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Digital Transformation and Financial Inclusion

The Case of Instant Payments in Brazil

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Abstract[1]

Pix represented one of the most profound transformations of Brazil's payment system by introducing a low-cost, interoperable, and public instant payment infrastructure available nationwide in November 2020. This paper examines how Pix diffusion has been associated with changes in local banking markets. The results indicate that Pix expansion is associated with deposit growth and credit expansion in municipalities with lower initial levels of digital infrastructure, with particular increases in savings deposits and rural credit. 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 constrained by limited digital infrastructure.

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

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1. Introduction

Reductions in payment frictions reshape how households and firms hold liquidity, access credit, and participate in the formal financial system. By lowering transaction costs and improving the speed and reliability of transfers, payment innovations broaden access to electronic transactions, especially in emerging economies, where reliance on cash, limited banking infrastructure, and large unbanked populations have long constrained financial inclusion. Brazil's experience with Pix offers a valuable case to study these dynamics. Launched by the Central Bank of Brazil in November 2020, Pix is an instant, low-cost, account-to-account payment system available 24/7. Within a few years, it became the country's dominant electronic payment instrument, eliminating fixed fees for individuals and substantially reducing operational and intermediation costs for merchants and financial institutions, relative to the legacy systems such as TED and DOC. Although Pix was rolled out simultaneously nationwide and was made available to all regulated institutions, its adoption varied substantially across municipalities. This combination of a uniform institutional rollout with heterogeneous local uptake provides a natural setting to study how reductions in payment frictions affect local banking markets.

The mechanisms at work are intuitive. By making transfers cheaper and faster, Pix alters how households and firms manage liquidity, receive income, and settle payments. In doing so, it can raise the demand for transaction balances, foster the formalization of economic activity, and improve borrowers' repayment capacity. These channels are likely to operate most strongly in areas where payment frictions were initially binding, that is, in municipalities with weaker digital infrastructure. We therefore test two hypotheses: first, that Pix adoption raises bank deposits, especially in less digitally connected municipalities; and second, that Pix is associated with higher credit provision, again with stronger effects in areas where digital connectivity was initially limited.

To examine these hypotheses, we analyze two sets of outcomes: the level and composition of bank deposits (including checking, savings, time, and total deposits) and credit outcomes, both in aggregate and by modality, with particular attention to real estate and rural credit. Looking at deposits and credit jointly provides an integrated perspective on how instant payments propagate through local financial systems. Throughout the analysis, we explore heterogeneity across municipalities with different levels of digital readiness, proxied by pre-Pix mobile penetration. This dimension allows us to assess whether reductions in payment frictions represent a larger shock to local financial intermediation in areas that were initially more constrained by limited digital infrastructure.

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, alongside cross-sectional variation in pre-Pix mobile penetration. We complement this approach with panel regressions that relate the continuous intensity of Pix usage to financial outcomes. All specifications include municipality and time fixed effects, along with a set of socioeconomic controls, allowing us to isolate within-municipality changes over time while accounting for common macroeconomic and institutional shocks.

The paper makes three contributions. First, it provides municipality-level evidence on the local effects of an instant payment system in a large emerging economy using detailed administrative data. Second, it identifies digital infrastructure as a key factor shaping the impact of payment technologies on financial intermediation. Third, by examining deposits and credit jointly, it offers an integrated perspective on how reductions in payment frictions translate into changes in liquidity management and lending. More broadly, the findings contribute to policy discussions on the design of public digital payment infrastructures and their potential to foster financial deepening in emerging markets.

The remainder of the paper is organized as follows. Section 2 presents the institutional background of Pix, Section 3 reviews the related literature, and Section 4 describes the data and empirical strategy. Section 5 reports the main results, and Section 6 concludes. The appendix contains additional descriptive evidence and robustness checks using banking density as an alternative proxy for pre-Pix local infrastructure.

2. Institutional and Financial Background in Brazil

The introduction of a new payment technology does not necessarily raise total transaction volume. In payment markets, innovations typically operate through substitution across existing instruments: when a new instrument lowers transaction costs, improves convenience or interoperability, or accelerates settlement, users tend to reallocate transactions away from less efficient payment methods. The magnitude and direction of substitution depend on the functional overlap between instruments. Methods that serve similar roles in day-to-day transactions are more likely to be displaced, while instruments that bundle additional services, such as embedded credit or liquidity smoothing, tend to face more limited direct substitution.

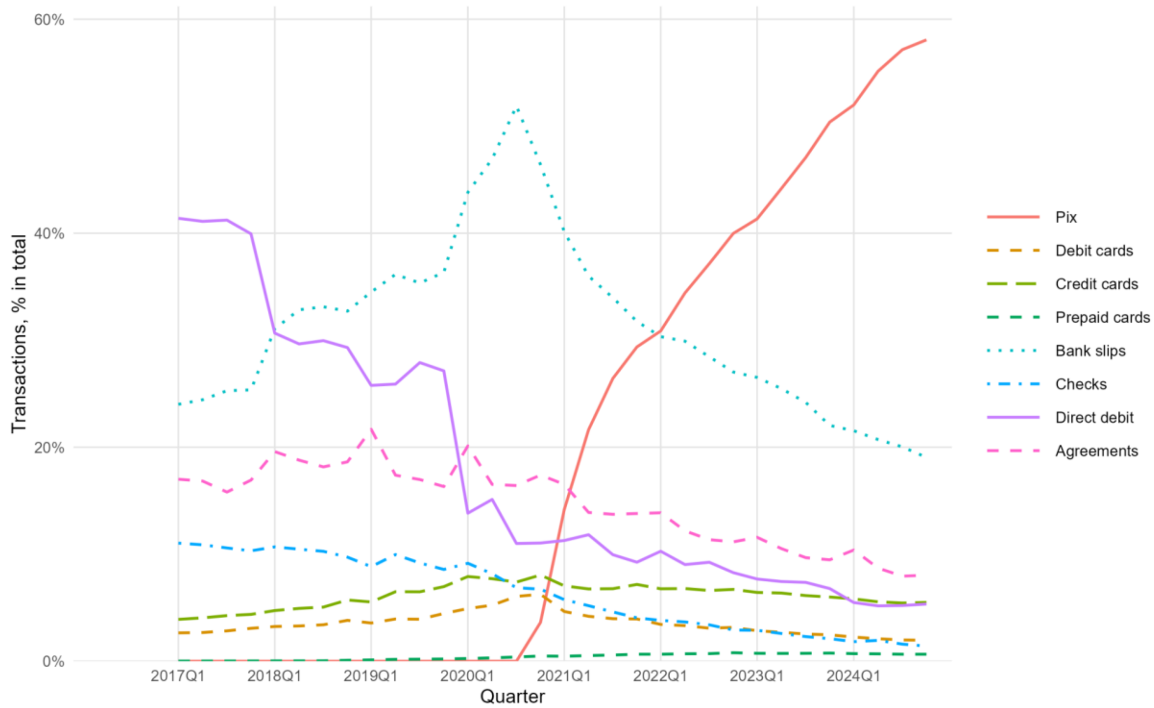
In this context, the economic impact of Pix should be understood not as the simple introduction of an additional payment channel, but rather as a broader reorganization of the payment ecosystem. Because Pix enables real-time, low-cost, account-to-account transfers with universal interoperability and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

Figure 1 illustrates how the composition of electronic payment methods in Brazil evolved between 2017 and 2024. Before Pix, electronic payments were dominated by bank slips, direct debit arrangements, and card-based instruments. Bank slips accounted for the largest share of transactions, while debit and credit cards represented a stable component of retail payments. Following the nationwide rollout, Pix adoption increased rapidly and within a few quarters surpassed all other instruments in transaction share. This expansion coincided with a sharp decline in direct debit arrangements and payment agreements, indicating 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 relatively stable, reflecting their dual role as both a payment instrument and a source of short-term financing.

These patterns motivate a closer examination of the institutional foundations and the operational design of Pix. Section 2.1 situates Pix within a broader sequence of coordinated reforms that expanded interoperability and lowered the risk of settlement in the Brazilian payment system. Section 2.2 then explains how Pix operates in practice, detailing its core features, transaction architecture, and the channels through which instant payments can reduce frictions and reshape payment behavior.

Figure 1: Share of Electronic Payment Methods in Brazil (2017–2024)



Notes: The figure reports the quarterly share of selected electronic payment methods in total electronic transactions in Brazil from 2017 to 2024, using data from the Central Bank of Brazil (ESTBAN). Cash transactions are not observed, so the denominator includes only electronic payment instruments. Debit card transactions refer to payments directly linked to a bank account and settled immediately. Credit card transactions are payments made through a credit line and settled at a later date. Prepaid cards refer to transactions using cards loaded with previously deposited funds. Bank slips correspond to boleto transactions, typically used for bill payments and commercial transactions. Checks refer to payments settled through the traditional check-clearing system. Direct debit denotes automated withdrawals authorized by the payer, usually for recurring payments. Agreements refer to payments processed through interbank collection agreements (convênios), often used for recurring or institutional payments. Pix denotes the Brazilian instant payment system, which allows real-time, low-cost, account-to-account transfers available 24 hours a day.

2.1. Institutional Evolution of the Brazilian Payment System

The modernization of the Brazilian payment system unfolded through a series of coordinated institutional reforms led primarily by the Central Bank of Brazil, as summarized in Table 1. Reforms implemented in the early 2000s established the legal and operational foundations of real-time gross settlement and electronic interbank transfers, thereby 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, further strengthened interoperability, competition, and digital integration within the financial system. The launch of Pix in 2020 consolidated this trajectory, adding a low-cost, 24/7 instant payment 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 systems
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 tax payments, 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 summarizes the major formal institutional and regulatory innovations introduced by the Central Bank of Brazil or the federal government. Together, 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, as 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 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 (Azevedo et al., 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.

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 depending on 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 the 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 (Azevedo et al., 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 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 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).

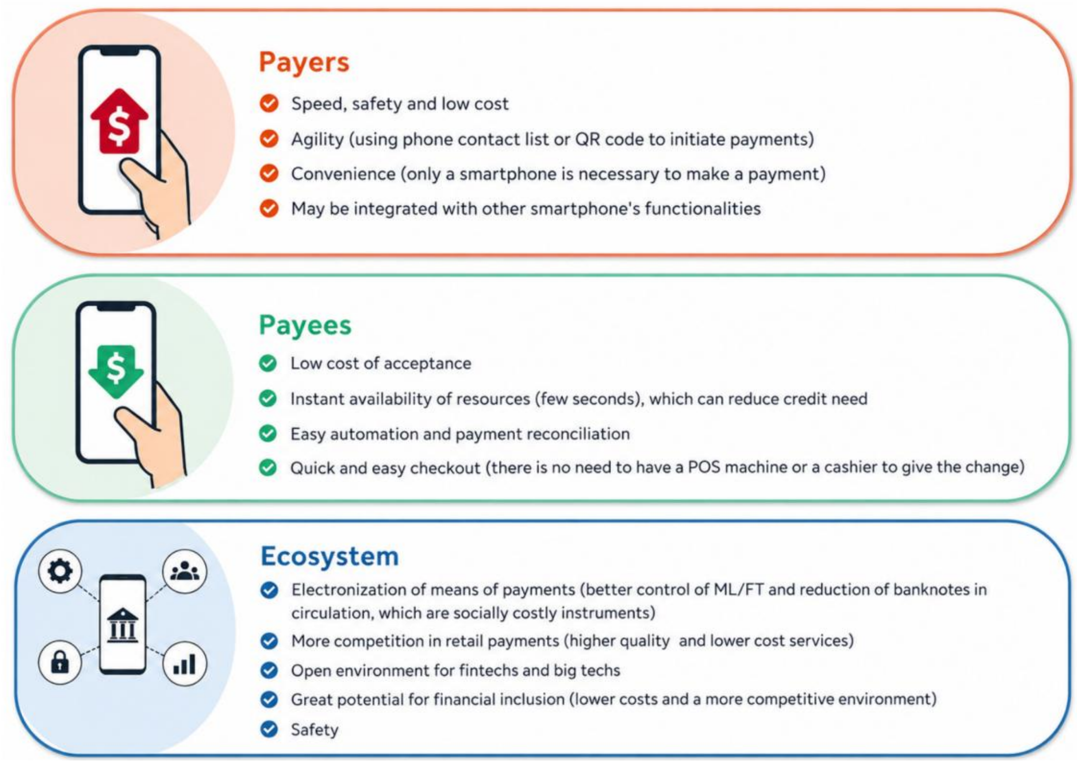
Beyond convenience, the transactional architecture of Pix is designed to reduce acceptance costs for merchants and firms. By relying on a public fully interoperable infrastructure with fewer intermediaries compared to traditional payment instruments, Pix allows transactions to be processed individually, irrevocably, and 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 the 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 range 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 individually 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 alongside 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 merely 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 along 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 the acceptance costs and ensures immediate availability of funds, which facilitates automation and reconciliation of payments, while also mitigating 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 banking and payments markets.

Figure 2: Economic Benefits of Instant Payments (Pix)



Notes: The figure illustrates the main benefits of instant payment systems for payers, payees, and the payment ecosystem.

Source: "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 these decisions. 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 the purchase value and convenience, and 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 shape 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 the cash held outside the banking system and demandable deposits. This mechanism establishes a direct channel linking instant payment innovations to deposit mobilization and bank funding structures.

The literature on technological change in banking further highlights how digital financial innovations shape competitive dynamics and financial intermediation. Advances in payment and financial technologies can erode the advantages of incumbents tied to legacy infrastructures, lowering barriers to entry and reshaping market structure (Sarkisyan, 2025; Vives, 2019). Evidence from Brazil suggests that the introduction of Pix intensified competition in deposit markets, facilitating entry and expanding deposit mobilization among smaller banks (Sarkisyan, 2025). More broadly, fintech innovations reduce information and transaction costs, expand access to financial services, and improve intermediation efficiency (Philippon, 2020). This literature suggests that instant payment systems may affect not only the payment behavior but also market competition, bank funding structures, and the organization of local banking markets.

Empirical analyses of Pix provide growing evidence supporting these mechanisms. Its rollout has been associated with wage effects concentrated in cash-intensive activities, consistent with lower transaction costs and improved payment efficiency (Burga et al., 2025). Greater adoption of Pix has also been associated with a higher share of demandable deposits, suggesting adjustments in household liquidity management and bank funding composition (Gonzalez et al., 2025). In addition, exogenous shocks, such as natural disasters, have accelerated the adoption across municipalities, underscoring the scalability and resilience of Pix as a payment infrastructure (Barros et al., 2025; Sampaio and Ornelas, 2024).

The Brazilian case fits within a broader international diffusion of fast payment systems. Countries that adopt real-time settlement platforms have typically experienced rapid growth in the use of digital payments, lower transaction frictions, and increased reliance on bank accounts, particularly where electronic instruments have previously been limited (Auer et al., 2020; Adrian and Mancini-Griffoli, 2019). In Latin America, the adoption patterns underscore the importance of interoperability, regulatory coordination, and public sector integration (Azevedo et al., 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 introduced real-time gross settlement and legal reforms that strengthen settlement finality, reduce systemic risk, and improve interbank efficiency (Bank for International Settlements, 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 and Matray, 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 digital infrastructure influences firm performance and labor market outcomes (Hjort and Poulsen, 2019). 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 based on pre-existing mobile penetration.

Digital payments may also generate broader welfare gains beyond banking outcomes. Cross-country differences in account ownership and usage remain substantial (Demirgüç-Kunt et al., 2020), and payment systems often act as gateways to formal financial participation (Allen et al., 2016). Micro-level evidence also shows that digital payment technologies reduce transaction costs and improve risk sharing (Suri and Jack, 2016; Jack and Suri, 2014; Klapper and Singer, 2017). Building on this broader literature, 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, with particular emphasis on how pre-existing digital infrastructure shapes 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 municipal 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

Our empirical analysis combines administrative and statistical data from official Brazilian sources into a balanced municipality-month panel spanning from January 2016 to December 2024. All datasets are merged using the official IBGE municipality code, ensuring spatial consistency over time, and all monetary variables are expressed in Brazilian reais (BRL).

Banking data. Information on deposits, credit, bank assets, and local market structure is drawn from Estatísticas Bancárias por Município (ESTBAN), a dataset of the Central Bank of Brazil that provides monthly balance-sheet and credit information for financial institutions with physical presence at the municipal level. Based on ESTBAN, we construct measures of total deposits and deposit composition (checking, savings, and time deposits), total credit and specific credit modalities (rural and real estate credit), as well as total bank assets. All values are normalized on a per capita basis using municipal population estimates from the Brazilian Institute of Geography and Statistics (IBGE).

Pix usage. Data on Pix transactions are obtained from the Central Bank of Brazil, which reports monthly Pix transaction values at the municipality level. Letting (m) index municipalities and (t) index months, our main explanatory variable is $\ln(1 + \text{Pix}_{m,t})$, defined as the natural logarithm of one plus the value of Pix transactions. This transformation mitigates the influence of extreme values, accommodates months with no transactions (which take the value zero), and provides a continuous measure of Pix usage intensity across municipalities and over time.

Mobile penetration. We measure local digital readiness using mobile penetration, defined as the number of active mobile lines per 100 inhabitants. The data come from the Brazilian National Telecommunications Agency (ANATEL) and refer to 2019, the year before the launch of Pix. This variable captures access to mobile networks, smartphones, and the practical ability to adopt app-based financial services. We use it to classify municipalities into groups with a lower and higher digital infrastructure for heterogeneity analysis.

Banking density. As an alternative measure of local financial infrastructure, we use banking density, defined as the number of bank branches per 100,000 inhabitants, measured in the pre-Pix period (2019). While mobile penetration captures digital readiness, banking density reflects the access to traditional physical banking services. We use this variable to define alternative groups of municipalities with lower vs. higher financial access and replicate our heterogeneity analysis accordingly.

Covariates. Municipality-level controls are drawn from IpeaData, a public platform maintained by the Institute of Applied Economic Research (IPEA) that consolidates socioeconomic indicators from multiple official sources, including IBGE and federal administrative records. The set of controls includes the total population, the share of the population living in urban areas, the share of men, the share of young individuals (defined using alternative age ranges across specifications), the illiteracy rate, and municipal GDP per capita. All controls are interacted with year dummies to allow for flexible, non-parametric trends. They enter the regression analysis alongside municipality and time fixed effects, thereby absorbing time-invariant local heterogeneity and common macroeconomic or institutional shocks.

4.2. Methodology

To analyze the 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 using a balanced municipality–month panel covering from January 2016 to December 2024. Heterogeneity is defined according to 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 the 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- vs. high-mobile-penetration groups (e.g., below-median vs. above-median, and Q25-Q50 versus Q50-Q75).

In practice, we implement heterogeneity using two complementary group comparisons: municipalities below vs. above the median of pre-Pix mobile penetration, and municipalities in the 25th–50th vs. 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, potentially generating modest pre-trend deviations, even in the absence of the anticipatory behavior. Importantly, potential deviations from parallel trends in extreme comparisons do not imply an absence of treatment effects in those municipalities; rather, they reflect limitations in cleanly isolating those effects within an event-study framework. As a complementary robustness check, we replicate all specifications using banking density (defined as the number of bank branches per 100,000 inhabitants, measured in 2019) as an alternative pre-Pix dimension of heterogeneity. This approach allows us to verify that the results replicate across different infrastructure channels—digital and physical—both determined prior to the implementation of Pix.

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

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

where $Y_{m,t}$ denotes the outcome variable in municipality m at month t; μ_m are fixed effects of the municipality; δ_t are month-by-year fixed effects, which absorb 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 following the introduction of Pix. This event-study design is more informative than static regressions from a causal perspective because it explicitly incorporates the timing of the institutional shock and allows us to verify whether group differences emerge only after 2020, thereby strengthening the plausibility of conditional parallel trends.

Identification strategy. The identification strategy exploits the nationwide and abrupt introduction of Pix in November 2020 together with pre-existing cross-municipality differences in mobile penetration. Because Pix was implemented simultaneously across the country, the identification does not rely on staggered adoption, but rather on differential exposure to the technology driven by pre-existing local digital readiness. Mobile penetration measured before Pix serves as a proxy for municipalities' capacity to adopt and intensively 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 the continuous variation in Pix usage intensity and summarizes average associations, while the event-study design provides transparency on timing and pre-trends, thereby strengthening the credibility of the identification strategy.

To measure municipalities' exposure to the infrastructure required for instant payment adoption, we use pre-Pix (2019) mobile penetration data based on the density of active mobile connections provided by ANATEL, following the identification strategy proposed by (Burga et al., 2025). As demonstrated in Burga et al. (2025), pre-Pix mobile penetration serves as an exogenous proxy for local digital infrastructure capacity for three reasons. First, mobile infrastructure investments were determined years prior to Pix's announcement, reflecting historical demand for telecommunications services rather than future payment innovations. Second, the geographic variation in mobile penetration captures cumulative infrastructure decisions made by telecommunications operators based on population density, historical demand, and economic fundamentals, rather than anticipatory responses to instant payment systems. Third, by using pre-Pix mobile penetration, this measure isolates variation in municipalities' capacity to adopt instant payments, while avoiding endogenous adjustments in digital infrastructure that might have occurred in response to the technology's introduction.

Specifically, we construct a mobile penetration variable defined as the number of active mobile connections 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 degree of diffusion of the digital communication infrastructure prior to the introduction of Pix. Formally, we define:

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

where Active Mobile Accesses$_m$ represents the number of active SIM cards registered by ANATEL within the SMP. As shown in Figure A.1, mobile penetration exhibits strong positive correlations with key financial variables measured in the pre-Pix baseline year (2019), including total deposits, credit provision, and bank density. These correlations support the interpretation of mobile penetration as a meaningful proxy for local financial capacity and technological readiness that shapes the intensive margin of Pix adoption.

Using a pre-treatment measure, our empirical strategy exploits exogenous variation in municipalities' technological capacity to adopt digital payments, while avoiding potential endogeneity arising from digital infrastructure investments undertaken in response to the introduction of Pix. Therefore, this variable captures local digital readiness by reflecting structural differences in the availability of mobile connectivity across municipalities prior to the implementation of the instant payment system.

For the banking density robustness specification, we construct an analogous variable measuring the number of bank branches per 100,000 inhabitants in each municipality, also measured in 2019. This alternative dimension of heterogeneity captures pre-Pix financial infrastructure through a different channel, physical branch presence rather than digital connectivity, allowing us to assess whether treatment effect heterogeneity is robust to alternative specifications of local absorptive capacity.

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

$$Y_{m,t} = \alpha + \gamma_m + \delta_t + \beta_1 \ln\left(1 + \text{Pix}_{m,t}\right) + \beta_2 \ln\left(1 + \text{Pix}_{m,t}\right) \times G_m + X'_{m,t}\theta + \varepsilon_{m,t}. \tag{3}$$

In Equation (3), β_1 summarizes the average association between Pix intensity and $Y_{m,t}$ in the reference group, for example municipalities with 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 for synthesizing average patterns and directly exploiting continuous variation in Pix usage, it is potentially more susceptible 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, thereby 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 population share, demographic composition measures, population shares by age groups, the illiteracy rate, income per capita, municipal GDP per capita, and a pandemic-period control. These controls serve two main purposes. First, they mitigate 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 within-municipality identification in Equations (1) and (3) more robust.

Outcomes. We apply this empirical framework to four families of local financial outcomes. For each group, we estimate both dynamic event-study specifications and panel OLS models 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 from 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 the adoption costs of app-based financial services. For bank deposits, we define the outcome variable as follows:

$$Y_{m,t} = \ln\left(1 + \text{Deposits}_{m,t}^{c}\right),$$

and estimate the model separately for each deposit category c ∈ {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

$$Y_{m,t} = \ln\left(1 + \text{Credit}_{m,t}^{c}\right),$$

and estimate the model separately for each credit category c ∈ {total, real estate, rural}. This specification enables us to examine 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 have 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 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 digital payment infrastructure has been more inclusive, by disproportionately affecting financial intermediation in lower-income municipalities.

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 across municipalities along the distribution of mobile penetration, both before and after November 2020. In the pre-Pix period, municipalities with higher mobile penetration exhibit substantially 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, both 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 deposit levels remain considerably higher in municipalities with greater mobile penetration. The summary statistics indicate that larger deposit volumes remain consistently 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 deposit levels and dynamics that are consistent with the broader distributional differences observed in the data. Overall, the descriptive evidence provides a snapshot of initial heterogeneity and aggregate financial dynamics in the period around 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$)

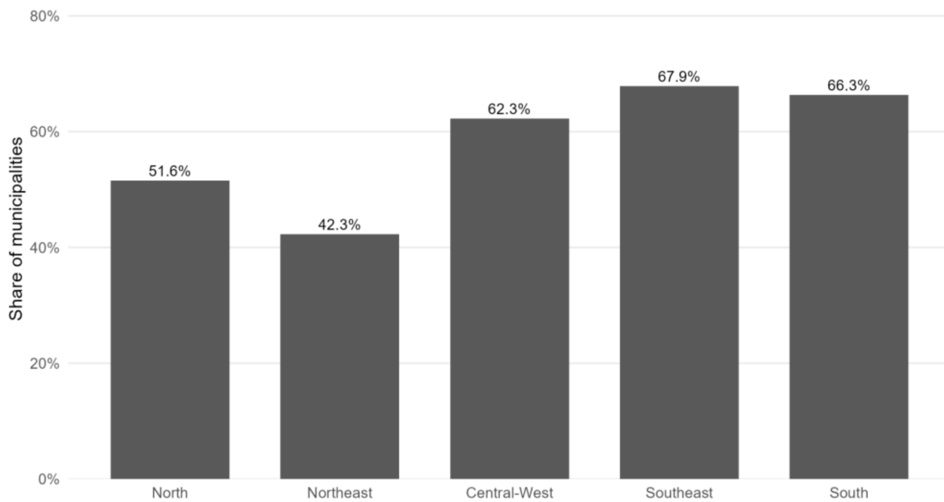
	Above				Below			
	Mean	Median	Max	Min	Mean	Median	Max	Min
Panel A: Above vs. below median								
Before Nov/2020								
Checking deposits	0.011	0.000	42.170	0.000	0.000	0.000	0.015	0.000
Saving deposits	0.421	0.091	142.098	0.000	0.034	0.020	0.781	0.000
Time deposits	0.645	0.031	698.336	0.000	0.010	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
After Nov/2020								
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
Panel B: 25th–50th vs. 50th–75th percentile								
Before Nov/2020								
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
After Nov/2020								
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

Notes: Values are expressed in billions of Brazilian reais (bn. R$). Each panel reports comparisons across 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 preceding and following the introduction of Pix.

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 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, at 57.3%, and in the Central-West, at 64.9%, while the Southeast and South display the highest levels of banking presence, at 67.9% and 66.4%, respectively. 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. In fact, more than one-third of municipalities have no bank branch at all.

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

2020)



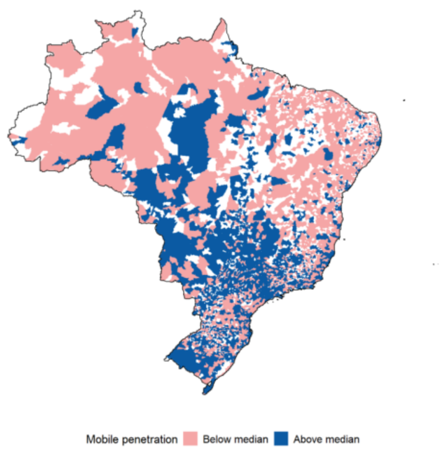
Notes: The figure reports the share of municipalities with at least one bank branch across Brazilian regions as of November 2020. Shares are calculated as the number of municipalities with at least one branch divided by the total number of municipalities in each region. Data on bank branches are drawn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

This spatial pattern reflects long-standing inequalities in financial access across Brazilian municipalities. Physical proximity to a bank branch has historically been a key determinant of households' ability to open accounts, access 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, as it documents the pre-existing disparities in banking infrastructure that motivate our focus on heterogeneity among municipalities with different baseline levels of financial access.

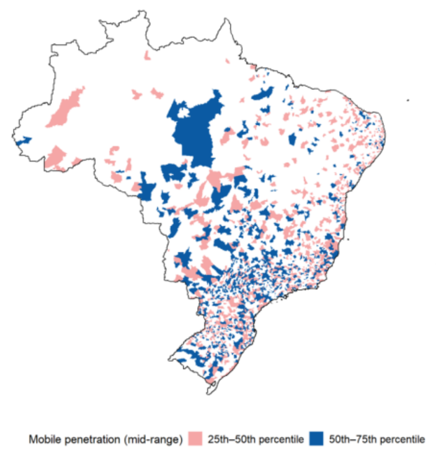
Figure 4 illustrates the spatial distribution of mobile penetration across Brazilian municipalities, highlighting regional heterogeneity in digital infrastructure. Panel (a) displays the classification of municipalities below and above the median level of mobile penetration, while Panel (b) compares 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, whereas 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 instead 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



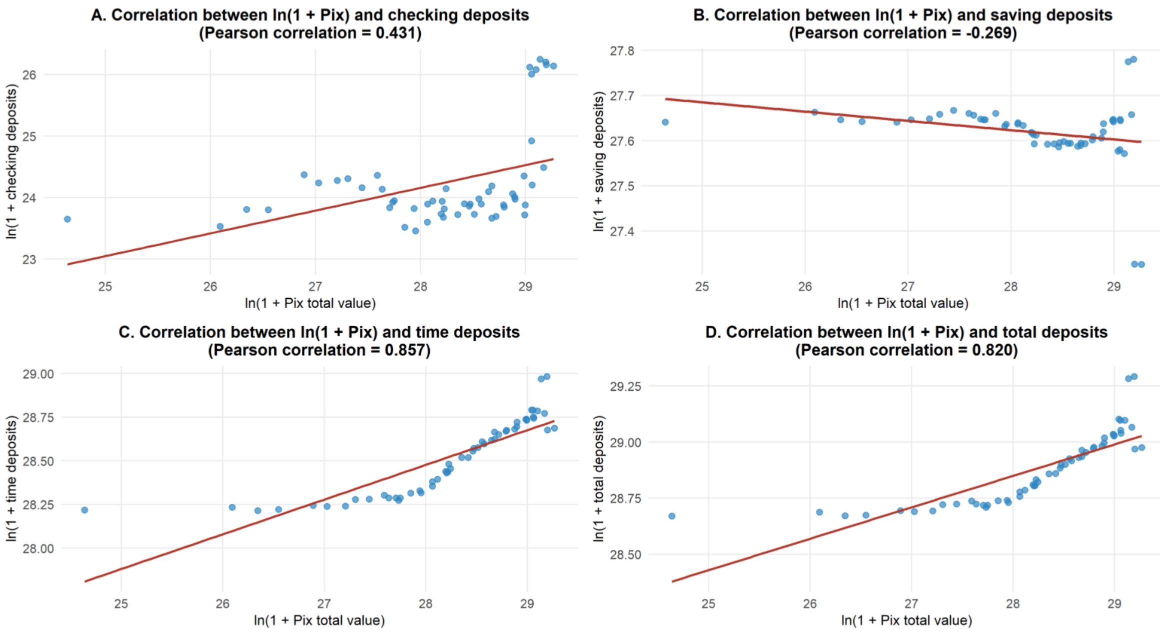
(b) Municipalities in the Q25–Q50 and Q50–Q75 ranges of mobile penetration



Notes: 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 classification range. The figure is purely 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 across municipalities. The positive relationships observed for checking, time, and total deposits suggest that areas with more intensive use of instant payments tend to hold larger volumes of bank deposits. However, the weak and slightly negative correlation for savings 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, obscuring the potential positive association between Pix activity and formal savings in more financially developed regions.

Figure 5: Correlation Between Pix Transactions and Bank Deposits

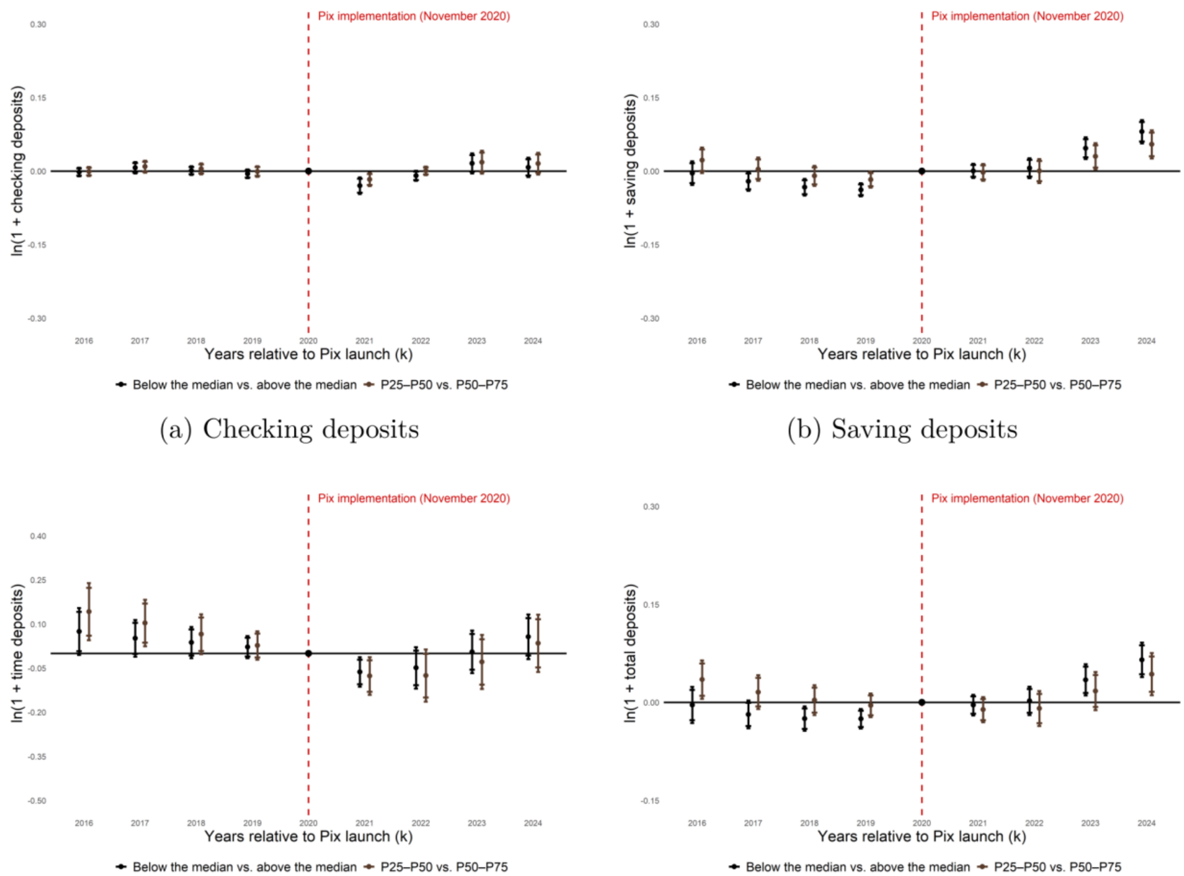


5.1. Heterogeneous Effects of Pix on Deposit Composition

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, where 2020 is defined as Year 0, reports the corresponding regression coefficients.

Overall, pre-treatment dynamics are broadly stable. Some pre-2020 coefficients, particularly for savings and total deposits, are statistically different from zero. However, these deviations are not monotonic and do not display any 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



(a) Checking deposits

(b) Saving deposits

(c) Time deposits

(d) Total deposits

Notes: The figure reports coefficients from event-study regressions comparing municipalities below and above the median of mobile penetration, as well as 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, with thick bars corresponding to 90% confidence intervals and thin bars corresponding to 95% confidence intervals.

Panel (a) of Figure 6 and the estimates in Table A.1 show that checking deposits do not exhibit a consistent pattern of increase across heterogeneity groups. Although the coefficients fluctuate around zero, there is no clear evidence of economically or statistically significant effects on transaction account balances after the implementation of Pix.

Panel (b) documents a clear and robust response for savings deposits. Both heterogeneity specifications, below-median vs. above-median and 25th–50th vs. 50th–75th percentiles, display positive and increasing coefficients beginning approximately three years after the implementation of Pix, with effects continuing through the fourth post-implementation year. As reported in Table A.1, the estimated effects for municipalities with lower digital penetration become large and statistically significant in the third and fourth years following the implementation of Pix. This pattern indicates a substantial increase in household savings held within the banking system in municipalities that initially had lower digital penetration.

Panel (c) shows that time deposits do not display a consistent response to Pix adoption. As reported in Table A.1, the coefficients remain close to zero throughout the sample period, suggesting that instant payments have no statistically meaningful effect on longer-term deposit instruments.

Panel (d) consolidates the deposit dynamics by presenting total deposits. Consistent with savings deposits, both heterogeneity specifications show clear and persistent increases in total deposits beginning approximately three years after the implementation of Pix, with effects continuing to grow through the fourth post-implementation year. The estimates in Table A.1 confirm that municipalities with lower pre-Pix mobile penetration experience larger effects. The positive and statistically significant coefficients across both heterogeneity measures indicate that Pix generates net deposit growth within the banking system, with the effect concentrated in savings and total deposits rather than distributed across all deposit categories.

The results using banking density as an alternative dimension of heterogeneity, presented in Figure B.2 and Table B.2, reinforce these main findings on savings and total deposits. Both heterogeneity specifications, below-median vs. above-median banking density and 25th–50th vs. 50th–75th percentiles, show statistically significant increases in savings deposits and total deposits beginning approximately three years after Pix implementation, with effects continuing to grow through the fourth post-implementation year. These results confirm that deposit expansion is not specific to digital infrastructure, proxied by mobile penetration, but rather reflects a more general pattern of local absorptive capacity and financial deepening. Additionally, the banking-density results reveal growth in time deposits in the third and fourth years after implementation, suggesting that, as liquidity formalizes through savings accounts, households gradually reallocate a share of balances to longer-term instruments. Checking deposits remain largely unresponsive across both dimensions of heterogeneity, consistent with the main findings. The consistency of results across distinct infrastructure measures supports the robustness of the identification strategy and strengthens the interpretation that Pix-induced deposit expansion reflects genuine financial deepening rather than measurement artifacts.

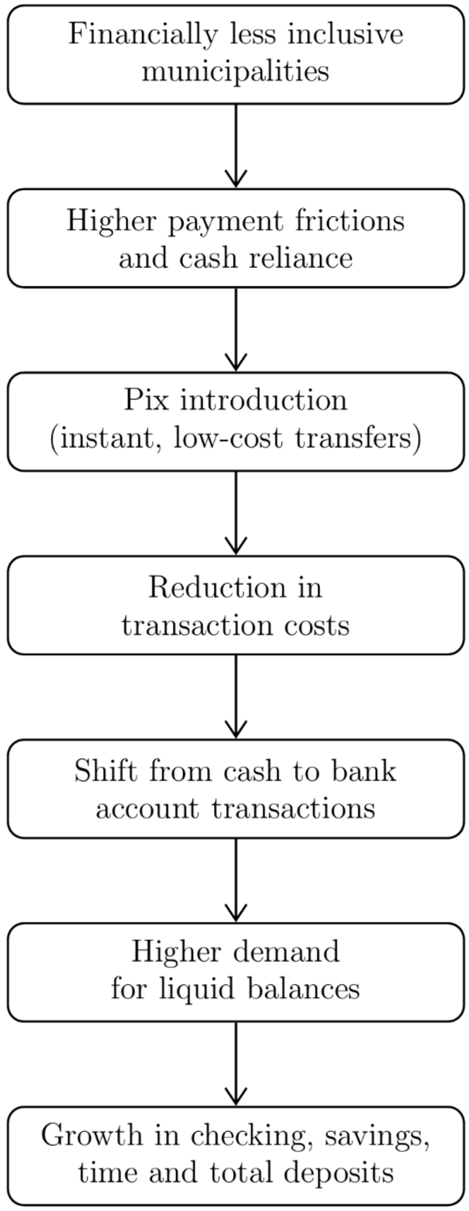
The heterogeneous responses documented above can be explained through a mechanism centered on reducing payment frictions and formalizing liquidity. Prior to Pix, electronic transfers such as TED and DOC involved non-negligible fixed and variable costs, which constrained their use in everyday transactions, 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 enabling instant, low-cost, and widely accessible account-to-account transfers. This innovation allowed small merchants to accept electronic payments without incurring prohibitive costs, thereby 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 raising 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 savings 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 bank deposits rather than merely 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. These dynamics are consistent with 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.

Figure 7 illustrates this mechanism. The introduction of Pix reduces transaction costs, shifting households and firms away from cash toward bank-account transactions, thereby increasing demand for liquid balances. The resulting growth in deposits is particularly pronounced in financially less inclusive municipalities, where payment frictions were historically binding.

Figure 7: Mechanism: Pix-induced Liquidity Formalization and Financial Deepening



Notes: This figure illustrates the causal mechanism through which Pix adoption generates deposit growth in financially less inclusive municipalities. Pix dramatically reduces transaction costs relative to pre-existing electronic transfer systems (TED, DOC), facilitating the substitution of cash-based transactions with bank-account transfers. This shift from informal to formal payment methods increases households' and firms' demand for liquid balances within the banking system, generating net deposit growth. The effect is particularly pronounced in municipalities with lower pre-Pix digital penetration, which historically relied more heavily on cash and faced higher barriers to formal financial participation.

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 as well as 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 the 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)
$\ln(1+\text{Pix})$	0.0070	0.0072·	0.0198*	0.0326*	0.1419***	0.2614***	0.0333***	0.0643***
	(0.0052)	(0.0038)	(0.0091)	(0.0132)	(0.0291)	(0.0505)	(0.0101)	(0.0152)
$\ln(1+\text{Pix})$ × Below median	0.0000	–	0.0078***	–	0.0008	–	0.0064***	–
	(0.0007)		(0.0014)		(0.0046)		(0.0016)	
$\ln(1+\text{Pix})$ × Q25–Q50 vs Q50–Q75	–	0.0005	–	0.0037*	–	-0.0050	–	0.0020
		(0.0008)		(0.0016)		(0.0056)		(0.0018)
Observations	338,044	169,081	338,044	169,081	338,044	169,081	338,044	169,081
Adjusted R^2	0.7393	0.6068	0.9366	0.9326	0.9096	0.8938	0.9381	0.9312
Within R^2	0.00991	0.00407	0.03460	0.04127	0.02092	0.02319	0.02150	0.02744
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

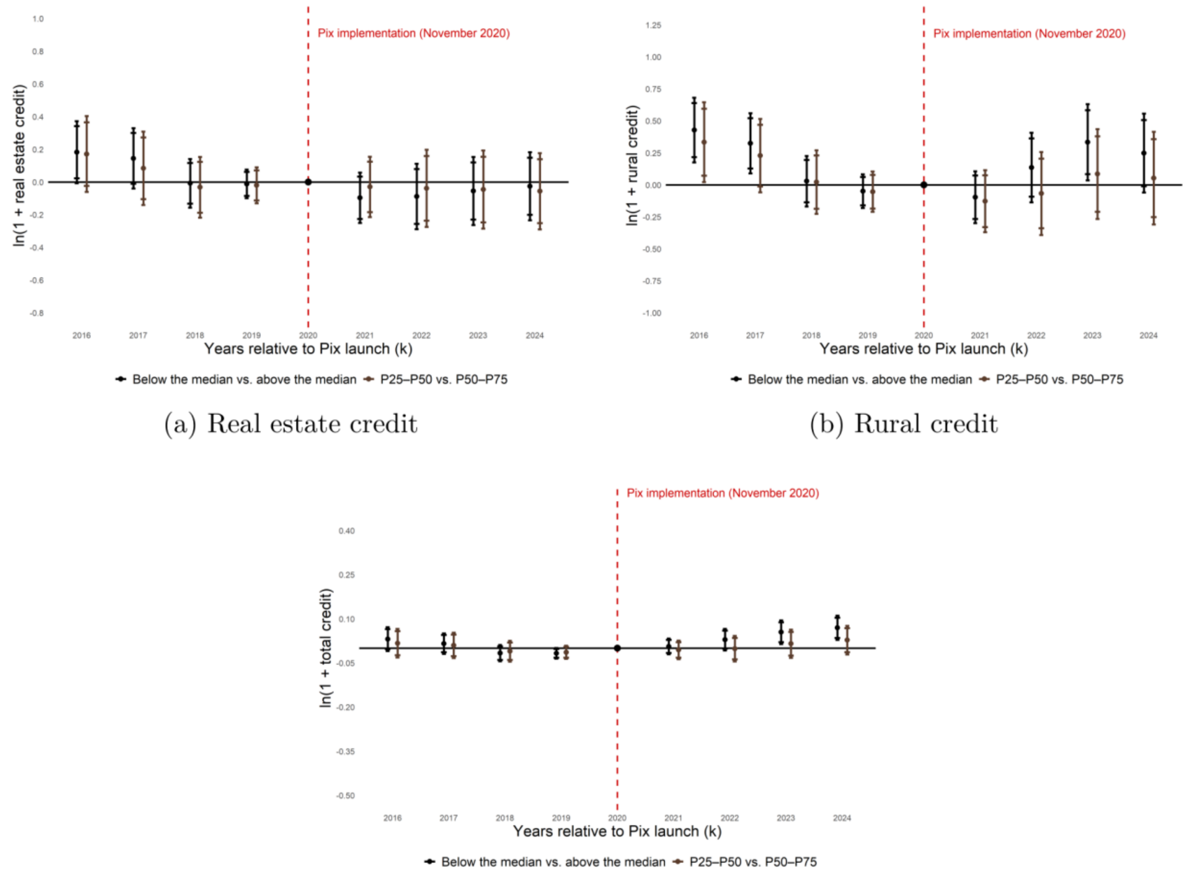
Notes: · $p < 0.1$; * $p < 0.05$; *** $p < 0.01$. All dependent variables are expressed as $\ln(1+\cdot)$. Odd-numbered columns interact $\ln(1+\text{Pix})$ with an indicator for municipalities below the median of mobile penetration, while even-numbered columns compare municipalities in the Q25–Q50 mobile penetration range to those in the Q50–Q75 range. The sample spans from January 2016 to December 2024. All specifications are estimated by OLS and include municipality and time fixed effects, with standard errors clustered at the municipality level.

5.2. Heterogeneous Effects of Pix on Credit Outcomes

This subsection analyzes the heterogeneous effects of Pix adoption on bank credit outcomes using the same event-study design employed in the previous section, exploiting cross-municipality variation in pre-Pix mobile penetration. Figure 8 presents the dynamic patterns, while Table A.2, where 2020 is defined as Year 0, reports the corresponding regression coefficients.

Pre-treatment coefficients do not indicate systematic or monotonic divergence prior to 2020. Although some pre-treatment coefficients, especially for rural credit, are statistically different from zero, they do not display an accelerating or consistent trend in the period 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.

Figure 8: Dynamic Effects of Pix Adoption on Bank Credit



(a) Real estate credit

(b) Rural credit

(c) Total credit

Notes: The figure reports event-study estimates comparing municipalities below the median of mobile penetration to those above the median, as well as 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 denote 90% and 95% confidence intervals.

Panel (a) shows that real estate credit does not display a consistent response to Pix adoption. Coefficients remain close to zero both before and after Pix implementation, with confidence intervals that overlap zero in most periods. This absence of effect 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.

Panel (b) documents the effects on rural credit. Following the implementation of Pix, municipalities below the baseline median of mobile penetration experience stronger growth in rural credit compared to their more digitally connected counterparts. As reported in Table A.2, the estimated effects for below-median municipalities are present but more modest in magnitude than total credit expansion, suggesting that, while rural areas benefit from reduced payment frictions, aggregate credit growth is also driven by broader financial mechanisms. This pattern is consistent with the ability of Pix to reduce transaction and payment frictions in geographically dispersed areas, where historically limited banking infrastructure increased the costs associated with servicing and repaying credit contracts.

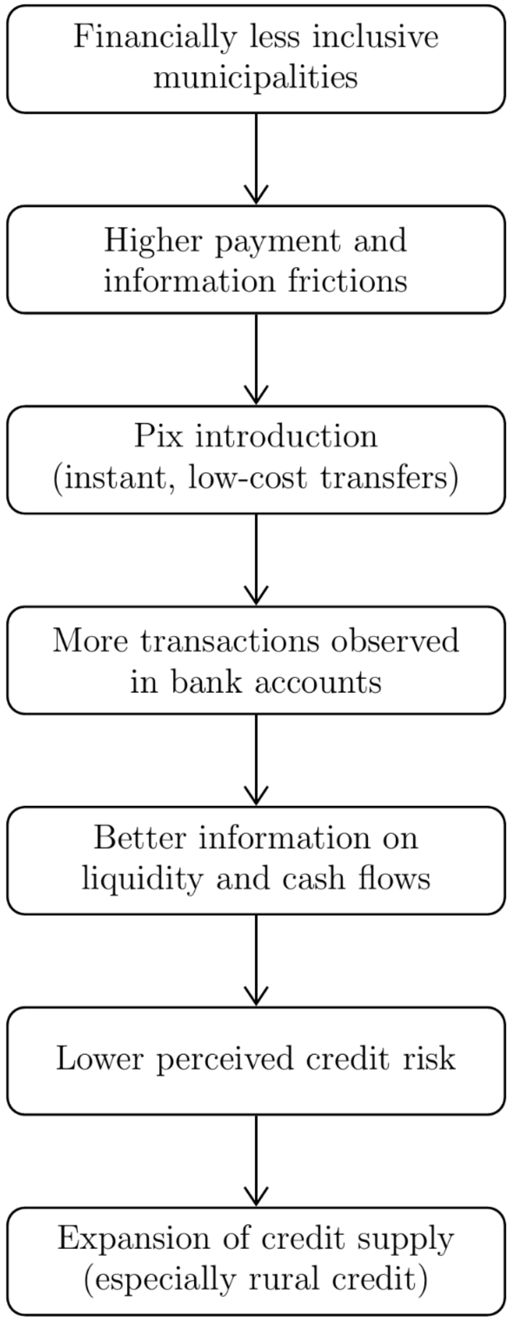
Panel (c) shows that Pix adoption is associated with an increase in total credit in municipalities with lower mobile penetration relative to those with more digitally connected populations. Pre-treatment coefficients remain economically small, while post-treatment estimates become positive and statistically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

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 associated with loan repayment and reduces delays in debt servicing, particularly in regions with historically limited banking penetration. Easier and more reliable repayment mechanisms improve borrowers' effective repayment capacity while reducing monitoring and collection costs for lenders.

Beyond improving payment efficiency, Pix also enhances the information available to banks regarding client liquidity and cash-flow dynamics. As transactions shift from cash to formal accounts, banks observe more frequent and 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 borrowers' repayment capacity. 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 in rural and less digitally connected municipalities, where informal liquidity previously limited the availability of observable financial histories.

Figure 9 illustrates this mechanism. The introduction of Pix enables banks to observe more transactions within the formal financial system, improving their information on borrowers' liquidity and cash-flow dynamics. This enhanced visibility reduces perceived credit risk, leading to an expansion of credit supply, particularly in rural and less digitally connected areas, where payment and information frictions have historically been the most binding.

Figure 9: Mechanism: Pix-induced Credit Expansion through Reduced Information Frictions



Notes: This figure illustrates the causal mechanism through which the adoption of Pix generates credit expansion in financially less inclusive municipalities. Pix dramatically reduces transaction costs and enables banks to observe borrower liquidity and cash flows in real time. By shifting transactions from cash to formal accounts, Pix provides banks with better information on borrower repayment capacity, reducing the perceived credit risk and relaxing the lending constraints. The effect is particularly pronounced in rural and less digitally connected areas, where information frictions and payment costs have historically been the most binding.

Table 5 complements the dynamic analysis by reporting the average effects estimated by OLS during the sample period. Unlike event-study estimates, which emphasize timing and evolution, the OLS specifications capture average heterogeneous responses associated with the intensity of Pix usage. The interaction terms indicate that total credit responds strongly in municipalities with lower pre-Pix mobile penetration. In contrast, while rural and real estate credit respond to the adoption of Pix, the OLS specifications do not present meaningful heterogeneity across mobile penetration levels for these categories. This pattern suggests that improvements in payment infrastructure benefit all municipalities, regardless of their initial level of digital connectivity.

Table 5: Pix and Credit Outcomes (OLS Regressions)

	Dependent variables					
	Total credit		Rural credit		Real estate credit	
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(1 + \text{Pix})$	0.0692***	0.0785***	0.4163***	0.5754***	0.1681*	0.2499*
	(0.0140)	(0.0215)	(0.0969)	(0.1555)	(0.0669)	(0.1169)
$\ln(1 + \text{Pix})$ × Below median	0.0079**	–	0.0200	–	-0.0078	–
	(0.0025)		(0.0165)		(0.0126)	
$\ln(1 + \text{Pix})$ × Q25–Q50 vs Q50–Q75	–	0.0034	–	0.0017	–	-0.0032
		(0.0030)		(0.0196)		(0.0148)
Observations	338,044	169,081	338,044	169,081	338,044	169,081
Adjusted R^2	0.9407	0.9368	0.8634	0.8745	0.9379	0.9463
Within R^2	0.01690	0.02200	0.01691	0.01447	0.01037	0.01827
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 expressed in $\ln(1 + \cdot)$. Odd-numbered columns interact $\ln(1 + \text{Pix})$ 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 from January 2016 to December 2024. All specifications are estimated by OLS and include municipality and time fixed effects, with standard errors clustered at the municipality level.

The results that use banking density as an alternative dimension of heterogeneity and that are presented in Figure B.3 and Table B.4 substantiate and strengthen the main findings on credit expansion. When banking density is used in place of mobile penetration, the effects of credit expansion become more persistent and pronounced across all credit categories. Municipalities with lower pre-Pix banking density experience larger and more sustained increases in total credit, rural credit, and real estate credit beginning approximately two to three years after Pix implementation, with effects continuing to strengthen through the end of the sample period. These results confirm that credit expansion is not driven solely by differences in digital infrastructure, but rather reflects a broader pattern of local absorptive capacity. The greater persistence of the effects when banking density is used suggests that municipalities with weaker pre-existing financial infrastructure benefit more durably from Pix-induced improvements in payment technology and information access.

Indeed, the absence of significant effects on mortgage lending when exploiting heterogeneity in mobile penetration, as shown in Figure 8, Panel (a), may appear at odds with the positive and more persistent effects observed when the sample is stratified by banking density, as shown in Figure B.3, Panel (a). However, these results reflect differences in the underlying constraints captured by each dimension of heterogeneity rather than a contradiction in the effects of Pix.

Banking density serves as a proxy for the local availability of financial intermediation and, therefore, for the tightness of credit supply constraints. When the sample is split along this dimension, the estimates indicate that the introduction of Pix is associated with a relative expansion in mortgage credit precisely in areas with lower initial banking presence. This pattern is consistent with the view that Pix contributes, both directly and indirectly, to alleviating frictions related to financial inclusion, information, and customer relationships in underserved markets, where such constraints are more likely to be binding.

In contrast, mobile penetration primarily captures variation in technological readiness and access to digital devices, making it only an imperfect proxy for effective exposure to Pix. Mortgage lending, being collateralized, long-term, and institutionally intensive, is unlikely to be directly constrained by payment technology adoption. Moreover, areas with low mobile penetration are also those where the adoption and usage of Pix are likely limited, weakening the effective treatment intensity along this margin. To the extent that mobile penetration is measured with error as a proxy for Pix exposure, this will further attenuate the estimated coefficients.

These findings suggest that the effects of Pix on mortgage credit operate predominantly through channels related to financial intermediation rather than through the diffusion of payment technology per se. As such, the absence of effects along the mobile penetration dimension does not contradict the results based on banking density, but rather helps to clarify the mechanism through which Pix influences credit outcomes.

6. Conclusions

This paper examined how Pix diffusion is associated with changes in local banking outcomes across Brazilian municipalities. Using a balanced municipal-month panel covering the period 2016–2024 and exploiting pre-existing heterogeneity in mobile penetration, the analysis documents heterogeneous associations between instant payment adoption and financial outcomes across municipalities with varying levels of digital readiness.

The empirical findings reveal a consistent pattern: Pix adoption is associated with stronger effects in municipalities with lower levels of pre-Pix digital infrastructure. On the deposit side, municipalities with below-median mobile penetration show associations with increases in savings deposits and total deposits, with effects beginning approximately three years after Pix implementation and continuing through the end of the sample period. In contrast, checking deposits show no consistent association, while time deposits remain largely unaffected by Pix adoption. This compositional pattern is consistent with instant payments affecting short-term liquidity management and transaction behavior, rather than long-term savings allocation.

On the credit side, total credit shows associations with expansion in less digitally connected municipalities, with positive and statistically significant coefficients emerging from 2022 onward. Rural credit also displays positive associations, though more modest in magnitude, consistent with the potential of Pix to reduce payment frictions in geographically dispersed areas. Real estate credit, by contrast, shows no meaningful association, reflecting its dependence on housing market conditions and macro-financial factors rather than on short-run improvements in payment technology.

Robustness checks using banking density as an alternative dimension of heterogeneity provide support for and strengthen these findings. When measured by physical banking infrastructure rather than digital connectivity, credit expansion appears more persistent and pronounced. Municipalities with lower banking density show larger and more sustained associations across all credit categories, suggesting that the underlying mechanism may reflect general local absorptive capacity rather than digital infrastructure alone.

The mechanisms potentially linking Pix to financial deepening could operate through two complementary channels. First, instant payments may reduce payment frictions by lowering the marginal cost of digital transactions and facilitating the substitution of cash with account-based payments. This could shift liquidity from informal holdings, such as cash, to formal holdings, such as bank accounts, thereby increasing the demand for deposits. Second, as transactions migrate to the formal financial system, banks may gain greater visibility into borrower cash flows and liquidity patterns, reducing information asymmetries and improving perceived credit risk. This improved informational environment may be particularly beneficial in rural and less digitally connected markets, where informal liquidity has historically constrained observable financial histories.

From a policy perspective, these findings highlight the importance of payment systems to financial infrastructure. Public instant payment systems such as Pix may influence not only the execution of transactions, but also the functioning of local credit markets and the depth of financial intermediation. By potentially reducing payment frictions, formalizing liquidity, and enhancing informational transparency, such infrastructures could contribute to financial deepening and broaden access to formal financial services, particularly in regions historically characterized by limited digital connectivity and higher transaction costs.

References

Adrian, T. and Mancini-Griffoli, T. (2019). The rise of digital money. IMF FinTech Notes, 19(01).

Allen, F., Demirguc-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, 27(C):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 Canadian Survey. Bank of Canada.

Auer, R., Cornelli, G., and Frost, J. (2020). Rise of the central bank digital currencies: Drivers, approaches and technologies. BIS Working Papers, 880.

Aurazo, J., Cantú, C., Frost, J., Kosse, A., and Velasquez, C. (2024). A revolution in digital payments: Faster, user-friendlier and cheaper. BIS Papers 152, Bank for International Settlements, Basel, Switzerland.

Aurazo, J., Franco, C., Frost, J., and McIntosh, J. (2025). Fast payments and financial inclusion in latin america and the caribbean. BIS Papers 153, Bank for International Settlements, Basel, Switzerland.

Azevedo, V., Garbay Flores, S. A., Vera-Cossio, D. A., Vlaicu, R., and Zárate Moreno, A. M. (2025). Beyond Cash: The Digital Payments Revolution in Latin America and the Caribbean.

Bank for International Settlements (2011). Payment, clearing and settlement systems in brazil. CPMI Country Report. Committee on Payment and Settlement Systems.

Barros, F., Delalibera, B. R., Pinho Neto, V., and Rodrigues, V. (2025). Natural disasters and financial technology adoption. Economics Letters, 247:1–4.

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.

Burga, C., Cespedes, J., Parra, C. R., and Ricca, B. (2025). Financial technologies, labor markets, and wage inequality: Evidence from instant payment systems. Working paper.

Central Bank of Brazil (2024). Pix: Instant payment system. Banco Central do Brasil. Accessed: 2026-01-24.

Demirgüç-Kunt, A., Klapper, L., Singer, D., Ansar, S., and Hess, J. (2020). The global findex database 2017: Measuring financial inclusion and opportunities to expand access to and use of financial services. World Bank Economic Review, 34:S2–S8.

Fonseca, J. and Matray, A. (2024). Financial inclusion, economic development, and inequality: Evidence from brazil. Journal of Financial Economics, 156(C).

Fonseca, J. and Van Doornik, B. (2022). Financial Development and Labor Market Outcomes: Evidence from Brazil.

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.

Greenwood, J. and Jovanovic, B. (1990). Financial development, growth, and the distribution of income. Journal of Political Economy, 98(5):1076–1107.

Hjort, J. and Poulsen, J. (2019). The arrival of fast internet and employment in Africa. American Economic Review, 109(3):1032–1079.

Jack, W. and Suri, T. (2014). Risk sharing and transactions costs: Evidence from Kenya's mobile money revolution. American Economic Review, 104(1):183–223.

Klapper, L. and Singer, D. (2017). The opportunities and challenges of digitizing government-to-person payments. World Bank Research Observer, 32(2):211–226.

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.

Sampaio, M. C. and Ornelas, J. R. H. (2024). Payment technology complementarities and their consequences on the banking sector: Evidence from Brazil's Pix. Bank for International Settlements, BIS Papers, No. 152, 17–36.

Sarkisyan, S. (2025). Instant payment systems and competition for deposits. Working paper, Fisher College of Business, The Ohio State University.

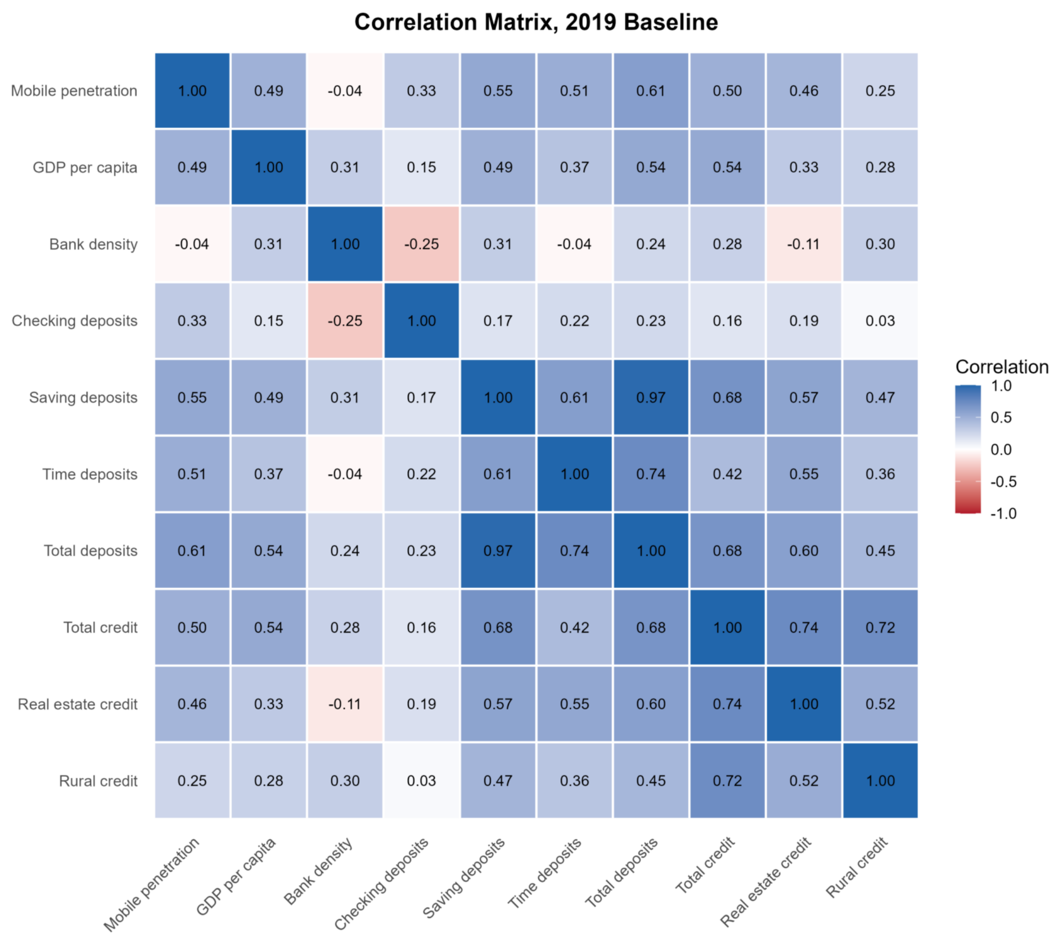
Suri, T. and Jack, W. (2016). The long-run poverty and gender impacts of mobile money. Science, 354(6317):1288–1292.

Vives, X. (2019). Digital disruption in banking. Annual Review of Financial Economics, 11:243–272.

Appendix A

Figure A.1 reports pairwise Pearson correlations among baseline municipal characteristics measured in 2019.

Figure A.1: Correlation Matrix across Municipalities, Baseline Year (2019)

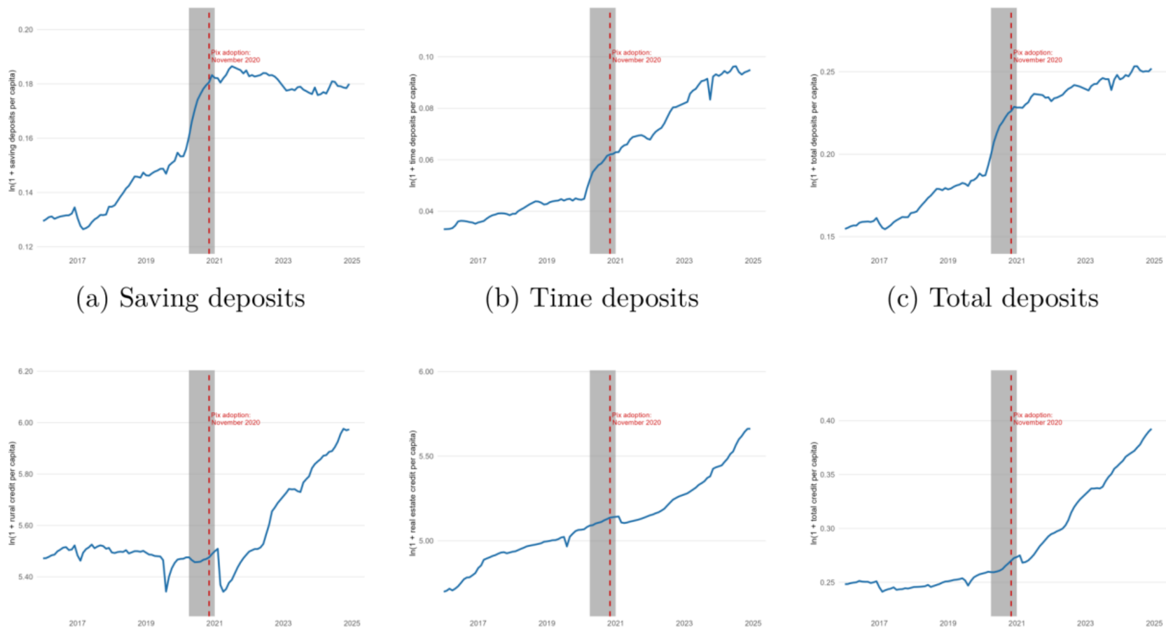


	Mobile penetration	GDP per capita	Bank density	Checking deposits	Saving deposits	Time deposits	Total deposits	Total credit	Real estate credit	Rural credit
Mobile penetration	1.00	0.49	-0.04	0.33	0.55	0.51	0.61	0.50	0.46	0.25
GDP per capita	0.49	1.00	0.31	0.15	0.49	0.37	0.54	0.54	0.33	0.28
Bank density	-0.04	0.31	1.00	-0.25	0.31	-0.04	0.24	0.28	-0.11	0.30
Checking deposits	0.33	0.15	-0.25	1.00	0.17	0.22	0.23	0.16	0.19	0.03
Saving deposits	0.55	0.49	0.31	0.17	1.00	0.61	0.97	0.68	0.57	0.47
Time deposits	0.51	0.37	-0.04	0.22	0.61	1.00	0.74	0.42	0.55	0.36
Total deposits	0.61	0.54	0.24	0.23	0.97	0.74	1.00	0.68	0.60	0.45
Total credit	0.50	0.54	0.28	0.16	0.68	0.42	0.68	1.00	0.74	0.72
Real estate credit	0.46	0.33	-0.11	0.19	0.57	0.55	0.60	0.74	1.00	0.52
Rural credit	0.25	0.28	0.30	0.03	0.47	0.36	0.45	0.72	0.52	1.00

Notes: This figure reports pairwise Pearson correlations among baseline municipal characteristics measured in 2019. Mobile penetration is defined as the number of mobile connections per capita using ANATEL data from December 2019. GDP per capita is constructed using IBGE municipal GDP divided by population. Bank density corresponds to the number of bank branches per 100,000 inhabitants. Financial variables include deposits and credit aggregates at the municipality level, expressed in logs of per capita values, $\ln(1+x)$. All variables are measured in December 2019, prior to the introduction of Pix.

Figure A.2: Evolution of Log Deposit and Credit Volumes across Brazilian Municipalities, 2016–2024

2016–2024



(a) Saving deposits (b) Time deposits (c) Total deposits

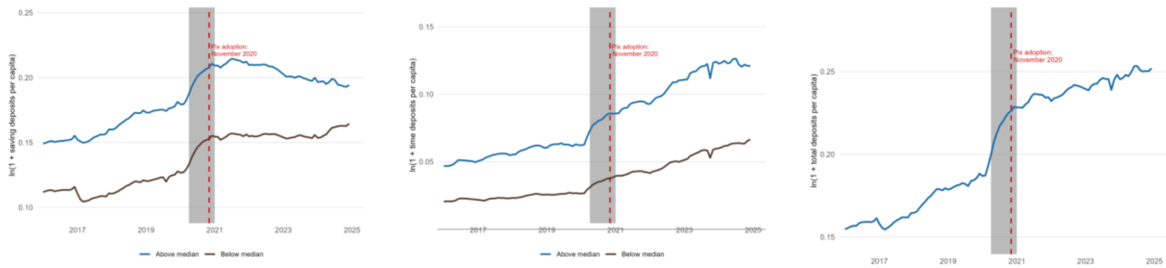
(d) Rural credit (e) Real estate credit (f) Total credit

Notes: These panels plot the monthly average of $\ln(1 + \text{outcome per capita})$ across Brazilian municipalities from 2016 to 2024. Deposit outcomes include savings deposits, time deposits, and total deposits. Credit outcomes include total credit, rural credit, and real estate credit. The vertical dashed red line marks Pix adoption in November 2020. The gray shaded area indicates the main period of Auxílio Emergencial payments, from April to December 2020. These trajectories are purely descriptive and are not adjusted for any controls, covariates, or fixed effects.

Figure A.3: Log Deposit Volumes over Time across Municipalities with Different Levels of Mobile Penetration, 2016–2024

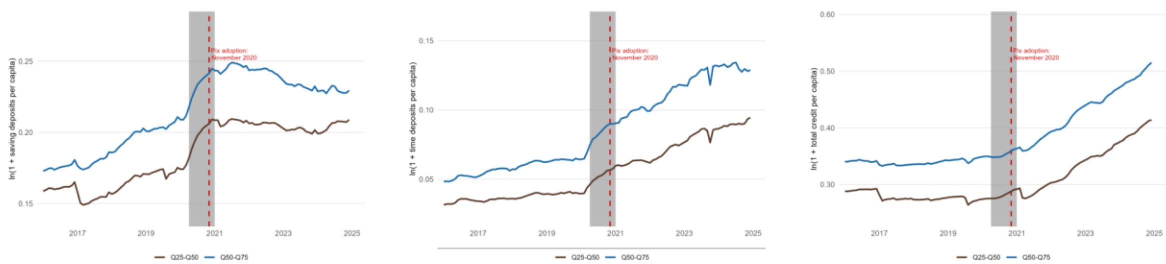
Mobile Penetration, 2016–2024

Panel A: Below vs. Above Median Mobile Penetration



(a) Saving deposits (b) Time deposits (c) Total deposits

Panel B: Q25–Q50 vs. Q50–Q75 Mobile Penetration



(d) Saving deposits (e) Time deposits (f) Total deposits

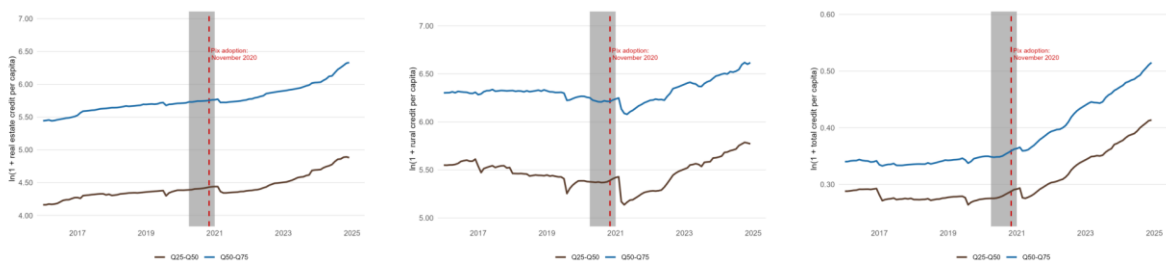
Notes: These panels plot the monthly average of $\ln(1 + \text{deposits per capita})$ across Brazilian municipalities from 2016 to 2024. Panel A compares municipalities below and above the median level of mobile penetration, while Panel B compares municipalities in the Q25–Q50 and Q50–Q75 ranges. The vertical dashed red line marks Pix adoption in November 2020. The gray shaded area indicates the main period of Auxílio Emergencial payments, from April to December 2020. These trajectories are purely descriptive and are not adjusted for any controls, covariates, or fixed effects.

Figure A.4: Effects of Pix Adoption on Credit Outcomes by Mobile Penetration

Panel A: Below vs. Above Median Mobile Penetration

(a) Real estate credit (b) Rural credit (c) Total credit

Panel B: Q25–Q50 vs. Q50–Q75 Mobile Penetration



(d) Real estate credit (e) Rural credit (f) Total credit

Notes: This figure shows the effects of Pix adoption on credit outcomes across municipalities with different levels of mobile penetration. Panel A compares municipalities below and above the median level of mobile penetration, while Panel B compares municipalities in the Q25–Q50 and Q50–Q75 ranges of the distribution. The outcomes are $\ln(1 + \text{real estate credit})$, $\ln(1 + \text{rural credit})$, and $\ln(1 + \text{total credit})$. All estimates are obtained from specifications including municipality and time fixed effects, with standard errors clustered at the municipality level.

Table A.1: Event-study Estimates across Deposit Types (2020 = Year 0)

	Checking deposits		Saving deposits		Time deposits		Total deposits	
Year	Below median	Q25–Q50	Below median	Q25–Q50	Below median	Q25–Q50	Below median	Q25–Q50
2016 (-4)	-0.0017	-0.0007	-0.0041	0.0223·	0.0747·	0.1420**	-0.0040	0.0246
	(0.0045)	(0.0047)	(0.0123)	(0.0133)	(0.0406)	(0.0495)	(0.0142)	(0.0150)
2017 (-3)	0.0070	0.0091	-0.0208*	0.0040	0.0515	0.1033*	-0.0186	0.0123
	(0.0059)	(0.0061)	(0.0099)	(0.0121)	(0.0319)	(0.0403)	(0.0108)	(0.0124)
2018 (-2)	0.0012	0.0046	-0.0327***	-0.0096	0.0373	0.0656·	-0.0248	0.0008
	(0.0045)	(0.0057)	(0.0087)	(0.0105)	(0.0271)	(0.0346)	(0.0094)	(0.0112)
2019 (-1)	-0.0054	-0.0006	-0.0380***	-0.0173*	0.0216	0.0271	-0.0249***	-0.0083
	(0.0045)	(0.0055)	(0.0068)	(0.0083)	(0.0192)	(0.0245)	(0.0070)	(0.0085)
2021 (1)	-0.0297***	-0.0170*	0.0006	-0.0023	-0.0629*	-0.0766*	-0.0061	-0.0119
	(0.0087)	(0.0068)	(0.0074)	(0.0088)	(0.0255)	(0.0326)	(0.0086)	(0.0103)
2022 (2)	-0.0093·	0.0007	0.0061	0.0003	-0.0490	-0.0753·	0.0029	-0.0103
	(0.0052)	(0.0044)	(0.0104)	(0.0125)	(0.0359)	(0.0452)	(0.0117)	(0.0140)
2023 (3)	0.0159	0.0182	0.0468***	0.0301*	0.0055	-0.0290	0.0346**	0.0153
	(0.0104)	(0.0119)	(0.0113)	(0.0138)	(0.0369)	(0.0470)	(0.0124)	(0.0148)
2024 (4)	0.0077	0.0153	0.0805***	0.0548***	0.0567	0.0345	0.0653***	0.0392*
	(0.0101)	(0.0113)	(0.0121)	(0.0146)	(0.0387)	(0.0497)	(0.0131)	(0.0156)
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
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 $\ln(1 + \text{deposits})$. 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. Note: the last two columns (Total deposits) reproduce the values reported in the original document; some entries were truncated in the source PDF and should be verified against the regression output.

Table A.2: Event-study Estimates across Credit Types (2020 = Year 0)

	Rural credit		Real estate credit		Total credit	
Year	**Below median**	**Q25–Q50**	**Below median**	**Q25–Q50**	**Below median**	**Q25–Q50**
2016 (-4)	0.4283***	0.3335*	0.1823·	0.1709	0.0309	0.0179
	(0.1288)	(0.1590)	(0.0970)	(0.1183)	(0.0208)	(0.0249)
2017 (-3)	0.3247**	0.2285	0.1446	0.0838	0.0158	0.0099
	(0.1197)	(0.1466)	(0.0944)	(0.1145)	(0.0177)	(0.0224)
2018 (-2)	0.0285	0.0214	-0.0080	-0.0321	-0.0167	-0.0148
	(0.1007)	(0.1269)	(0.0758)	(0.0947)	(0.0141)	(0.0184)
2019 (-1)	-0.0490	-0.0533	-0.0115	-0.0204	-0.0172·	-0.0148
	(0.0672)	(0.0801)	(0.0444)	(0.0561)	(0.0090)	(0.0112)
2021 (1)	-0.0969	-0.1277	-0.0963	-0.0299	0.0061	-0.0048
	(0.1032)	(0.1234)	(0.0787)	(0.0940)	(0.0136)	(0.0167)
2022 (2)	0.1356	-0.0676	-0.0887	-0.0384	0.0291	-0.0048
	(0.1387)	(0.1654)	(0.1021)	(0.1203)	(0.0186)	(0.0224)
2023 (3)	0.3333*	0.0844	-0.0551	-0.0461	0.0546**	0.0151
	(0.1521)	(0.1791)	(0.1064)	(0.1220)	(0.0204)	(0.0243)
2024 (4)	0.2480	0.0526	-0.0263	-0.0563	0.0693***	0.0271
	(0.1573)	(0.1847)	(0.1061)	(0.1190)	(0.0210)	(0.0249)
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
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 $\ln(1 + \text{credit})$. 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.

Appendix B

7. Banking Density: Alternative Robustness Specification

This appendix presents robustness checks that use banking density, measured as the number of bank branches per 100,000 inhabitants in 2019, as an alternative pre-Pix dimension of heterogeneity. Unlike mobile penetration, which captures digital connectivity, banking density captures local financial infrastructure through the physical branch presence of banking institutions. This allows us to validate that treatment heterogeneity is robust across multiple infrastructure dimensions determined prior to the introduction of Pix. Banking density is defined as:

$$\text{Banking Density}_m = \frac{\text{Number of Bank Branches}_m}{\text{Population}_m} \times 100{,}000, \tag{4}$$

We estimate event-study regressions that replace the mobile penetration indicator with a banking density indicator D_m^{BD}:

$$Y_{m,t} = \alpha + \gamma_m + \delta_t + \sum_{k=-4}^{-1} \gamma_k D_{k,t} \times D_m^{BD} + \sum_{k=1}^{4} \beta_k D_{k,t} \times D_m^{BD} + X'_{m,t}\theta + \varepsilon_{m,t}. \tag{5}$$

We also estimate panel OLS regressions exploiting continuous variation in Pix intensity:

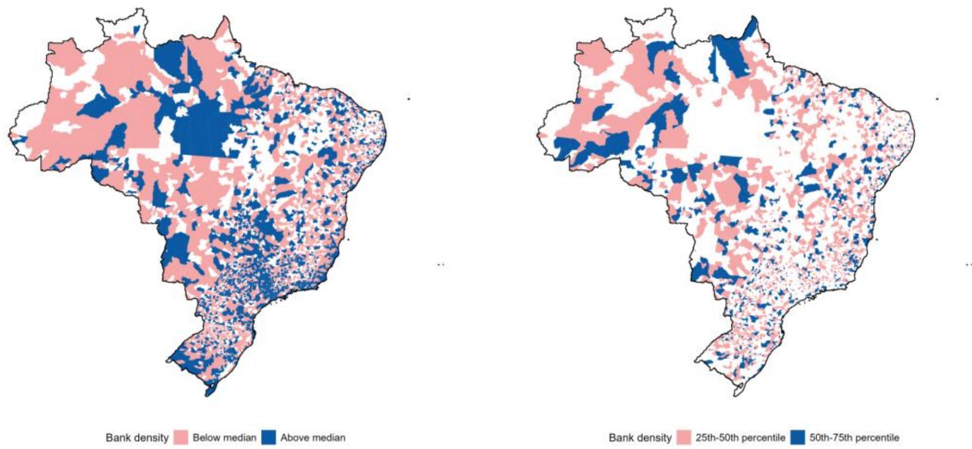
$$Y_{m,t} = \alpha + \gamma_m + \delta_t + \beta_1 \ln\left(1 + \text{Pix}_{m,t}\right) + \beta_2 \ln\left(1 + \text{Pix}_{m,t}\right) \times D_m^{BD} + X'_{m,t}\theta + \varepsilon_{m,t}. \tag{6}$$

All specifications use the same outcome variables, total and disaggregated deposits as well as total, rural, and real estate credit, controls, and fixed effects as the main analysis. Municipalities are partitioned by banking density, below vs. above median and 25th–50th vs. 50th–75th percentiles, with standard errors clustered at the municipality level. The consistency of the results obtained using both mobile penetration and banking density validates the identification strategy and reduces concerns that treatment heterogeneity is driven by omitted variables specific to digitalization rather than general local absorptive capacity.

Figure B.1: Banking Density across Brazilian Municipalities

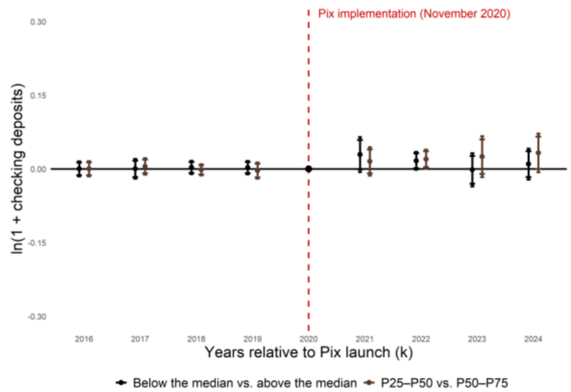
(a) Municipalities below and above the median of banking density

(b) Municipalities in the Q25–Q50 and Q50–Q75 ranges of banking density

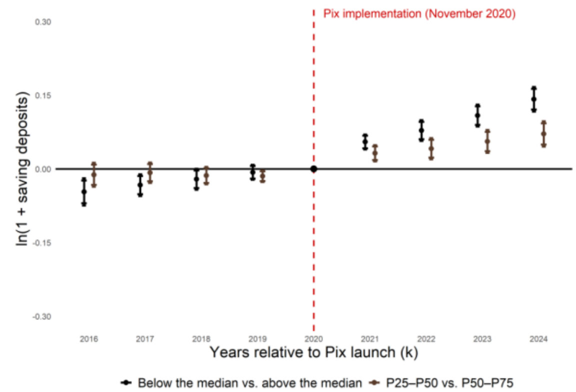


Notes: The maps illustrate the spatial distribution of banking density across Brazilian municipalities. Panel (a) classifies municipalities below and above the median level of banking density, while Panel (b) compares municipalities in the 25th–50th and 50th–75th percentiles of the distribution. Banking density is measured in the pre-Pix period and serves as a proxy for the local availability of banking infrastructure. 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 trends across groups.

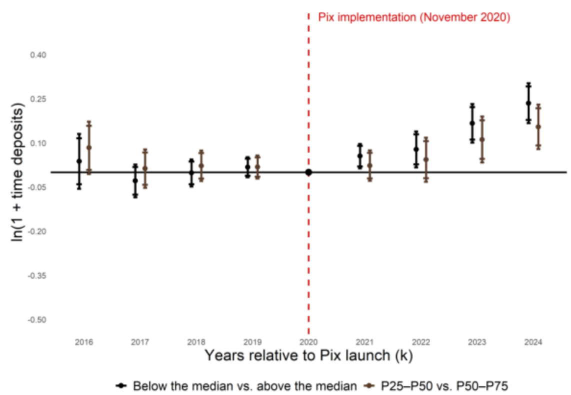
Figure B.2: Event-study Estimates of the Impact of Pix Adoption on Bank Deposits (Banking Density)



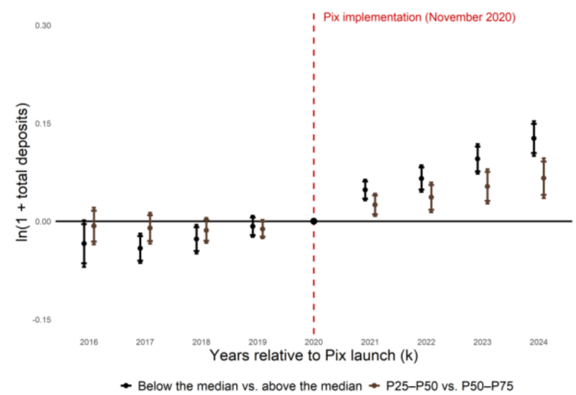
(a) Checking deposits



(b) Saving deposits



(c) Time deposits



(d) Total deposits

Notes: The figure reports coefficients from event-study regressions comparing municipalities below the median to those above the median of banking density, measured as bank branches per capita, as well as 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.

Table B.1: Pix and Deposit Outcomes by Banking Density (OLS Regressions)

	Checking deposits		Saving deposits		Time deposits		Total deposits	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\ln(1+\text{Pix})$	0.0109·	0.0088	0.0039	-0.0171·	0.1271***	0.0833*	0.0186*	0.0032
	(0.0057)	(0.0055)	(0.0083)	(0.0091)	(0.0292)	(0.0326)	(0.0094)	(0.0112)
$\ln(1+\text{Pix})$ × Below median BD	0.0016	–	0.0139***	–	0.0147***	–	0.0126***	–
	(0.0011)		(0.0015)		(0.0038)		(0.0015)	
$\ln(1+\text{Pix})$ × Q25–Q50 vs Q50–Q75 BD	–	0.0032***	–	0.0068***	–	0.0072·	–	0.0063***
		(0.0012)		(0.0015)		(0.0043)		(0.0017)
Observations	347,924	169,353	347,924	169,353	347,924	169,353	347,924	169,353
Adjusted R^2	0.7089	0.5979	0.8946	0.9574	0.8855	0.9021	0.8861	0.9523
Within R^2	0.0055	0.0047	0.0171	0.0774	0.0228	0.0160	0.0121	0.0251
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

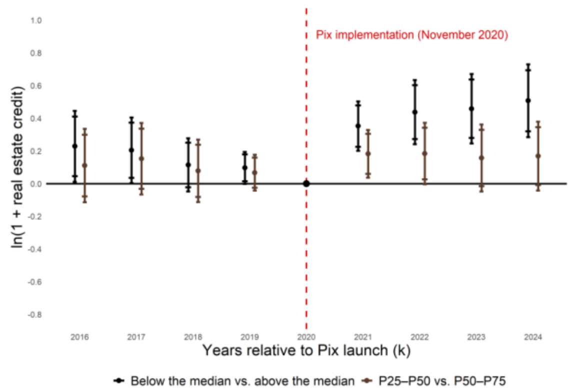
Notes: · $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. All dependent variables are expressed in $\ln(1+\cdot)$. "BD" denotes banking density. Odd-numbered columns interact $\ln(1+\text{Pix})$ with a below-median banking density indicator, while even-numbered columns compare municipalities in the Q25–Q50 banking density range to those in the Q50–Q75 range. The sample spans from January 2016 to December 2024. All specifications are OLS and include municipality and time fixed effects, with standard errors clustered at the municipality level.

Table B.2: Event-study Estimates across Deposit Types by Banking Density (2020 = Year 0)

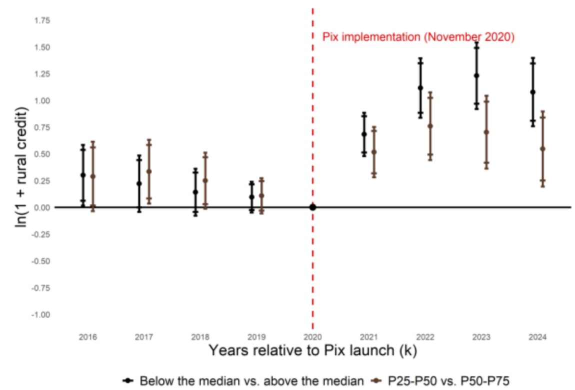
	Checking deposits		Saving deposits		Time deposits		Total deposits	
Year	Below median	Q25–Q50	Below median	Q25–Q50	Below median	Q25–Q50	Below median	Q25–Q50
2016 (-4)	0.0003	0.0004	-0.0466***	-0.0117	0.0375	0.0834·	-0.0341·	-0.0033
	(0.0078)	(0.0079)	(0.0141)	(0.0125)	(0.0475)	(0.0455)	(0.0188)	(0.0149)
2017 (-3)	0.0003	0.0053	-0.0328**	-0.0076	-0.0289	0.0127	-0.0411***	-0.0040
	(0.0102)	(0.0085)	(0.0113)	(0.0106)	(0.0284)	(0.0333)	(0.0114)	(0.0118)
2018 (-2)	0.0032	-0.0017	-0.0209·	-0.0135	-0.0020	0.0222	-0.0276*	-0.0067
	(0.0068)	(0.0058)	(0.0110)	(0.0091)	(0.0235)	(0.0264)	(0.0115)	(0.0095)
2019 (-1)	0.0029	-0.0032	-0.0067	-0.0147*	0.0173	0.0182	-0.0035	-0.0095
	(0.0069)	(0.0085)	(0.0078)	(0.0061)	(0.0175)	(0.0199)	(0.0084)	(0.0070)
2021 (1)	0.0293	0.0155	0.0551***	0.0321***	0.0551**	0.0228	0.0481***	0.0294***
	(0.0181)	(0.0147)	(0.0078)	(0.0084)	(0.0213)	(0.0265)	(0.0085)	(0.0083)
2022 (2)	0.0168·	0.0202*	0.0783***	0.0413***	0.0781*	0.0430	0.0655***	0.0383***
	(0.0093)	(0.0098)	(0.0108)	(0.0110)	(0.0312)	(0.0383)	(0.0107)	(0.0107)
2023 (3)	-0.0016	0.0252	0.1088***	0.0561***	0.1666***	0.1115**	0.0955***	0.0539***
	(0.0173)	(0.0213)	(0.0115)	(0.0119)	(0.0335)	(0.0399)	(0.0114)	(0.0114)
2024 (4)	0.0100	0.0329	0.1421***	0.0713***	0.2350***	0.1546***	0.1268***	0.0700***
	(0.0161)	(0.0201)	(0.0128)	(0.0132)	(0.0345)	(0.0384)	(0.0131)	(0.0125)
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	347,924	169,353	347,924	169,353	347,924	169,353	347,924	169,353

Notes: Columns report event-study estimates across deposit categories using banking density as the source of heterogeneity. Below median vs. above median compares municipalities below the median of pre-Pix banking density 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 $\ln(1+\text{deposits})$. 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. Some entries in the Total deposits columns were truncated in the source PDF and should be verified against the regression output.

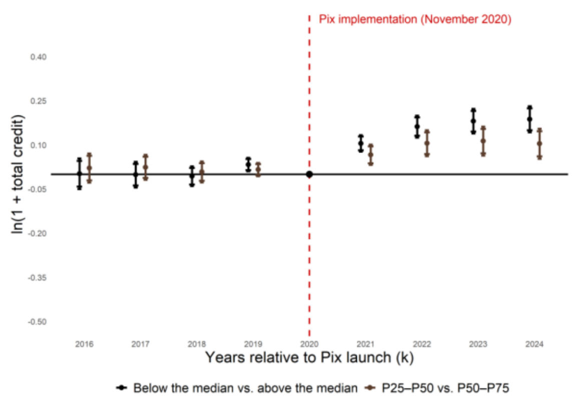
Figure B.3: Dynamic Effects of Pix Adoption on Bank Credit (Banking Density)



(a) Real estate credit



(b) Rural credit



(c) Total credit

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

Table B.3: Pix and Credit Outcomes by Bank Density (OLS Regressions)

	Total credit		Rural credit		Real estate credit	
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(1+\text{Pix})$	0.0550***	0.0248	0.3609***	0.2354*	0.2097**	0.0218
	(0.0131)	(0.0166)	(0.0914)	(0.1136)	(0.0707)	(0.0821)
$\ln(1+\text{Pix})$ × Below median (BD)	0.0178***	–	0.0966***	–	0.0327*	–
	(0.0026)		(0.0156)		(0.0131)	
$\ln(1+\text{Pix})$ × Q25–Q50 vs Q50–Q75 (BD)	–	0.0097***	–	0.0479*	–	0.0090
		(0.0031)		(0.0186)		(0.0134)
Observations	347,924	169,353	347,924	169,353	347,924	169,353
Adjusted R^2	0.904	0.947	0.825	0.874	0.888	0.955
Within R^2	0.0110	0.0218	0.0170	0.0154	0.0041	0.0145
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 expressed in $\ln(1+\cdot)$. "BD" denotes bank density. Odd-numbered columns interact $\ln(1+\text{Pix})$ with an indicator for municipalities below the median level of bank density, while even-numbered columns compare municipalities in the Q25–Q50 range of bank density to those in the Q50–Q75 range. The sample spans from January 2016 to 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 population share, demographic shares, illiteracy share, income per capita, municipality-level GDP per capita, and a pandemic control.

Table B.4: Event-study Estimates across Credit Types by Bank Density (2020 = Year 0)

	Rural credit		Real estate credit		Total credit	
Year	**Below median**	**Q25–Q50**	**Below median**	**Q25–Q50**	**Below median**	**Q25–Q50**
2016 (-4)	0.3002*	0.2894·	0.2284*	0.1108	0.0019	0.0210
	(0.1448)	(0.1654)	(0.1107)	(0.1145)	(0.0265)	(0.0254)
2017 (-3)	0.2213·	0.3338*	0.2040*	0.1523	-0.0010	0.0234
	(0.1345)	(0.1521)	(0.1025)	(0.1115)	(0.0223)	(0.0215)
2018 (-2)	0.1414	0.2499·	0.1142	0.0783	-0.0063	0.0084
	(0.1118)	(0.1335)	(0.0828)	(0.0973)	(0.0172)	(0.0185)
2019 (-1)	0.0962	0.1085	0.0963·	0.0672	0.0331**	0.0163
	(0.0730)	(0.0837)	(0.0500)	(0.0556)	(0.0116)	(0.0115)
2021 (1)	0.6824***	0.5171***	0.3519***	0.1823*	0.1051***	0.0664***
	(0.1033)	(0.1201)	(0.0770)	(0.0743)	(0.0144)	(0.0173)
2022 (2)	1.116***	0.7589***	0.4374***	0.1840·	0.1621***	0.1058***
	(0.1413)	(0.1615)	(0.1002)	(0.0958)	(0.0189)	(0.0224)
2023 (3)	1.231***	0.7026***	0.4582***	0.1569	0.1805***	0.1129***
	(0.1584)	(0.1735)	(0.1085)	(0.1045)	(0.0214)	(0.0254)
2024 (4)	1.078***	0.5460**	0.5073***	0.1685	0.1872***	0.1040***
	(0.1628)	(0.1787)	(0.1136)	(0.1075)	(0.0226)	(0.0263)
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	347,924	169,353	347,924	169,353	347,924	169,353

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 bank density to those above the median (reference group). Q25–Q50 vs. Q50–Q75 compares municipalities in the 25th–50th percentile range of bank density to those in the 50th–75th percentile range (reference group). The dependent variable is $\ln(1+\text{credit})$. 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.