Pix should be interpreted not merely as the introduction of an additional payment channel but as a reorganization of the payment ecosystem. Because Pix enables real time, low cost, account to account transfers with universal interoperability and continuous availability, it overlaps functionally with several existing instruments, including direct debit, debit cards, and informal cash payments. The degree of substitution in each case depends on the relative transaction costs, institutional constraints, and user preferences.

Figure 1 illustrates the evolution of the composition of electronic payment methods in Brazil between 2017 and 2024. Prior to the introduction of Pix in late 2020, electronic payments were primarily dominated by bank slips, direct debit arrangements, and card-based instruments. Bank slips accounted for the largest share of transactions during the pre-Pix period, while debit and credit cards represented a stable component of retail payments.

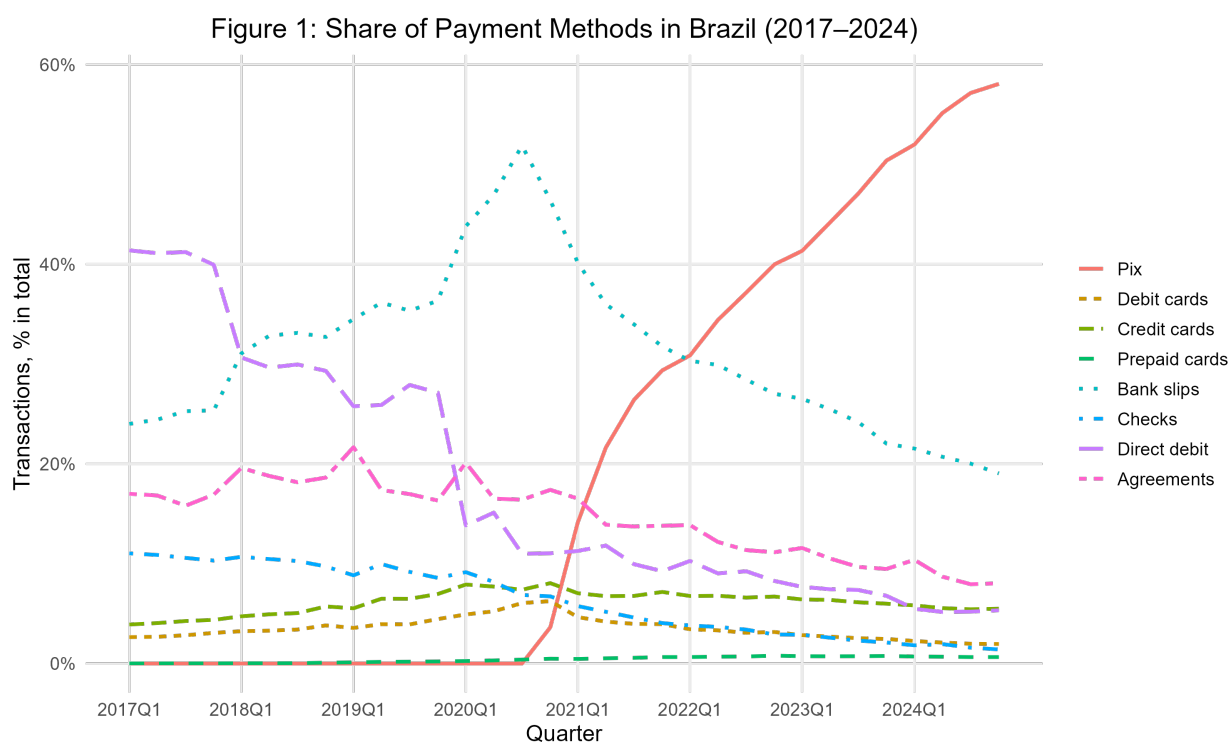
Following the nationwide rollout of Pix, its adoption increased rapidly and it quickly became the dominant electronic payment method. Within a few years, Pix surpassed all other instruments in terms of transaction share. This expansion coincided with a sharp decline in direct debit and agreements, suggesting substantial substitution in recurring and account-based payments.

Other traditional payment instruments also exhibit declining trends after 2020. Bank slips and checks show a steady reduction over time, indicating a broader transition away from legacy payment systems. Debit card usage declines moderately, suggesting partial substitution in retail transactions where Pix offers a faster and lower-cost alternative. In contrast, credit card transactions remain comparatively stable, reflecting their dual role as both a

payment instrument and a source of short-term financing.

Although cash transactions are not directly observed in the dataset, the magnitude and speed of Pix adoption suggest that substitution likely extends beyond the electronic instruments shown in the figure. The rapid expansion of instant digital transfers is consistent with a broader shift away from cash toward formal digital payment systems. Overall, the figure indicates that Pix did not simply introduce an additional payment method but contributed to a substantial reallocation in the composition of payment instruments used by households and firms in Brazil.

Figure 1: Share of Electronic Payment Methods in Brazil (2016–2024)



Note: The figure reports the quarterly share of selected electronic payment methods in total electronic transactions in Brazil between 2017 and 2024. Data are from the Central Bank of Brazil (ESTBAN). Cash transactions are not available in the dataset, so the figure includes only electronic payment instruments. Debit card transactions correspond to payments made with a card directly linked to a bank account, with immediate debit of funds. Credit card transactions refer to payments made using a credit line provided by a financial institution and settled at a later date. Bank slips are payment orders typically used for bill payments and commercial transactions. Direct debit refers to automated withdrawals authorized by the payer, usually for recurring payments such as utilities or subscriptions. Pix is an instant payment system operated by the Central Bank of Brazil that enables real-time, low-cost, account-to-account transfers available 24 hours a day.

This discussion motivates us to take a closer look at the institutional foundations and operational design of Pix. The next subsections provide this background in two steps. Section 2.1 describes the institutional evolution of the Brazilian payment system and situates Pix within a sequence of coordinated reforms that expanded interoperability and lowered settlement risk. Subsection 2.2 then explains how Pix works in practice, detailing its core features, transaction architecture, and the channels through which instant payments can reduce frictions and reshape payment behavior.

2.1. Institutional Evolution of the Brazilian Payment System

The modernization of the Brazilian payment system occurred through a series of coordinated institutional reforms led primarily by the Central Bank, as shown in Table 1. The early 2000s reforms established the legal and operational foundations of real-time gross settlement and electronic interbank transfers, significantly reducing systemic risk and improving the efficiency of interbank clearing. Subsequent reforms, including the regulation of payment institutions in 2013 and the phased implementation of Open Banking and Open Finance between 2019 and 2022, strengthened interoperability, competition, and digital integration within the financial system. The launch of Pix in 2020 represents the consolidation of this trajectory, introducing a low-cost, 24/7 instant infrastructure that expanded access to digital payments and reduced transaction frictions.

Table 1: Formal Policy Innovations in the Brazilian Payment System

| Year | Policy Innovation | Authority | Main Contribution |
|-----------|---|-----------------------------------|---|
| 2001 | Law 10.214 (Legal Framework of the Brazilian Payment System) | Federal Government / Central Bank | Establishment of the legal foundation for settlement finality, risk management, and systemic stability in payment systems |
| 2002 | Reform of the Brazilian Payment System (SPB) and creation of STR (RTGS) | Central Bank | Establishment of real-time gross settlement infrastructure and modernization of interbank clearing |
| 2002 | TED (Electronic Funds Transfer System) | Central Bank | Introduction of same-day interbank electronic transfers |
| 2013 | Law 12.865 (Payment Institutions Regulation) | Federal Government / Central Bank | Creation of the legal category of payment institutions, enabling fintech entry and expanding competition in digital payments |
| 2019–2022 | Open Banking / Open Finance (Phased Implementation) | Central Bank | Gradual implementation of standardized data-sharing and interoperability rules to promote competition and financial integration |
| 2020 | Pix Instant Payment System | Central Bank | Implementation of a 24/7 instant, low-cost, interoperable payment system |
| 2023 | Pix Integration into Government Payments | Federal Government / Central Bank | Adoption of Pix for taxes, public services, and social transfers |
| 2025 | Pix Automático (Recurring Payments) | Central Bank | Introduction of automatic recurring payments within the Pix infrastructure |
| 2025 | Pix Parcelado (Installment Payments) | Central Bank | Enables installment-based payments through the Pix system |

Notes: The table includes major formal institutional and regulatory innovations introduced by the Central Bank of Brazil or the federal government. These reforms reflect the gradual transition from traditional clearing-based payments to a real-time, interoperable digital payment infrastructure.

Source: Central Bank of Brazil; BIS Committee on Payments and Market Infrastructures; World Bank Fast Payments Report.

This institutional evolution provides the foundation for our empirical analysis. By lowering transaction costs and standardizing digital payment infrastructure nationwide, Pix represents a structural shift in the retail payment environment rather than an isolated technological innovation. In particular, the reduction in payment frictions and the expansion of interoperable digital access are likely to affect liquidity management, deposit mobilization, and credit dynamics at the local level. These effects are expected to be heterogeneous across municipalities, especially depending on their pre-existing level of digital readiness, proxied by mobile penetration prior to the introduction of Pix.

While Table 1 highlights the domestic institutional trajectory that culminated in the creation of Pix, it is also important to situate this reform within the broader regional transformation of retail payment systems. Over the past decade, several Latin American and Caribbean countries have implemented fast retail payment systems (FRPS), reflecting a common policy effort to modernize payment infrastructures, reduce transaction costs, and expand digital financial inclusion. Comparing these experiences helps clarify which features of Pix are part

of a regional trend and which reflect distinctive institutional choices in Brazil.

Table 2 places Pix within the broader regional expansion of fast retail payment systems (FRPS) in Latin America and the Caribbean. The diffusion of instant or near-instant account-to-account transfer infrastructures has been widespread across the region, although institutional design varies substantially (IDB, 2025). As shown in the table, countries differ in governance structure — ranging from central bank-led systems to private or hybrid arrangements — as well as in the degree of interoperability, mobile integration, and coordination with other components of the financial system.

The regional comparison suggests that the economic relevance of these systems does not depend solely on the availability of real-time settlement technology, but also on complementary institutional features such as regulatory coordination, pricing structure, integration with government payments, and levels of digital readiness. From this perspective, Pix represents a relatively comprehensive institutional arrangement that combines central bank leadership, broad interoperability, continuous availability, and low transaction costs. Therefore, regional evidence indicates that Brazil’s experience should be understood as part of a larger digital transformation process, whose economic effects are likely to vary according to pre-existing technological and institutional conditions.

Table 2: Fast Retail Payment Systems in Latin America and the Caribbean

| Country | System(s) | Operator | Operational Feature |
|----------------------------|--------------------------------------|-------------------------------------|--|
| Mexico | SPEI, CoDi, Dimo | Public | Real-time interbank transfers with QR-based mobile payment functionality |
| Dominican Republic | Transfer 365 | Private | Instant 24/7 account-to-account transfers |
| Costa Rica | SINPE Móvil | Public | Mobile-number linked instant bank transfers |
| El Salvador | ACH Xpress | Private | Fast ACH clearing with near-real-time settlement |
| Guatemala | Electronic transfers | Private | Traditional electronic banking transfer system |
| Honduras | Bre-b, Transfiya, Entrecuentas | Private | Mobile-enabled instant and near-instant transfers |
| Nicaragua | SPI, Pago Directo (WIP) | Private | Interbank instant transfer infrastructure under development |
| Panama | Wallet interoperability, QR payments | Private | Interoperable digital wallet and QR payment ecosystem |
| Colombia | BCB QR | Public and Private | QR-based interoperable payment infrastructure |
| Venezuela | PMIB – Pago Móvil BDV | Public | Mobile-number based instant transfers |
| Guyana / Suriname | Real-time payment system | Hybrid regional system | Domestic real-time clearing network |
| Caribbean (regional) | APSSS | Multi-institutional regional system | Regional cross-border instant payment platform |
| Central America (regional) | Unired ACH | Regional payment network | Regional ACH-based clearing network |
| Brazil | Pix | Public | Instant 24/7 transfers using payment keys and QR codes |
| Argentina | Transferencias 3.0 | Public | Interoperable QR-based instant payment ecosystem |
| Uruguay | Toke – PCT | Public | Mobile instant transfers integrated with banking system |
| Paraguay | SIPAP | Public | Real-time interbank transfer infrastructure |
| Chile | Electronic fund transfers | Private | Near-real-time electronic banking transfers |
| Peru | Interbank transfers and QR payments | Private | Mobile-enabled interoperable QR payment ecosystem |
| Bolivia | SPI | Private | Fast interbank electronic transfer system |

Notes: Fast retail payment systems (FRPS) facilitate instant or near-instant account-to-account transfers, typically operating 24 hours a day and supporting mobile-based payments such as QR codes and digital wallets. Hybrid or regional systems are operated jointly by multiple central banks or financial institutions and cannot be classified as purely public or private.

Source: IDB staff calculations based on Aurazo et al. (2024, 2025), Inter-American Development Bank (2025), BIS Committee on Payments and Market Infrastructures, and publicly available central bank data.

2.2. How Pix Works

Instant payment systems in Brazil were designed to reduce transaction frictions and expand access to low-cost electronic payments. Within this framework, Pix enables transfers of funds between transaction accounts to be executed within seconds, at any time of day and on any day of the week, including non-business days. Payment initiation does not require the beneficiary’s full bank account information; instead, transactions can be started using

simplified identifiers, such as Pix aliases, or through static or dynamic QR codes. This design reduces informational frictions, simplifies the user experience, and reduces coordination costs associated with electronic transactions (Central Bank of Brazil , 2024).

Beyond convenience, the transactional architecture of Pix is structured to reduce acceptance costs for merchants and firms. By relying on a public and fully interoperable infrastructure with fewer intermediaries than traditional payment instruments, Pix allows transactions to be processed individually, in an irrevocable manner, and settled in real time. Immediate notification to both the payer and the payee ensures certainty of payment completion and instantaneous availability of funds to the recipient. These features mitigate liquidity constraints associated with payment delays and reduce working-capital needs, thereby limiting the reliance on short-term credit for transactional purposes (Central Bank of Brazil , 2024).

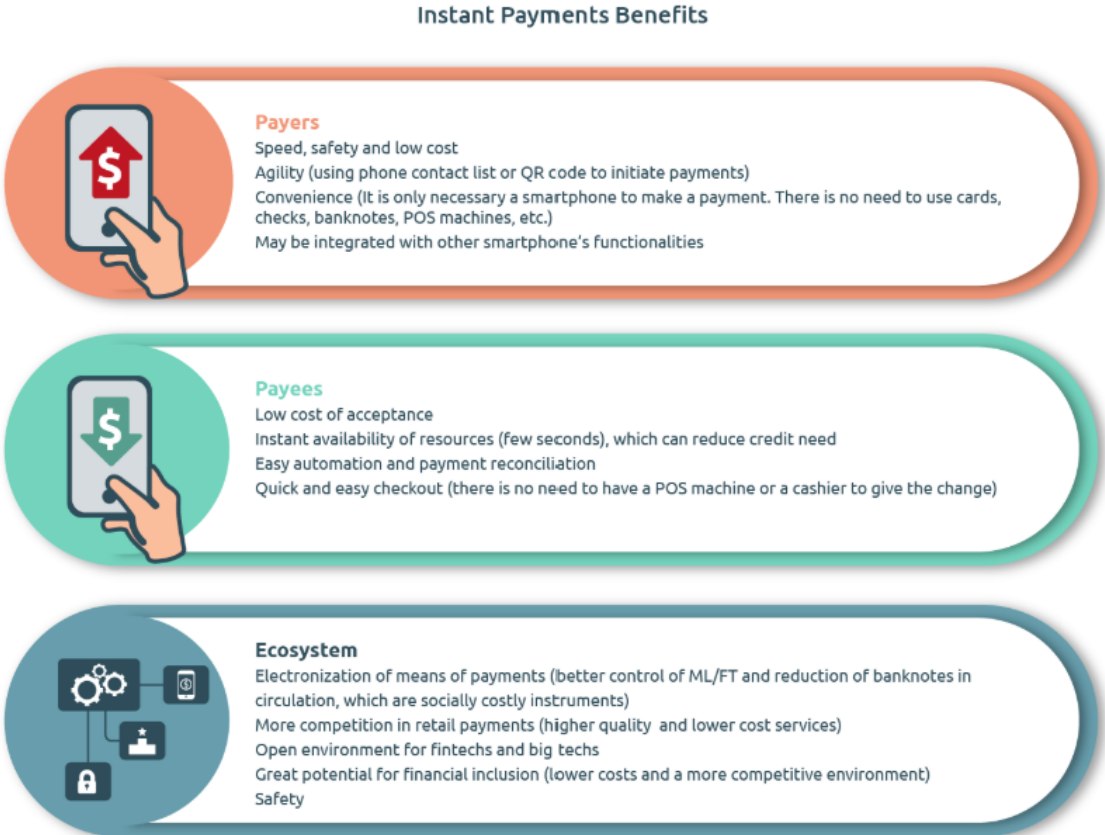
Pix supports a broad set of transaction types, including person-to-person (P2P), person-to-business (P2B), business-to-business (B2B), person-to-government (P2G), and business-to-government (B2G) payments. This wide scope of applicability reflects its design as a general-purpose retail payment instrument, suitable for both private and public sector transactions. Transactions are processed one by one rather than in batches, which distinguishes Pix from legacy interbank transfer systems designed around fixed settlement windows and operational cutoffs. As a result, Pix operates continuously and independently of the banking calendar, allowing payments to be finalized at any time of day.

The institutional design of Pix does not eliminate pre-existing payment instruments but rather integrates them into a broader retail payments ecosystem. Traditional instruments such as interbank transfers (TED and DOC), bank slips (boletos), and debit and credit cards continue to coexist with Pix, and the choice of payment method remains at the discretion of the end user (Central Bank of Brazil , 2024). In this sense, Pix expands the range of payment options available to users. Importantly, Pix is not simply a faster version of legacy transfer systems; it is built on a distinct technological and institutional architecture centered on full automation and a centralized clearing and settlement infrastructure operated by the Central Bank of Brazil.

Figure 2 summarizes these operational features and economic mechanisms. The diagram organizes the benefits of instant payments into three dimensions: payers, payees, and the payment ecosystem. For payers, Pix provides speed, safety and convenience by enabling payments through simplified identifiers such as QR codes or aliases, reducing informational friction and improving usability. For payees, the system lowers acceptance costs and ensures immediate availability of funds, which facilitates automation and reconciliation of payments

and mitigates liquidity constraints and working-capital needs. At the ecosystem level, Pix contributes to the digitization of retail payments, the reduction of cash usage, and a more competitive and open market structure, fostering entry by new providers and promoting financial inclusion. By lowering fixed and variable transaction costs and standardizing the payment infrastructure across institutions, Pix has the potential to reshape user behavior, merchant acceptance decisions, and competitive conditions in the banking and payments markets.

Figure 2: Economic Benefits of Instant Payments (Pix)



Note: The figure illustrates the main benefits of instant payment systems for payers, payees, and the payment ecosystem. *Source:* Central Bank of Brazil (2024), “Pix: Instant Payment System” (Central Bank of Brazil , 2024).

3. Literature Review

Research on payment behavior examines how consumers choose among alternative instruments and how technological change reshapes this decision. Micro-level evidence shows that the choice between cash, debit, credit, and electronic payments depends on transaction size, liquidity constraints, and relative transaction costs. Substitution across instruments varies with purchase value and convenience, and both fixed and marginal costs play a central role in shaping payment behavior (Arango and Taylor, 2008; Bolt et al., 2010; Klee, 2008). This evidence provides a microeconomic foundation for understanding how reductions in transaction costs shift the composition of payment usage and induce substitution away from cash toward electronic instruments.

Theoretical models of money demand that incorporate payment technologies highlight how reductions in transaction frictions alter the optimal allocation of monetary holdings. Improvements in payment efficiency can reduce the demand for currency relative to interest-bearing assets and reshape the liquidity structure of the economy (Alvarez and Lippi, 2009). Technological change in payment systems therefore affects not only the choice of point-of-sale instruments but also the allocation between cash held outside banks and demandable deposits. This mechanism establishes a direct channel linking instant payment innovations to deposit mobilization and bank funding structures.

The work on technological change in banking further emphasizes that digital financial innovations shape competitive dynamics. Improvements in payment and financial technologies can weaken the advantages of incumbents tied to legacy infrastructures and alter the market structure (Sarkisyan, 2025; Vives, 2019). Evidence from Brazil shows that the introduction of Pix intensified competition in deposit markets, facilitating entry and expanding deposit mobilization by smaller banks (Sarkisyan, 2025). Digital innovation in a more general way reduces information and transaction costs and expands access to financial services, with implications for both competition and intermediation (Philippon, 2020). Together, these mechanisms suggest that instant payment systems can influence not only payment behavior but also the structure of local banking markets.

Empirical analyzes of Pix provide support for these channels. Its rollout is associated with wage effects concentrated in cash-intensive activities, consistent with lower transaction costs and improved payment efficiency (Burga et al., 2025). Increased Pix usage is related to a higher share of demandable deposits, indicating adjustments in household liquidity management and bank funding composition (Gonzalez et al., 2025). Exogenous shocks such as natural disasters have also accelerated adoption in municipalities, highlighting their scala-

bility and resilience as payment infrastructure (Barros Jr. et al., 2025).

The Brazilian case fits within the broader international diffusion of fast payment systems. Countries that introduce real-time settlement platforms have experienced rapid growth in the use of digital payments, lower transaction frictions, and increased reliance on bank accounts, particularly where electronic instruments were previously limited (Auer et al., 2020; Adrian and Mancini-Griffoli, 2019). In Latin America, adoption patterns reflect the importance of interoperability, regulatory coordination, and public sector integration (IDB, 2025). This global transformation provides an important comparative backdrop for evaluating Pix.

At the same time, Pix builds on earlier institutional reforms in Brazil. The modernization of the Brazilian Payment System (SPB) in the early 2000s, including the implementation of real-time gross settlement and legal reforms strengthening settlement finality, reduced systemic risk, and improved interbank efficiency (BIS 2011). Enhanced liquidity management and greater confidence in settlement infrastructure created a stable environment for financial intermediation. Broader improvements in financial infrastructure and regulatory quality are associated with deeper intermediation and sustained deposit growth (Levine, 1997; Beck et al., 2000). Financial inclusion policies further expanded access to formal banking services and increased household participation in the financial system (Beck et al., 2007; Fonseca et al., 2024). The expansion of deposits in Brazil therefore reflects a cumulative institutional process rather than a single technological break.

The economic effects of payment innovation are unlikely to be spatially uniform. The diffusion of general-purpose technologies depends on the local absorptive capacity, and the digital infrastructure influences firm performance and labor outcomes (Comin and Hobijn, 2010; Hjort and Poulsen, 2019). The complementarities between information and communication technologies and economic activity reinforce the importance of digital readiness (Goldfarb and Tucker, 2019). These considerations motivate an examination of heterogeneous municipal-level effects depending on pre-existing mobile penetration.

Digital payments also have broader welfare implications. Cross-country differences in account ownership and usage remain substantial (Demirgüç-Kunt et al., 2020), and payment systems often serve as entry points into formal financial participation (Allen et al., 2016). Micro-level evidence shows that digital payment technologies reduce transaction costs and improve risk sharing (Suri and Jack, 2016; Jack and Suri, 2014; Klapper and Singer, 2016). Within this broader context, this paper provides municipal-level evidence on how the diffusion of a nationwide instant payment system is associated with deposit mobilization, credit provision, and local banking outcomes, emphasizing the role of pre-existing digital infrastructure in

shaping heterogeneous effects.

4. Data and Methodology

This section describes the data sources, the construction of variables, and the empirical strategy used in the analysis. We first present the administrative and statistical datasets that form the municipality-level panel, detailing the measurement of banking outcomes, Pix usage, and digital infrastructure. We then outline the set of socioeconomic covariates and the econometric framework used to identify the association between Pix diffusion and local banking outcomes.

4.1. Data

The empirical analysis is based on the integration of administrative and statistical data from official Brazilian sources, organized into a balanced municipality-month panel covering the period from January 2016 to December 2024. All datasets are merged using the official IBGE municipality code, ensuring spatial consistency over time. All monetary variables are expressed in Brazilian reais (BRL).

Banking data. Information on deposits, credit, bank assets and local market structure is obtained from *Estatísticas Bancárias por Município* (ESTBAN), provided by the Central Bank of Brazil. ESTBAN reports monthly balance-sheet and credit information for financial institutions with physical presence at the municipality level, allowing for a detailed characterization of local banking activity.

From ESTBAN, we construct measures of total deposits and deposit composition (checking, savings, and time deposits), total credit, and specific credit modalities (rural credit and real estate credit), as well as total bank assets. All monetary variables are expressed in Brazilian reais (BRL) and normalized per capita using municipal population estimates from the Brazilian Institute of Geography and Statistics (IBGE).

Pix usage. Data on Pix usage are obtained from the Open Data Portal of the Central Bank of Brazil, which reports monthly municipal-level information on the value of Pix transactions. Let m denote municipalities and t denote months. Our main explanatory variable is constructed as the natural logarithm of one plus the value of Pix transactions in the municipality m and month t , $\ln(1 + \text{Pix}_{m,t})$. This transformation mitigates the influence of extreme

values and provides a continuous measure of the intensity of Pix usage across municipalities and over time. In particular, it associates a value of zero in observations with no transaction.

Mobile penetration. Mobile penetration measures the extent of the mobile telephony infrastructure at the municipality level and is defined as the number of active mobile lines per 100 inhabitants. Data are obtained from the Brazilian National Telecommunications Agency (ANATEL) and refer to the year 2019, i.e., the pre-Pix period. This variable is used as a proxy for local digital readiness, reflecting access to mobile networks, smartphones, and the practical ability to adopt app-based financial services such as Pix. Mobile penetration is measured prior to the introduction of Pix and is used to define groups of municipalities with a lower versus a higher digital infrastructure, which serve as the basis for the heterogeneity analysis.

Covariates. Municipality-level covariates are obtained from IpeaData, a public data platform maintained by the Institute of Applied Economic Research (Instituto de Pesquisa Econômica Aplicada, IPEA), which consolidates and harmonizes socioeconomic indicators from multiple official sources, including the Brazilian Institute of Geography and Statistics (IBGE) and administrative records from federal agencies. The set of controls includes the total population, the share of the population living in urban areas, the share of men in the total population, the share of young individuals (defined over alternative age ranges depending on the specification), the illiteracy rate, the share of households with a single responsible adult, and municipal GDP per capita. In all specifications, these covariates are interacted with year dummies to allow for flexible and non-parametric trends over time.

These covariates are included alongside municipality and time fixed effects in the regression analysis, controlling for time-invariant local heterogeneity and common macroeconomic or institutional shocks affecting all municipalities.

4.2. Methodology

To analyze heterogeneous effects of Pix on local financial outcomes, our empirical strategy uses pre-Pix mobile penetration as the central dimension of heterogeneity and combines a dynamic event-study design with panel OLS regressions. The analysis is conducted on a balanced municipality–month panel covering January 2016 to December 2024. Heterogeneity is defined on the basis of each municipality’s position in the distribution of mobile penetration measured in the pre-Pix period. We interpret mobile penetration as a proxy for local digital readiness - namely, access to smartphones and mobile connectivity that lowers adoption costs

of app-based financial services and facilitates the intensive margin of Pix usage. Consistent with the figures and tables reported, heterogeneity is implemented via an indicator G_m that partitions municipalities into low- versus high-mobile-penetration groups (e.g. below-median versus above-median, and Q25-Q50 versus Q50-Q75).

In practice, we implement heterogeneity using two complementary group comparisons: municipalities below versus above the median of pre-Pix mobile penetration, and municipalities in the 25th–50th versus 50th–75th percentiles of the mobile penetration distribution. The second comparison is intentionally more local in the distribution and serves as a robustness and identification check, as municipalities closer to digital readiness are more likely to satisfy parallel trends prior to Pix. By contrast, extreme comparisons may mechanically amplify structural differences that can generate modest pre-trend deviations, even in the absence of anticipatory behavior. Importantly, potential deviations from parallel trends in extreme comparisons do not imply the absence of treatment effects in those municipalities, but rather reflect limitations in cleanly isolating those effects within an event-study framework.

Event-study specification. We begin by estimating an event-study regression that takes advantage of the nationwide introduction of Pix in November 2020. To keep the notation consistent with an annual reference period while retaining the variation at the month-level in the results, define the year dummies $D_{y,t} = 1\{\text{year}(t) = y\}$ and adopt 2020 as the omitted reference year. The dynamic specification is as follows:

$$Y_{m,t} = \alpha + \gamma_m + \delta_t + \sum_{k=-4}^{-1} \gamma_k (D_{k,t} \times G_m) + \sum_{k=1}^4 \beta_k (D_{k,t} \times G_m) + X'_{m,t} \theta + \varepsilon_{m,t}, \quad (1)$$

where $Y_{m,t}$ denotes the outcome in municipality m at month t ; γ_m are fixed effects of the municipality; δ_t are month-by-year fixed effects (absorbing national shocks and seasonality); G_m is the group indicator defined by pre-Pix mobile penetration; $X_{m,t}$ is a vector of time-varying controls; and $\varepsilon_{m,t}$ is the error term. In Equation (1), the coefficients γ_k capture relative differences between groups in the pre-2020 years and provide a direct test for differential pre-trends. The coefficients β_k measure post-2020 differences relative to the 2020 baseline, documenting how the gaps between low- and high-mobile-penetration municipalities evolve after Pix. This event-study design is more informative than static regressions from a causal perspective because it makes the timing of the institutional shock explicit and allows us to verify whether group differences emerge only after 2020, strengthening the plausibility of conditional parallel trends.

Identification strategy. The identification strategy exploits the nationwide and sudden introduction of Pix in November 2020 together with pre-existing cross-municipality differences in mobile penetration. Because Pix was implemented simultaneously across the country, identification does not rely on staggered adoption, but rather on differential exposure to the technology driven by local digital readiness. Mobile penetration measured before Pix serves as a proxy for the intensity with which municipalities are able to adopt and use instant payments, and is predetermined with respect to post-2020 banking outcomes.

The event-study specification allows us to assess the plausibility of conditional parallel trends by testing whether low- and high-mobile penetration municipalities followed similar trajectories prior to 2020. Under the assumption that, conditional on municipality fixed effects, time fixed effects, and observable controls, no other shocks differentially affected banking outcomes across these groups exactly at the time of Pix adoption, the post-2020 interaction coefficients can be interpreted as capturing heterogeneous responses to the diffusion of instant payments. The complementary panel OLS specification exploits continuous variation in Pix usage intensity and summarizes average associations, while the event-study design provides transparency on timing and pre-trends, strengthening the credibility of the identification strategy.

To measure the exposure of municipalities to the infrastructure required for instant payment adoption, we use pre-Pix (2019) mobile penetration data based on the density of active mobile accesses provided by the Brazilian National Telecommunications Agency (Anatel), following the identification strategy proposed by (Burga et al., 2025).

Specifically, we construct a mobile penetration variable defined as the number of active mobile accesses in the Personal Mobile Service (SMP) per 100 inhabitants in each municipality. This measure corresponds to the density of active SIM cards associated with mobile telecommunications services and reflects the extent of digital communication infrastructure diffusion prior to the introduction of Pix.

Formally, we define:

$$\text{Mobile Penetration}_m = \frac{\text{Active Mobile Accesses}_m}{\text{Population}_m} \times 100, \quad (2)$$

where $\text{Active Mobile Accesses}_c$ represents the number of operating SIM cards registered by Anatel within the Personal Mobile Service (SMP).

Using a pre-treatment measure, our empirical strategy exploits exogenous variation in municipalities' technological capacity to adopt digital payments, avoiding potential endogeneity

arising from digital infrastructure investments that may have occurred in response to Pix’s introduction.

Therefore, this variable captures local digital readiness, reflecting structural differences in the availability of mobile connectivity in municipalities prior to the implementation of the instant payment system.

Panel OLS specification. As a second step, we report panel OLS regressions that summarize the average association between Pix intensity and outcomes while allowing for heterogeneity through an interaction with G_m :

$$Y_{m,t} = \alpha + \gamma_m + \delta_t + \beta_1 \ln(1 + Pix_{m,t}) + \beta_2 [\ln(1 + Pix_{m,t}) \times G_m] + X'_{m,t}\theta + \varepsilon_{m,t}. \quad (3)$$

In Equation (3), β_1 summarizes the average association between Pix intensity and $Y_{m,t}$ in the reference group (e.g., higher mobile penetration), while β_2 captures how this association differs for municipalities with lower-mobile-penetration. All regressions are estimated by OLS with standard errors clustered at the municipality level, allowing for arbitrary heteroskedasticity and serial correlation within local markets. While the OLS specification is useful to synthesize average patterns and directly exploit continuous variation in Pix usage, it is potentially more vulnerable to contemporaneous endogeneity if unobserved local shocks affect both Pix usage and banking outcomes. By contrast, the event-study specification provides a more transparent assessment of dynamics and offers direct evidence on pre-trends, improving the evaluation of the plausibility of heterogeneous effects.

Controls. The control vector $X_{m,t}$ follows the structure reported in the regression tables. Specifically, it includes population interacted with year dummies, the urban-area share, demographic composition measures (population shares by groups), the illiteracy rate, income per capita, municipal GDP per capita, and a pandemic-period control. These controls play two roles. First, they reduce the risk that the estimated Pix coefficients capture coincident changes in local socioeconomic conditions that also shape deposits, credit, bank balance sheets, and market structure. Second, by absorbing observable trajectories potentially correlated with digital adoption, they strengthen the comparability of municipalities over time and make the identification within the municipality in Equations (1) and (3) more robust.

Outcomes We apply this empirical framework to four families of local financial outcomes. For each family, we estimate both dynamic event-study specifications and panel OLS mod-

els that exploit continuous variation in Pix usage intensity. All specifications consistently explore heterogeneity associated with local digital infrastructure, proxied by pre-Pix mobile penetration. The analysis uses a balanced municipality–month panel spanning January 2016 to December 2024. Mobile penetration is measured prior to the introduction of Pix and is interpreted as a proxy for local digital readiness, capturing access to smartphones and mobile connectivity that lower adoption costs for app-based financial services.

For bank deposits, we define the outcome variable as

$$Y_{m,t} = \ln(1 + Deposits_{m,t}^c),$$

and estimate the model separately for each deposit category $c \in \{\text{checking, savings, time, total}\}$. This disaggregation allows us to assess whether Pix diffusion is associated with differential adjustments in the composition of bank liabilities, distinguishing between highly liquid transaction accounts, savings instruments, and longer-maturity deposits, as well as the aggregate response of total deposits.

For credit outcomes, we define

$$Y_{m,t} = \ln(1 + Credit_{m,t}^c),$$

and estimate the model separately for each credit category $c \in \{\text{total, real estate, rural}\}$. This specification enables an examination of whether the expansion of instant payments is associated with greater financial intermediation on the asset side of bank balance sheets and whether such effects are systematically stronger in municipalities with lower digital readiness, where payment frictions historically constrained access to formal credit.

The empirical approach allows us to assess four key mechanisms through which Pix adoption may affect local financial systems. First, for deposit outcomes, we examine whether greater Pix usage is associated with higher levels of deposit mobilization and changes in deposit composition, capturing shifts across checking, savings, time, and total deposits. Second, for credit outcomes, we assess whether increased Pix usage is associated with higher levels of credit provision and whether access to different credit modalities expands disproportionately across municipalities.

Across all specifications, heterogeneity is introduced through interactions between Pix usage and municipal income groups. The interaction coefficient captures whether the association between Pix adoption and each financial outcome differs systematically between poorer and richer municipalities. Therefore, these estimates provide direct evidence on whether the

expansion of the digital payment infrastructure has been more inclusive, disproportionately affecting financial intermediation.

5. Results

This section presents the main empirical results on the evolution of banking activity and market structure at the municipality level around the introduction of instant payments through Pix.

The summary statistics reported in Table 3 document substantial differences in the level of bank deposits between municipalities along the distribution of mobile penetration, both before and after November 2020. In the pre-Pix period, municipalities with higher mobile penetration exhibit markedly larger volumes of deposits across all categories, with particularly pronounced differences in time deposits and total deposits. These patterns reflect pre-existing heterogeneity in local financial depth and digital connectivity.

In the period following the introduction of Pix, the average and median deposit values increase across all categories and mobile penetration groups. From a descriptive perspective, growth is observed in checking, savings, and time deposits, although levels remain considerably higher in municipalities with greater mobile penetration. Summary statistics indicate that larger deposit volumes continue to be concentrated in more digitally connected municipalities throughout the sample period.

Comparisons among intermediate segments of the mobile penetration distribution reveal qualitatively similar patterns. Municipalities located between the 25th-50th and 50th-75th percentiles display deposits levels and changes that are consistent with the broader distributional differences observed in the data. Overall, descriptive evidence provides a snapshot of initial heterogeneity and aggregate financial dynamics in the period surrounding the implementation of Pix, serving as the basis for the econometric analysis that follows.

Table 3: Summary Statistics: Bank Deposits by Mobile Penetration (bn. R\$)

| | Above | | | | Below | | | |
|---------------------------------------|--------|--------|------------|-------|-------|--------|--------|-------|
| | Mean | Median | Max | Min | Mean | Median | Max | Min |
| Panel A: Above vs Below Median | | | | | | | | |
| <i>Before Nov/2020</i> | | | | | | | | |
| Checking deposits | 0.011 | 0.000 | 42.170 | 0.000 | 0.000 | 0.000 | 0.015 | 0.000 |
| Saving deposits | 0.421 | 0.091 | 142.098 | 0.000 | 0.034 | 0.020 | 0.781 | 0.000 |
| Time deposits | 0.645 | 0.031 | 698.336 | 0.000 | 0.010 | 0.003 | 1.528 | 0.000 |
| Total deposits | 1.077 | 0.126 | 853.481 | 0.000 | 0.044 | 0.023 | 1.852 | 0.000 |
| Total assets | 31.578 | 0.516 | 34,968.000 | 0.000 | 0.211 | 0.077 | 72.625 | 0.000 |
| Total credit | 1.829 | 0.193 | 1,538.510 | 0.000 | 0.063 | 0.035 | 1.575 | 0.000 |
| Real estate credit | 0.423 | 0.050 | 154.613 | 0.000 | 0.013 | 0.001 | 0.883 | 0.000 |
| Rural credit | 0.129 | 0.034 | 25.904 | 0.000 | 0.021 | 0.005 | 1.330 | 0.000 |
| <i>After Nov/2020</i> | | | | | | | | |
| Checking deposits | 0.017 | 0.000 | 29.912 | 0.000 | 0.000 | 0.000 | 0.157 | 0.000 |
| Saving deposits | 0.571 | 0.134 | 138.611 | 0.000 | 0.056 | 0.034 | 0.834 | 0.000 |
| Time deposits | 1.464 | 0.063 | 1,190.450 | 0.000 | 0.021 | 0.008 | 1.771 | 0.000 |
| Total deposits | 2.051 | 0.207 | 1,345.590 | 0.000 | 0.077 | 0.043 | 2.118 | 0.000 |
| Total assets | 30.427 | 0.501 | 35,934.800 | 0.000 | 0.253 | 0.103 | 92.407 | 0.000 |
| Total credit | 2.880 | 0.303 | 2,195.060 | 0.000 | 0.117 | 0.061 | 3.408 | 0.000 |
| Real estate credit | 0.651 | 0.081 | 325.823 | 0.000 | 0.022 | 0.001 | 1.533 | 0.000 |
| Rural credit | 0.239 | 0.048 | 49.884 | 0.000 | 0.041 | 0.006 | 2.985 | 0.000 |

| | Above | | | | Below | | | |
|---|-------|--------|-------|------|-------|--------|---------|------|
| | Mean | Median | Max | Min | Mean | Median | Max | Min |
| Panel B: 25th–50th vs 50th–75th Percentile | | | | | | | | |
| <i>Before Nov/2020</i> | | | | | | | | |
| Checking deposits | 0.00 | 0.00 | 0.02 | 0.00 | 0.00 | 0.00 | 0.05 | 0.00 |
| Saving deposits | 0.04 | 0.03 | 0.41 | 0.00 | 0.09 | 0.05 | 2.85 | 0.00 |
| Time deposits | 0.01 | 0.00 | 1.53 | 0.00 | 0.04 | 0.01 | 1.75 | 0.00 |
| Total deposits | 0.06 | 0.03 | 1.85 | 0.00 | 0.13 | 0.07 | 4.04 | 0.00 |
| Total assets | 0.31 | 0.11 | 72.62 | 0.00 | 0.96 | 0.28 | 249.77 | 0.00 |
| Total credit | 0.08 | 0.05 | 1.58 | 0.00 | 0.17 | 0.11 | 2.50 | 0.00 |
| Real estate credit | 0.02 | 0.00 | 0.73 | 0.00 | 0.05 | 0.02 | 1.33 | 0.00 |
| Rural credit | 0.03 | 0.01 | 1.33 | 0.00 | 0.05 | 0.03 | 0.72 | 0.00 |
| <i>After Nov/2020</i> | | | | | | | | |
| Checking deposits | 0.00 | 0.00 | 0.16 | 0.00 | 0.00 | 0.00 | 0.13 | 0.00 |
| Saving deposits | 0.07 | 0.04 | 0.54 | 0.00 | 0.13 | 0.08 | 2.97 | 0.00 |
| Time deposits | 0.03 | 0.01 | 1.77 | 0.00 | 0.08 | 0.03 | 2.26 | 0.00 |
| Total deposits | 0.10 | 0.06 | 2.12 | 0.00 | 0.21 | 0.11 | 4.94 | 0.00 |
| Total assets | 0.36 | 0.14 | 92.41 | 0.00 | 1.11 | 0.28 | 1160.75 | 0.00 |
| Total credit | 0.15 | 0.09 | 3.41 | 0.00 | 0.27 | 0.18 | 4.34 | 0.00 |
| Real estate credit | 0.03 | 0.00 | 1.05 | 0.00 | 0.08 | 0.04 | 2.37 | 0.00 |
| Rural credit | 0.05 | 0.01 | 2.98 | 0.00 | 0.08 | 0.03 | 1.52 | 0.00 |

Note: Values are in billions of Brazilian reais (bn. R\$). Each panel compares municipalities at different points of the mobile penetration distribution. Panel A splits municipalities by the median of mobile penetration, and Panel B by quartiles of mobile penetration. Before/After Nov 2020 indicates periods before and after the introduction of Pix.

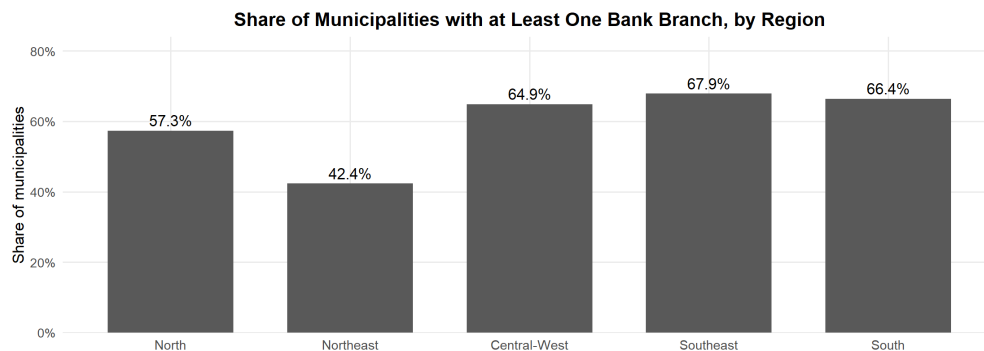
In the period following the introduction of Pix, the average and median deposit values increase across all categories and mobile penetration groups. From a descriptive perspective, growth is observed in checking, savings, and time deposits, although levels remain considerably higher in municipalities with greater mobile penetration. Summary statistics indicate that larger deposit volumes continue to be concentrated in more digitally connected municipalities throughout the sample period.

Comparisons among intermediate segments of the mobile penetration distribution reveal qualitatively similar patterns. Municipalities located between the 25th-50th and 50th-75th percentiles display deposits levels and changes that are consistent with the broader distributional differences observed in the data. Overall, descriptive evidence provides a snapshot of initial heterogeneity and aggregate financial dynamics in the period surrounding the implementation of Pix, serving as the basis for the econometric analysis that follows.

Figure 3 presents the share of municipalities with at least one bank branch across Brazilian regions as of November 2020, immediately before the nationwide introduction of Pix. The

figure reveals substantial regional heterogeneity in the availability of formal banking infrastructure. The Northeast shows the lowest coverage, with only about 42.4% of municipalities hosting at least one bank branch. Coverage is higher in the North (57.3%) and the Central-West (64.9%), while the Southeast (67.9%) and the South (66.4%) display the highest levels of banking presence. Despite this greater availability, a significant fraction of municipalities in all regions still lack physical bank branches, highlighting important spatial disparities in access to traditional banking services in the pre-Pix period.

Figure 3: Share of Municipalities with at Least One Bank Branch, by Region (November 2020)



Note: : The figure reports the share of municipalities with at least one bank branch across Brazilian regions as of November 2020. Shares are calculated as the number of municipalities with at least one branch divided by the total number of municipalities in each region. Data on bank branches come from the Central Bank of Brazil (ESTBAN).

This spatial pattern reflects long-standing inequalities in financial access in Brazilian municipalities. Physical proximity to a bank branch has historically shaped the ability of households to open accounts, obtain credit, and participate in formal financial activities. In the empirical analysis, municipalities without any bank presence are excluded from the sample, since banking outcomes cannot be observed in the absence of local financial institutions. Nevertheless, Figure 3 remains informative because it documents the pre-existing disparities in banking infrastructure that motivate our focus on heterogeneity among municipalities with different initial levels of financial access.

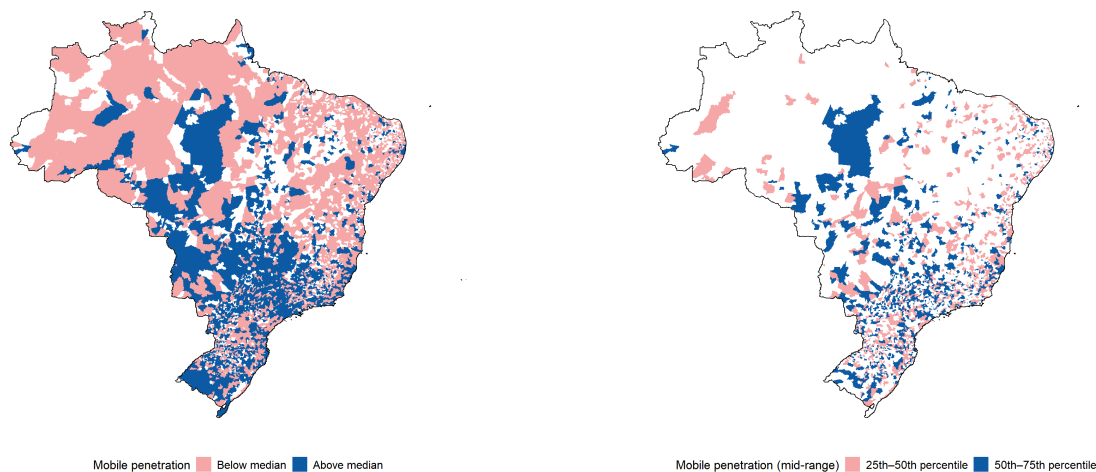
Figure 4 illustrates the spatial distribution of mobile penetration in Brazilian municipalities, highlighting regional heterogeneity in digital infrastructure. Panel (a) displays the classification of municipalities below and above the median level of mobile penetration, while Panel (b) compares municipalities in the intermediate ranges of the distribution, between the 25th–50th and 50th–75th percentiles. Municipalities with higher mobile penetration are predominantly concentrated in the South, Southeast, and parts of the Center-West, while

lower mobile penetration is more prevalent in the North and Northeast regions. Although this spatial heterogeneity is pronounced, the map itself does not imply systematic differences in pre-treatment outcome trajectories, which are assessed directly in the event-study analysis as a test of ex-ante homogeneity.

Figure 4: Mobile Penetration Across Brazilian Municipalities

(a) Municipalities below and above the median of mobile penetration

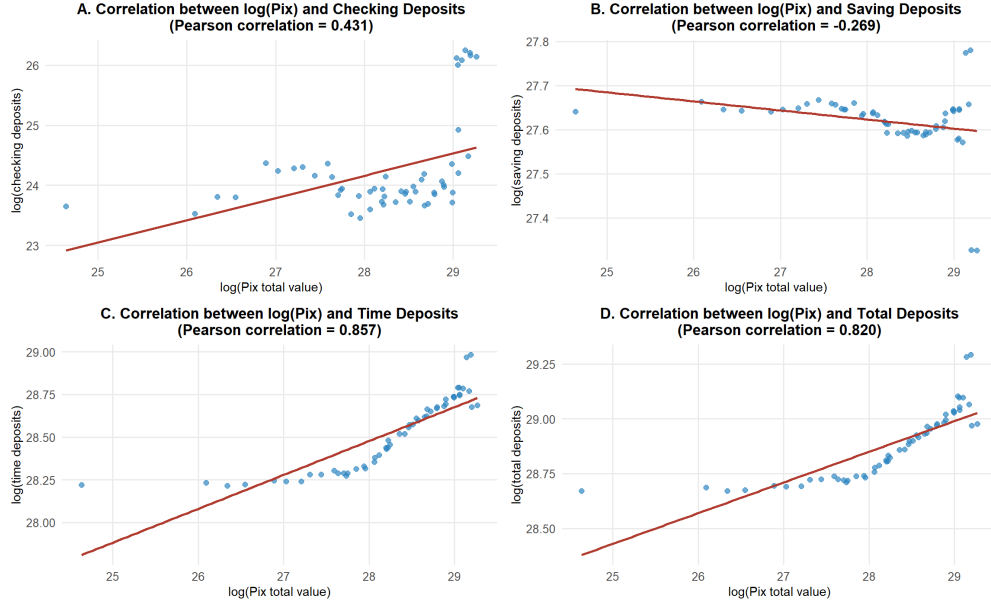
(b) Municipalities in the Q25–Q50 and Q50–Q75 ranges of mobile penetration



Note: The maps display the spatial distribution of mobile penetration across Brazilian municipalities. Panel (a) classifies municipalities below and above the median level of mobile penetration, while Panel (b) compares municipalities in the 25th–50th and 50th–75th percentiles of the distribution. Mobile penetration is measured in the pre-Pix period and reflects access to mobile telephony infrastructure. In Panel (a), blank areas correspond to municipalities with missing data (NA) or values outside the distribution used for classification. The figure is descriptive and does not imply differences in pre-treatment outcome trends across groups.

Figure 5 displays the correlation between Pix transaction volumes and different categories of bank deposits in municipalities. The positive relationships observed for checking, time, and total deposits suggest that areas with a more intensive use of instant payments tend to hold larger amounts of bank deposits. However, the weak and slightly negative correlation for saving deposits is partly driven by a large number of municipalities reporting zero or near-zero savings balances. This lack of variation in the lower tail of the distribution may bias the estimated correlation downward, masking the potential positive association between Pix activity and formal savings in more financially developed regions.

Figure 5: Correlation Between Pix Transactions and Bank Deposits

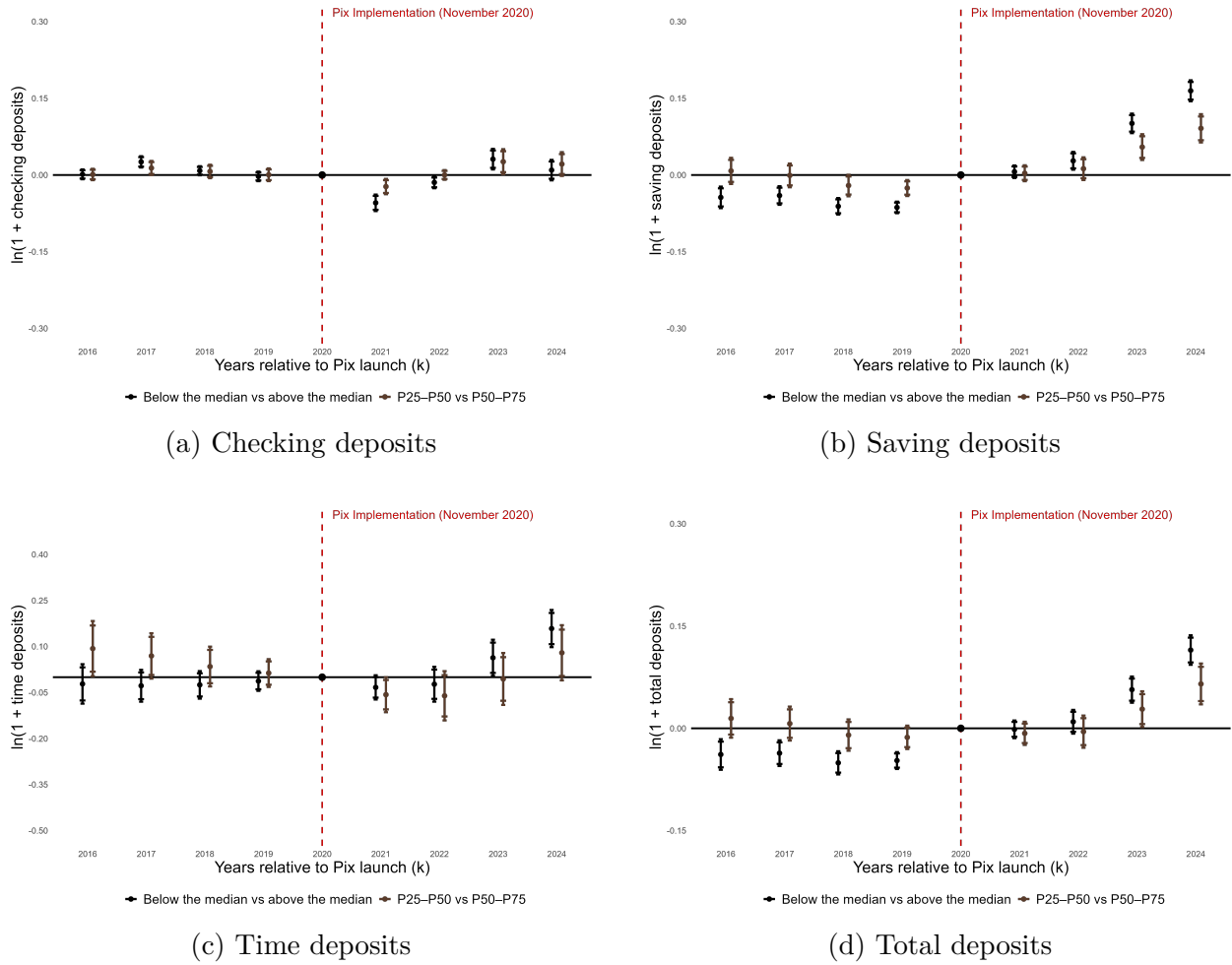


5.1. Heterogeneous Effects of Pix on Deposit Composition

This subsection analyzes the heterogeneous effects of Pix adoption on the composition of bank deposits using an event-study design that exploits cross-municipality variation in pre-Pix mobile penetration. Figure 6 presents the dynamic graphical evidence, while Table A.1 (2020 = Year 0) reports the corresponding regression coefficients. Together, they allow a transparent assessment of both pre-treatment trends and post-treatment adjustments across deposit categories.

Overall, pre-treatment dynamics are broadly stable. In the comparison between municipalities in the 25th–50th and 50th–75th percentiles of mobile penetration, coefficients remain close to zero prior to 2020 across all deposit types, supporting the plausibility of parallel trends. In the below- versus above-median specification, some pre-2020 coefficients—particularly for saving and total deposits—are statistically different from zero. However, these deviations are not monotonic and do not display a systematic divergence over time. The absence of a clear pre-treatment trend break, combined with the stability of the intermediate percentile comparison, strengthens the interpretation that post-Pix changes reflect structural effects rather than pre-existing trajectories.

Figure 6: Event-study estimates of the impact of Pix adoption on bank deposits



Note: The figure reports coefficients from event-study regressions comparing municipalities below the median to those above the median of mobile penetration, and municipalities between the 25th–50th and 50th–75th percentiles. Dashed vertical lines indicate the implementation of Pix in November 2020. Error bars represent confidence intervals: thick bars correspond to 90% confidence intervals, while thin bars correspond to 95% confidence intervals.

Panel (a) of Figure 6 and the estimates in Table A.1 show that checking deposits experience a short-run decline in 2021 in municipalities below the baseline median of mobile penetration relative to the reference group. This initial contraction is followed by a statistically significant expansion beginning around 2023. By 2023–2024, the coefficients become positive and economically meaningful, indicating a delayed but persistent increase in transaction balances in less digitally connected municipalities.

Panel (b) documents an even stronger medium-run response for saving deposits. While the

pre-treatment coefficients are negative relative to the 2020 baseline, post-Pix dynamics turn positive and increase over time. As reported in Table A.1, the estimated effect for below-median municipalities becomes large and statistically significant in the subsequent years after treatment, especially in 2024. This pattern indicates a substantial expansion of household savings held within the banking system in municipalities that initially had a lower digital penetration.

Panel (c) shows that the time deposits adjust more gradually. The coefficients remain close to zero in the short run, but become consistently positive four years after Pix implementation. The magnitudes observed in 2024 are sizeable, suggesting that while Pix primarily affects short-term liquidity and transaction balances, its effects eventually extend to longer-term portfolio allocation decisions. This delayed adjustment is consistent with a mechanism in which formalized liquidity first accumulates in liquid instruments before partially reallocating to longer-term deposits.

Panel (d) consolidates these dynamics by presenting total deposits. The estimates in Table A.1 indicate a clear and persistent increase in total deposits in municipalities with lower pre-Pix mobile penetration, particularly from 2023 onward. The positive and statistically significant coefficients in the subsequent years confirm that Pix does not simply reallocate funds across deposit categories. Instead, it generates net deposit growth within the banking system.

The heterogeneous responses documented above can be explained by a mechanism centered on reducing payment frictions and formalizing liquidity. Prior to Pix, electronic transfers such as TED and DOC involved non-negligible fixed and variable costs, which constrained their use in everyday transactions, particularly in small-scale local commerce. As a result, cash played a central role in retail transactions, and both households and firms held a substantial share of their liquidity outside the banking system, facing effective barriers to full financial participation.

Pix dramatically reduced the marginal cost of digital payments by offering instant, low-cost, and widely accessible account-to-account transfers. This innovation allowed small merchants to accept electronic payments without incurring prohibitive costs, facilitating the substitution of cash transactions with bank-based payments. As Pix became ubiquitous in local commerce, consumers and merchants increasingly relied on bank accounts to conduct routine transactions, mechanically increasing the demand for liquid balances held within the banking system.

This mechanism generates two complementary effects. First, it expands transaction-oriented

deposits, as reflected in the pronounced increases in checking and saving deposits observed in municipalities with lower pre-Pix mobile penetration. Second, by shifting liquidity from cash to formal accounts, Pix increases the total volume of deposits in the banking system rather than simply reallocating funds across deposit categories. The gradual adjustment of time deposits is consistent with the interpretation that Pix primarily affects short-term liquidity management and payment behavior, with longer-term portfolio adjustments occurring only over time. Taken together, these dynamics characterize a financial deepening process driven by the formalization of payments and liquidity, with particularly strong effects in local markets that were initially less digitally connected.

Table 4 reports the OLS estimates that capture the average effect of Pix adoption on different categories of bank deposits, providing a complementary perspective to the dynamic event-study analysis presented earlier. While the event-study framework allows for an assessment of pre-trends and the temporal evolution of treatment effects, the OLS regressions summarize the average post-implementation impact over the full sample period, controlling for rich covariates and municipality and time fixed effects. Accordingly, the results in Table 4 should be interpreted as complementary evidence that confirms the direction and average magnitude of the effects identified in the dynamic analysis, rather than as a substitute for causal interpretation based on event-study patterns. These heterogeneous effects are consistent with the findings of Gonzalez et al. (2025), which show that higher Pix usage increases the share of demandable deposits, particularly checking deposits.

Table 4: Pix and Deposit Outcomes (OLS Regressions)

| | Dependent variables | | | | | | | |
|--|----------------------|---------------------|------------------------|-----------------------|---------------------|-----------------------|-----------------------|---------------------|
| | Checking deposits | | Saving deposits | | Time deposits | | Total deposits | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| $\ln(1+Pix)$ | 0.0168** (0.0054) | 0.0070* (0.0039) | -0.0340*** (0.0063) | -0.0166 (0.0102) | 0.0141 (0.0184) | 0.1234*** (0.0355) | -0.0088 (0.0069) | 0.0177 (0.0116) |
| $\ln(1+Pix) \times$ <i>Below Median</i> | 0.0003 (0.0007) | – | 0.0125*** (0.0013) | – | 0.0098* (0.0043) | – | 0.0097*** (0.0014) | – |
| $\ln(1+Pix) \times$ <i>Q25–Q50 vs Q50–Q75</i> | – | 0.0007 (0.0008) | – | 0.0056*** (0.0016) | – | -0.0003 (0.0055) | – | 0.0036* (0.0018) |
| Observations | 338,044 | 169,081 | 338,044 | 169,081 | 338,044 | 169,081 | 338,044 | 169,081 |
| Adjusted R^2 | 0.7359 | 0.6018 | 0.9346 | 0.9304 | 0.9074 | 0.8911 | 0.9368 | 0.9294 |
| Within R^2 | 0.00822 | 0.00275 | 0.01531 | 0.02130 | 0.00888 | 0.01018 | 0.01249 | 0.01419 |
| Time fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| City fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Clustered SE (Municipality) | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. All dependent variables are in $\ln(1 + \cdot)$. Odd-numbered columns interact $\ln(1+Pix)$ with a below-median mobile penetration indicator, while even-numbered columns compare municipalities in the Q25–Q50 mobile penetration range to those in the Q50–Q75 range. The sample spans January 2016–December 2024. All specifications are OLS and include municipality and time fixed effects, with standard errors clustered at the municipality level. Control variables include population interacted with year dummies, urban area share, demographic shares, illiteracy share, income per capita, municipality-level GDP per capita, and a pandemic control.

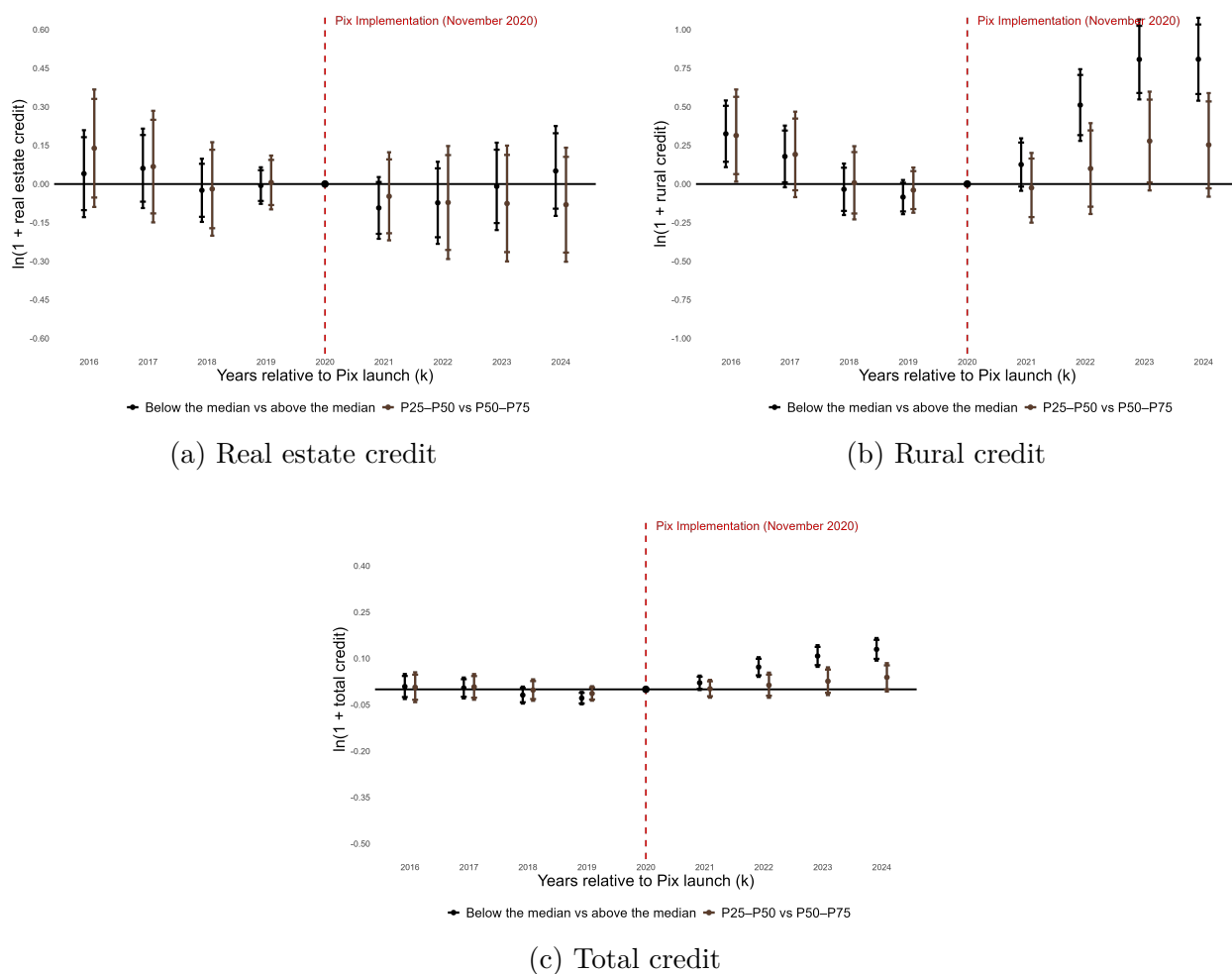
5.2. Heterogeneous Effects of Pix on Credit Outcomes

This subsection analyzes heterogeneous effects of Pix adoption on bank credit outcomes using the same event-study design as in the previous section, exploiting cross-municipality variation in pre-Pix mobile penetration. Figure 7 presents the dynamic patterns, while Table A.2 (2020 = Year 0) reports the corresponding regression coefficients.

Pre-treatment coefficients do not indicate systematic or monotonic divergence prior to 2020, particularly in the comparison between municipalities in the 25th–50th and 50th–75th percentiles of mobile penetration. Although some pre-treatment coefficients—especially for rural credit in the below- versus above-median specification—are statistically different from zero, these estimates do not display an accelerating or consistent trend leading up to Pix implementation. Moreover, post-treatment effects are substantially larger in magnitude than pre-treatment deviations, suggesting that the main expansion occurs after 2020 rather than reflecting the continuation of prior trajectories. Importantly, both heterogeneity specifications exhibit post-Pix dynamics that evolve in the same direction, reinforcing a causal

interpretation of the estimated effects.

Figure 7: Dynamic effects of Pix adoption on bank credit



Note: The figure reports event-study estimates comparing municipalities below the median of mobile penetration to those above the median, and municipalities between the 25th–50th and 50th–75th percentiles of the mobile penetration distribution. The dashed vertical line marks the nationwide introduction of Pix in November 2020. Error bars indicate 90% and 95% confidence intervals.

Panel (c) shows that Pix adoption is associated with a gradual and persistent increase in total credit in municipalities with lower mobile penetration relative to those with a more digitally connected population. Pre-treatment coefficients remain economically small, while post-treatment estimates become positive and statistically significant from 2022 onward, increasing through the end of the sample period. This pattern indicates a sustained expansion of aggregate credit supply in less digitized local markets.

Panel (b) documents particularly strong effects on rural credit. Following Pix implementation, municipalities below the baseline median mobile penetration experience sizable and statistically significant increases in rural credit compared to their more digitally connected counterparts. The magnitude of the post-2022 coefficients is large relative to pre-treatment estimates, pointing to a structural shift in rural credit provision rather than a transitory fluctuation. This pattern is consistent with Pix’s ability to reduce transaction and payment frictions in geographically dispersed areas, where historically limited banking infrastructure increased the cost of servicing and repaying credit contracts.

In contrast, panel (a) shows limited evidence of a meaningful response to real estate credit. Coefficients remain close to zero both before and after Pix adoption, with confidence intervals overlapping zero in most periods. This muted response aligns with the long-term, collateral-intensive nature of real estate lending, which is driven primarily by housing market conditions, contractual rigidities, and macro-financial factors rather than short-run improvements in payment technology.

A central mechanism linking Pix adoption to credit expansion operates through both reduced transaction frictions and improved informational transparency. By enabling instant and low-cost transfers, Pix reduces the operational cost of loan repayment and reduces delays in servicing debt, particularly in regions with historically low banking penetration. Easier and more reliable repayment improves the effective repayment capacity of borrowers and reduces the monitoring and collection costs of lenders.

Beyond payment efficiency, Pix also enhances the information banks have on client liquidity and cash-flow dynamics. As transactions move from cash to formal accounts, banks observe more frequent and more granular inflows and outflows. The expansion of deposits documented in the previous section implies that a larger share of household and firm liquidity is held within the banking system. This visibility reduces information asymmetries and allows financial institutions to better assess the repayment capacity of borrowers. When banks observe stable balances and regular transaction flows, perceived credit risk improves, potentially relaxing lending constraints. This information channel helps explain why credit provision expands more strongly in rural and less digitally connected municipalities, where informal liquidity previously limited observable financial histories.

Table 5 complements the dynamic analysis by reporting average OLS effects over the sample period. Unlike event-study estimates, which emphasize timing and evolution, the OLS specifications capture average heterogeneous responses associated with Pix intensity. The interaction terms indicate that total and rural credit respond more strongly in municipalities

with lower pre-Pix mobile penetration, while real estate credit remains largely unresponsive. Together, dynamic and average estimates suggest that Pix contributes to credit deepening primarily through channels sensitive to transaction frictions, liquidity formalization, and informational improvements, with particularly strong effects in less digitally connected local markets.

Table 5: Pix and Credit Outcomes (OLS Regressions)

| | Dependent variables | | | | | |
|---|-----------------------|----------------------|-----------------------|--------------------|--------------------|----------------------|
| | Total credit | | Rural credit | | Real estate credit | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\ln(1+Pix)$ | 0.0051 (0.0105) | 0.0393** (0.0176) | -0.0720 (0.0744) | 0.1790 (0.1224) | 0.0377 (0.0497) | 0.2149** (0.0964) |
| $\ln(1+Pix) \times \textit{Below Median}$ | 0.0124*** (0.0024) | – | 0.0577*** (0.0157) | – | 0.0007 (0.0118) | – |
| $\ln(1+Pix) \times \textit{Q25-Q50 vs Q50-Q75}$ | – | 0.0047 (0.0029) | – | 0.0161 (0.0192) | – | -0.0025 (0.0146) |
| Observations | 338,044 | 169,081 | 338,044 | 169,081 | 338,044 | 169,081 |
| Adjusted R^2 | 0.940 | 0.936 | 0.860 | 0.872 | 0.937 | 0.946 |
| Within R^2 | 0.0103 | 0.0185 | 0.0051 | 0.0056 | 0.0091 | 0.0181 |
| Time fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| City fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Clustered SE (Municipality) | Yes | Yes | Yes | Yes | Yes | Yes |

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. All dependent variables are in $\ln(1 + \cdot)$. Odd-numbered columns interact $\ln(1+Pix)$ with an indicator for municipalities below the median level of mobile penetration, while even-numbered columns compare municipalities in the Q25-Q50 range of mobile penetration to those in the Q50-Q75 range. The sample spans January 2016–December 2024. All specifications are OLS and include municipality and time fixed effects, with standard errors clustered at the municipality level. Control variables include population interacted with year dummies, urban area share, demographic shares, illiteracy share, income per capita, municipality-level GDP per capita, and a pandemic control.

6. Conclusions

This paper examined how Pix diffusion is associated with changes in local banking outcomes in Brazilian municipalities. Using a balanced municipal-month panel covering the period 2016–2024 and exploiting pre-existing heterogeneity in mobile penetration, the analysis documents systematic differences in financial outcomes following the nationwide introduction of instant payments in November 2020.

The results indicate that increased Pix usage is associated with meaningful adjustments in

bank deposits and credit provision. Municipalities with lower digital readiness prior to Pix show stronger responses in deposit growth—particularly in checking and saving deposits—as well as in total and rural credit. These patterns are consistent with a reduction in payment frictions, the formalization of liquidity previously held outside the banking system, and an expansion of access to formal financial intermediation.

On the deposit side, evidence suggests that Pix generates net deposit growth rather than simply reallocating funds across categories. The increase in transaction-oriented balances appears first, followed by gradual adjustments in longer-term deposits. This dynamic is consistent with a mechanism in which instant payments increase the demand for liquid balances by lowering the marginal cost of digital transactions and facilitating the substitution of cash with account-based payments.

On the credit side, the expansion is concentrated in segments that are more sensitive to liquidity visibility and transaction costs, particularly rural credit. A plausible mechanism operates through reduced payment frictions and improved information. By enabling instant and low-cost transfers, Pix reduces the operational costs of loan servicing and repayment. At the same time, as transactions migrate from cash to formal accounts, banks observe more granular and frequent information about the cash flows and balances of the borrowers. This improved informational environment can reduce perceived credit risk and relax lending constraints, particularly in less digitally connected municipalities.

From a policy perspective, these findings highlight the broader implications of public digital payment infrastructures. Instant payment systems such as Pix may influence not only payment behavior, but also the functioning of local credit markets and the depth of financial intermediation. By reducing transaction costs, improving liquidity formalization and enhancing informational transparency within the banking system, such infrastructures can contribute to financial deepening, particularly in regions historically characterized by limited digital connectivity and higher transaction frictions.

At the same time, the analysis is subject to limitations. Although the event-study design and the use of pre-Pix heterogeneity provide supportive evidence, the empirical strategy identifies differential associations rather than strictly exogenous variation in adoption. Local economic shocks or evolving demand for financial services may still partially correlate with Pix diffusion. In addition, the results capture short- and medium-term adjustments following the introduction of instant payments, leaving open questions about the longer-term effects on credit allocation, bank profitability, and financial stability.

Future research could build on these findings by exploiting quasi-experimental variation

in Pix exposure or regulatory thresholds, and by linking payment-level data to firm- and household-level outcomes. Such extensions would help clarify the causal mechanisms through which digital payment infrastructures shape financial intermediation and assess their distributional consequences across regions and socioeconomic groups.

In general, the evidence presented in this paper suggests that Pix diffusion is closely intertwined with recent transformations in Brazil's local banking systems. Instant payments appear to influence not only how transactions are executed, but also how financial resources are mobilized and how credit is supplied in less digitally connected markets, underscoring the role of payment systems as a central component of modern financial infrastructure.

Appendix

Table A.1: Event-study estimates across deposit types (2020 = Year 0)

| Year | Checking Deposits | | Saving Deposits | | Time Deposits | | Total Deposits | |
|-----------------|---------------------------------|-----------------------|---------------------------------|-----------------------|---------------------------------|-----------------------|---------------------------------|-----------------------|
| | Below Median vs Above Median | Q25–Q50 vs Q50–Q75 | Below Median vs Above Median | Q25–Q50 vs Q50–Q75 | Below Median vs Above Median | Q25–Q50 vs Q50–Q75 | Below Median vs Above Median | Q25–Q50 vs Q50–Q75 |
| 2016 (-4) | 0.0013 (0.0049) | 0.0010 (0.0057) | -0.0438*** (0.0108) | 0.0080 (0.0131) | -0.0219 (0.0328) | 0.0933* (0.0458) | -0.0384*** (0.0115) | 0.0146 (0.0144) |
| 2017 (-3) | 0.0257*** (0.0056) | 0.0137 (0.0071) | -0.0401*** (0.0093) | -0.0008 (0.0118) | -0.0280 (0.0265) | 0.0694 (0.0377) | -0.0364*** (0.0096) | 0.0069 (0.0127) |
| 2018 (-2) | 0.0083 (0.0045) | 0.0069 (0.0067) | -0.0612*** (0.0082) | -0.0206 (0.0108) | -0.0250 (0.0229) | 0.0347 (0.0330) | -0.0506*** (0.0087) | -0.0099 (0.0117) |
| 2019 (-1) | -0.0027 (0.0048) | 0.0005 (0.0064) | -0.0634*** (0.0058) | -0.0255** (0.0080) | -0.0126 (0.0163) | 0.0135 (0.0231) | -0.0473*** (0.0063) | -0.0132 (0.0087) |
| 2021 (1) | -0.0544*** (0.0083) | -0.0226** (0.0076) | 0.0064 (0.0063) | 0.0034 (0.0079) | -0.0333 (0.0202) | -0.0570 (0.0291) | -0.0015 (0.0066) | -0.0073 (0.0087) |
| 2022 (2) | -0.0145* (0.0058) | 0.0001 (0.0048) | 0.0278** (0.0089) | 0.0123 (0.0113) | -0.0229 (0.0290) | -0.0606 (0.0410) | 0.0096 (0.0089) | -0.0049 (0.0120) |
| 2023 (3) | 0.0310** (0.0103) | 0.0260* (0.0124) | 0.1010*** (0.0098) | 0.0547*** (0.0129) | 0.0634* (0.0300) | -0.0057 (0.0432) | 0.0568*** (0.0098) | 0.0282* (0.0133) |
| 2024 (4) | 0.0096 (0.0102) | 0.0214 (0.0119) | 0.1647*** (0.0105) | 0.0913*** (0.0141) | 0.1586*** (0.0309) | 0.0796 (0.0459) | 0.1148*** (0.0111) | 0.0651*** (0.0153) |
| Municipality FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Clustered S.E. | Municipality | Municipality | Municipality | Municipality | Municipality | Municipality | Municipality | Municipality |
| Observations | 338,044 | 169,081 | 338,044 | 169,081 | 338,044 | 169,081 | 338,044 | 169,081 |

Notes: Columns report event-study estimates for different deposit categories. "Below Median vs Above Median" compares municipalities below the median of pre-Pix mobile penetration to those above the median (reference group). "Q25–Q50 vs Q50–Q75" compares municipalities in the 25th–50th percentile range to those in the 50th–75th percentile range (reference group). The dependent variable is $\log(1 + \text{deposits})$. Year 2020 is the omitted reference period. All regressions include municipality and year fixed effects, with standard errors clustered at the municipality level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.2: Event-study estimates across credit types (2020 = Year 0)

| Year | Rural Credit | | Real Estate Credit | | Total Credit | |
|-----------------|---------------------------------|-----------------------|---------------------------------|-----------------------|---------------------------------|-----------------------|
| | Below Median vs Above Median | Q25–Q50 vs Q50–Q75 | Below Median vs Above Median | Q25–Q50 vs Q50–Q75 | Below Median vs Above Median | Q25–Q50 vs Q50–Q75 |
| 2016 (-4) | 0.3623** (0.1136) | 0.3203* (0.1531) | 0.0807 (0.0887) | 0.1623 (0.1163) | 0.0133 (0.0195) | 0.0117 (0.0237) |
| 2017 (-3) | 0.2133* (0.1054) | 0.1997 (0.1413) | 0.0820 (0.0816) | 0.0796 (0.1105) | -0.0036 (0.0169) | 0.0066 (0.0212) |
| 2018 (-2) | -0.0223 (0.0893) | 0.0109 (0.1227) | -0.0324 (0.0658) | -0.0234 (0.0937) | -0.0356** (0.0130) | -0.0134 (0.0169) |
| 2019 (-1) | -0.0842 (0.0601) | -0.0411 (0.0761) | -0.0175 (0.0380) | -0.0012 (0.0540) | -0.0287*** (0.0085) | -0.0163 (0.0106) |
| 2021 (1) | 0.1399 (0.0884) | -0.0218 (0.1131) | -0.0497 (0.0636) | -0.0229 (0.0875) | 0.0280* (0.0120) | 0.0043 (0.0146) |
| 2022 (2) | 0.5450*** (0.1230) | 0.1002 (0.1494) | -0.0321 (0.0842) | -0.0509 (0.1122) | 0.0719*** (0.0165) | 0.0119 (0.0204) |
| 2023 (3) | 0.8396*** (0.1362) | 0.2840 (0.1636) | 0.0146 (0.0892) | -0.0640 (0.1148) | 0.1039*** (0.0182) | 0.0256 (0.0228) |
| 2024 (4) | 0.8366*** (0.1409) | 0.2614 (0.1720) | 0.0558 (0.0910) | -0.0762 (0.1129) | 0.1196*** (0.0187) | 0.0373 (0.0233) |
| Municipality FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Clustered S.E. | Municipality | Municipality | Municipality | Municipality | Municipality | Municipality |
| Observations | 338,044 | 169,081 | 338,044 | 169,081 | 338,044 | 169,081 |

Notes: Columns (1)–(2) report rural credit, (3)–(4) real estate credit, and (5)–(6) total credit. "Below Median vs Above Median" compares municipalities below the median of the baseline distribution to those above the median (reference group). "Q25–Q50 vs Q50–Q75" compares municipalities in the 25th–50th percentile range to those in the 50th–75th percentile range (reference group). The dependent variable is $\log(1 + \text{credit})$. Year 2020 is the omitted baseline. All regressions include municipality and year fixed effects, with standard errors clustered at the municipality level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

References

- Adrian, T. and Mancini-Griffoli, T. (2019). The rise of digital money. *IMF FinTech Notes*, Note/19/01.
- Allen, F., Demirgüç-Kunt, A., Klapper, L., and Martinez Peria, M. S. (2016). The foundations of financial inclusion: Understanding ownership and use of formal accounts. *Journal of Financial Intermediation*, vol. 27, pp. 1–30.
- Alvarez, F. and Lippi, F. (2009). Financial innovation and the transactions demand for cash. *Econometrica*, 77(2), 363–402.
- Arango, C. and Taylor, V. (2008). Merchant acceptance, costs, and perceptions of retail payments: A microeconomic analysis. *Bank of Canada Working Paper*.
- Auer, R., Cornelli, G., and Frost, J. (2020). Rise of the central bank digital currencies: drivers, approaches and technologies. *BIS Working Papers*, No. 880.
- Bank for International Settlements (2011). Payment, clearing and settlement systems in brazil. *CPMI Country Report*. Committee on Payment and Settlement Systems.
- Barros Jr., F., Delalibera, B. R., Pinho Neto, V., and Rangel, V. (2025). Natural disasters and financial technology adoption. *Economics Letters*, 247, 112092.
- Basel Committee on Banking Supervision (2018). Implications of fintech developments for banks and bank supervisors. *Bank for International Settlements*.
- Beck, T., Demirguc-Kunt, A., and Martinez Peria, M. S. (2007). Reaching out: Access to and use of banking services across countries. *Journal of Financial Economics*, 85(1), 234–266.
- Beck, T., Levine, R., and Loayza, N. (2000). Finance and the sources of growth. *Journal of Financial Economics*, 58(1-2), 261–300.
- Bolt, W., Jonker, N., and van Renselaar, C. (2010). Incentives at the counter: An empirical analysis of surcharging card payments and payment behaviour in the netherlands. *Journal of Banking and Finance*, 34(8), 1738–1744.
- Bruhn, M. and Love, I. (2014). The real impact of improved access to finance: Evidence from mexico. *Journal of Finance*, 69(3), 1347–1376.
- Burga, C., Cespedes, J., Parra, C., and Ricca, B. (2025). Financial innovation, labor markets, and wage inequality: Evidence from instant payment systems. Working paper.

- Burgess, R. and Pande, R. (2005). Do rural banks matter? evidence from the indian social banking experiment. *American Economic Review*, 95(3), 780–795.
- Central Bank of Brazil (2024). Pix: Instant payment system. *Banco Central do Brasil*. Accessed: 2026-01-24.
- Comin, D. and Hobijn, B. (2010). An exploration of technology diffusion. *American Economic Review*, 100(5), 2031–2059.
- Demirgüç-Kunt, A., Klapper, L., Singer, D., Ansar, S., and Hess, J. (2020). The global finindex database 2017: Measuring financial inclusion and opportunities to expand access to and use of financial services. *World Bank Economic Review*, vol. 34, Supplement, pp. S2–S8.
- Fonseca, J. et al. (2024). Financial inclusion, economic development, and inequality. *Journal of Financial Economics*.
- Fonseca, J. and Van Doornik, B. (2022). Bankruptcy reform and the labor market: The effect of increased access to bank credit on skill demand. *Journal of Financial Economics*, 143(2), 550–568.
- Goldfarb, A. and Tucker, C. (2019). Digital economics. *Journal of Economic Literature*, 57(1), 3–43.
- Gonzalez, R. B., Ma, Y., and Zeng, Y. (2025). The effect of instant payments on the banking system. *Banco Central do Brasil Working Paper Series*, No. 619. Working Paper.
- Greenwood, J. and Jovanovic, B. (1990). Financial development, growth, and the distribution of income. *Journal of Political Economy*, vol. 98, no. 5, pp. 1076–1107.
- Hjort, J. and Poulsen, J. (2019). The arrival of fast internet and employment in africa. *American Economic Review*, 109(3), 1032–1079.
- IDB (2025). Beyond cash: The digital payments revolution in latin america and the caribbean. *Inter-American Development Bank*, Report. Washington, DC.
- Inter-American Development Bank (2023). The ongoing digital payments revolution in latin america and the caribbean. *Inter-American Development Bank*, Washington, DC.
- Jack, W. and Suri, T. (2014). Risk sharing and transactions costs: Evidence from kenya’s mobile money revolution. *American Economic Review*, vol. 104, no. 1, pp. 183–223.
- Klapper, L. and Singer, D. (2016). The opportunities and challenges of digitizing government-to-person payments. *World Bank Research Observer*, 31(2), 211–226.

- Klapper, L. and Singer, D. (2017). The role of digital payments in financial inclusion. *World Bank Policy Research Working Paper*.
- Klee, E. (2008). How people pay: Evidence from grocery store data. *Journal of Monetary Economics*, 55(3), 526–541.
- Levine, R. (1997). Financial development and economic growth: Views and agenda. *Journal of Economic Literature*, 35(2), 688–726.
- Philippon, T. (2020). On fintech and financial inclusion. *BIS Working Papers*, no. 841.
- Sarkisyan, S. (2025). Instant payment systems and competition for deposits. *Working paper*. Working paper, Fisher College of Business, The Ohio State University.
- Suri, T. and Jack, W. (2016). The long-run poverty and gender impacts of mobile money. *Science*, vol. 354, no. 6317, pp. 1288–1292.
- Vives, X. (2019). Digital disruption in banking. *Annual Review of Financial Economics*, vol. 11, pp. 243–272.