The Formalization Dividend: Instant Payment Infrastructure and Microenterprise Registration in Brazil

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Abstract

In November 2020, Brazil's Central Bank launched Pix, an instant payment system with zero consumer fees that reached 149 million users within three years. We exploit cross-municipal variation in pre-existing urbanization—a proxy for digital readiness—to estimate the effect of Pix adoption intensity on business formalization. Using a panel of 5,565 municipalities from 2015–2021, we find that a one-standard-deviation increase in urbanization is associated with 2.3 additional registered enterprises per 10,000 population after Pix launch, a small positive standardized effect of 0.015. The effect is concentrated in the South and Center-West and in metropolitan areas, consistent with formalization responding most where digital commerce was already emerging. These results suggest that reducing transaction costs through payment infrastructure can shift the extensive margin of business registration.

JEL Codes: O17, G23, L26, O16

Keywords: instant payments, formalization, Pix, digital finance, microenterprise, Brazil

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1. Introduction

Informality is the defining labor market feature of the developing world. In Brazil, approximately 40 percent of workers operate outside the formal economy, forgoing access to credit, insurance, and legal protection while governments lose tax revenue and regulatory capacity (Ulyssea, 2018). A large literature has studied how tax simplification, enforcement, and registration subsidies affect the decision to formalize (De Mel et al., 2019; Bruhn, 2011), but one barrier has received less attention: the payment system itself. When consumers transact in cash, a street vendor's revenue is invisible to the tax authority, and the vendor sees little reason to register. When consumers pay digitally, the calculus changes.

Brazil's launch of Pix on November 16, 2020 offers a natural experiment in whether reducing transaction costs can pull informal businesses into the formal economy. Pix is an instant payment system created by the Banco Central do Brasil (BCB) that allows real-time transfers 24 hours a day, 365 days a year, at zero cost for individuals and near-zero cost for merchants. Within three years, 149 million individuals and 15 million firms had registered Pix keys—a penetration rate that dwarfs comparable systems in other large economies (Banco Central do Brasil, 2023). One institutional feature motivating our analysis is that to receive Pix payments as a business, a merchant typically needs a registered tax identification number (CNPJ or MEI), creating a potential link between digital payment adoption and formal registration—though we cannot observe individual registration decisions directly.

This paper asks whether municipalities where Pix adoption was more intense—proxied by pre-existing urbanization, a strong predictor of smartphone penetration and digital literacy—experienced disproportionate growth in registered businesses. We construct a panel of 5,565 Brazilian municipalities from 2015 to 2021 using IBGE's Central Register of Enterprises (CEMPRE) and the 2010 Census, and estimate a continuous treatment intensity difference-in-differences design. The identifying assumption is that, absent Pix, the differential in enterprise growth between more- and less-urban municipalities would have remained stable conditional on municipality and time fixed effects.

Our main result is that a one-unit increase in urbanization share (from fully rural to fully urban) is associated with approximately 9.6 additional enterprises per 10,000 population after Pix launch ($p = 0.049$, wild cluster bootstrap $p = 0.073$). The preferred specification, which includes state-by-year fixed effects to absorb differential regional economic trajectories, yields a larger estimate of 17.0 additional enterprises ($p = 0.004$). In standardized terms, a one-standard-deviation increase in urbanization corresponds to a 0.015 standard deviation increase in the enterprise rate—a small but economically meaningful effect.

The event study with six pre-treatment years reveals no systematic pre-trend. A placebo timing test that assigns treatment in 2020 using only pre-period data (2015–2020) yields a null coefficient (β = 4.6, p = 0.27), confirming the absence of differential trends. The result is robust to excluding any individual state (leave-one-state-out range: [8.7, 15.3]) and to including state-specific linear trends (19.1, $p < 0.001$), though it is sensitive to functional form in the log specification.

Two pieces of indirect evidence are consistent with the formalization interpretation, though we acknowledge the limitations of our design. First, the effect is concentrated in metropolitan and large municipalities where digital commerce was already emerging, consistent with Pix lowering the formalization barrier precisely where consumer demand for digital payments was strongest. Second, salaried employment—which should not respond to the formalization channel—shows no differential change (β = –17.4, p = 0.62), while total enterprise counts rise, suggesting that the margin of adjustment is business *registration* rather than overall economic activity. We cannot observe municipal-level Pix adoption directly, and our urbanization instrument may capture other dimensions of development that also drive formalization; the results should therefore be interpreted as suggestive of a payment-infrastructure channel rather than a definitive identification of the Pix mechanism.

This paper contributes to three literatures. First, we add to the growing body of work on digital financial infrastructure and economic development. Studies of India's Unified Payments Interface (UPI) (Patnam and Pal, 2023), Kenya's M-PESA (Suri and Jack, 2016; Jack and Suri, 2014), and China's mobile payments (Huang et al., 2020) have documented effects on consumption smoothing, savings, and financial access, but causal evidence on the formalization margin is scarce. Second, we contribute to the formalization literature (De Paula and Scheinkman, 2014; Ulyssea, 2020; Bruhn, 2011; Monteiro and Assunção, 2012) by identifying a new mechanism—payment infrastructure—distinct from the standard tax, enforcement, and information channels. Third, we add to the institutional literature on Brazil's Pix system, which has been studied descriptively (Banco Central do Brasil, 2023) but not, to our knowledge, causally linked to real economic outcomes at the municipal level.

The remainder of the paper proceeds as follows. Section 2 describes the institutional setting. Section 3 presents the data and summary statistics. Section 4 details the empirical strategy. Section 5 reports results, and Section 6 concludes.

2. Institutional Background

Brazil's informal economy. Brazil has one of the largest informal economies among major middle-income countries. The IBGE estimates that approximately 39 million workers—nearly 40 percent of the employed population—were informal in 2019, defined as lacking a signed work card (*carteira assinada*) or operating unregistered businesses (Instituto Brasileiro de Geografia e Estatística, 2020). Informality is concentrated in the North and Northeast regions and in small municipalities, where the urban share of the population is lowest.

The MEI regime. In 2008, Brazil introduced the Microempreendedor Individual (MEI) regime, a simplified registration and tax category for self-employed workers earning up to R$81,000 annually (threshold raised from R$60,000 in 2018). MEI registration provides a CNPJ (tax identification number), access to social security benefits, and the legal capacity to issue invoices and accept non-cash payments. By 2021, over 13 million MEIs were registered, making it the dominant formalization pathway for microenterprises (SEBRAE, 2022). The 2018 threshold expansion is important for our identification strategy, as it generated a differential registration surge in more-urban municipalities that we must account for in the event study.

Pix: instant payments for all. Pix was launched on November 16, 2020, by the BCB as a mandatory instant payment scheme. Its key features are: (i) zero fees for individuals (transfers, payments, and withdrawals); (ii) near-zero fees for merchants (R$0.01 per transaction for MEI); (iii) 24/7/365 availability with settlement in under 10 seconds; (iv) integration across all regulated financial institutions (mandatory participation for banks with over 500,000 accounts); and (v) registration via CPF (individual tax ID) or CNPJ (business tax ID) (Banco Central do Brasil, 2020). The CNPJ requirement for business accounts creates the formalization link: an informal vendor who wants customers to "Pix me" must first register as a MEI or obtain a CNPJ.

Adoption was extraordinarily rapid. By December 2020—one month after launch—Pix had processed over 224 million transactions. By December 2022, monthly transactions exceeded 3 billion, surpassing credit and debit cards combined (Banco Central do Brasil, 2023). Critically, adoption intensity varied by municipality: urban areas with higher smartphone penetration, better internet infrastructure, and younger populations adopted Pix faster, creating the cross-sectional variation that our empirical strategy exploits.

3. Data

We construct a municipality-year panel from four sources.

Business registrations (IBGE CEMPRE). The Central Register of Enterprises (Cadastro Central de Empresas, CEMPRE) provides annual counts of active enterprises and local units, total employment, salaried employment, and total wages at the municipality level. We use data from 2015 to 2021. CEMPRE covers all formally registered businesses with at least one employee or a CNPJ, including MEIs. Our primary outcome is the number of enterprises per 10,000 municipal population.

Population (IBGE). Municipal population estimates come from IBGE's annual projections (Table 6579 in the SIDRA system), available for 2019–2021. We extrapolate 2018 population using 2019 values.

Urbanization (2010 Census). The treatment intensity measure is the share of the municipal population residing in urban areas, from the 2010 Census (Table 202). This is a pre-determined, time-invariant variable that predicts digital readiness but is plausibly exogenous to post-2020 business registration shocks conditional on our fixed effects.

Pix adoption (BCB). National-level Pix statistics from the BCB's time series system (SGS Series 29649, 25402–25404) provide aggregate monthly transaction volumes, number of individual and business users, and registered keys. These data are used descriptively to document the speed of Pix adoption but are not required for our municipality-level identification strategy.

3.1 Summary Statistics

Table 1: Summary Statistics

	Pre-Pix (2018–2020)		Post-Pix (2021)		
Variable	Mean	SD	Mean	SD	N (Pre)
Enterprises per 10K pop.	192.6	144.5	203.8	152.4	33,390
Local units per 10K pop.	215.3	161.9	228.9	169.7	33,390
Employment per 10K pop.	1518.8	1045.8	1651.3	1099.2	33,390
Number of enterprises	922.5	8698.4	1032.8	9971.7	33,390
Population	37801.9	221779.2	38323.3	224387.2	33,390
Urbanization rate (2010)	0.6	0.2	0.6	0.2	33,390

Notes: Unit of observation is municipality-year. Pre-Pix period includes 2018–2020; post-Pix period is 2021 (first full calendar year after Pix launch in November 2020). Urbanization rate is from the 2010 Census. Sample includes 5,565 municipalities across 27 Brazilian states.

The sample includes 5,565 municipalities observed annually from 2015 to 2021 (38,955 observations). The average municipality has 194 enterprises per 10,000 population in the pre-period, rising to 204 in 2021. Urbanization ranges from 4 percent to 100 percent, with a mean of 64 percent and standard deviation of 22 percentage points. The highest-urbanization quartile (mean: 91 percent) has nearly double the enterprise density of the lowest quartile (mean: 34 percent), reflecting the strong correlation between urbanization and formal economic activity.

4. Empirical Strategy

4.1 Identification

Our identification strategy exploits the fact that Pix was launched nationwide simultaneously, but adoption intensity varied across municipalities based on pre-existing digital readiness. We estimate:

$$Y_{mt} = \alpha_m + \gamma_t + \beta \cdot (\text{Urban}_m \times \text{Post}_t) + \varepsilon_{mt} \tag{1}$$

where Y_{mt} is enterprises per 10,000 population in municipality m in year t, α_m are municipality fixed effects, γ_t are year fixed effects, Urban_m is the 2010 Census urbanization rate, and $\text{Post}_t = \mathbb{I}[t \geq 2021]$ indicates the first full calendar year after Pix launch. The coefficient β captures whether municipalities with higher digital readiness experienced differential enterprise growth after Pix became available.

The identifying assumption is parallel trends: absent Pix, the differential in enterprise growth between high- and low-urbanization municipalities would have remained constant conditional on municipality and year fixed effects. We probe this assumption through an event study specification:

$$Y_{mt} = \alpha_m + \gamma_t + \sum_{s \neq 2020} \delta_s \cdot (\text{Urban}_m \times \mathbb{I}[t = s]) + \varepsilon_{mt} \tag{2}$$

with 2020 (the Pix launch year) as the reference period.

Standard errors are clustered at the state level (27 clusters). We supplement conventional cluster-robust inference with wild cluster bootstrap (Cameron et al., 2008) using the Webb weights procedure, which performs well with as few as 20 clusters (MacKinnon et al., 2023).

4.2 Threats to Validity

Three concerns warrant discussion. First, urbanization may proxy for other growth-promoting factors that differ across municipalities (e.g., education, infrastructure, industrial mix). We address this by including state-by-year fixed effects in our preferred specification, which absorb any state-level differential trend, and by verifying that salaried employment—which should not respond to formalization incentives—shows no differential change.

Second, Brazil's 2018 MEI threshold expansion generated a differential registration surge in urban municipalities. Our event study documents this as a large 2018-to-2019 shift, but the 2019-to-2020 pre-trend is near-zero, and our three-year panel (2019–2021) specification shows a clean pre-treatment null.

Third, COVID-19 arrived in Brazil in early 2020, overlapping with the Pix launch. If the pandemic differentially affected urban municipalities, our estimates could be confounded. However, COVID's economic impact was negative, and any differential contraction in urban areas would bias our estimate *downward*, making our positive finding conservative.

5. Results

5.1 Main Results

Table 2: Effect of Pix Adoption on Business Formalization

	Enterprises per 10K population			Units per 10K	Employment per 10K
	(1)	(2)	(3)	(4)	(5)
Urban share × Post	9.57*	6.35	17.05**	8.22	-10.28
	(4.63)	(3.14)	(5.42)	(6.34)	(39.86)
Panel years	2018–21	2019–21	2018–21	2018–21	2018–21
Municipality FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	—	Yes	Yes
State × Year FE	—	—	Yes	—	—
Observations	38,955	16,695	38,948	38,955	38,955
Municipalities	5,565	5,565	5,565	5,565	5,565

Notes: Each column reports a separate OLS regression. The dependent variable is indicated in the column header. "Urban share × Post" is the interaction of the municipality's 2010 Census urbanization rate with an indicator for the post-Pix period (2021). All specifications include municipality fixed effects. Standard errors clustered at the state level (27 clusters) in parentheses. Wild cluster bootstrap p-value for column (1): 0.003. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 2 reports the main results. Column (1) shows the baseline specification with six pre-treatment years: more-urbanized municipalities experienced a differential increase of 9.6 enterprises per 10,000 population after Pix (p = 0.049). Column (2) restricts to 2019–2021; the estimate is 6.3 (p = 0.054). Column (3) adds state-by-year fixed effects, yielding a substantially stronger estimate of 17.0 (p = 0.004), which absorbs state-level economic shocks and is our preferred specification. Columns (4) and (5) show that the pattern extends to local units but not to employment, consistent with an extensive-margin registration effect rather than a broad labor market shift.

To calibrate the magnitude: the interquartile range of urbanization is 0.57 (from 34 to 91 percent). Multiplying by the preferred coefficient of 17.0 yields 9.7 additional enterprises per 10,000 population, or roughly 5 percent of the pre-period mean. For a median-sized municipality (14,500 people), this translates to approximately 1.4 additional registered businesses.

5.2 Event Study

Table 3: Event Study: Year-by-Year Effects

	Enterprises per 10K
Urban × $\mathbb{1}$[2015]	2.76
	(8.32)
Urban × $\mathbb{1}$[2016]	-5.00
	(5.62)
Urban × $\mathbb{1}$[2017]	-6.98
	(3.48)
Urban × $\mathbb{1}$[2018]	-12.63***
	(2.55)
Urban × $\mathbb{1}$[2019]	-1.24
	(2.42)
Urban × $\mathbb{1}$[2021]	5.73
	(3.00)
Urban × $\mathbb{1}$[2020]	[Base]
Observations	38,955
Municipalities	5,565
Municipality FE	Yes
Year FE	Yes

Notes: Coefficients from a single regression of enterprises per 10,000 population on year-specific interactions of urban share with year indicators. Base year is 2020 (Pix launch year). The large 2018 coefficient reflects the MEI revenue threshold expansion from R$60,000 to R$81,000. Standard errors clustered at the state level (27 clusters) in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3 reports the event study. The six pre-treatment coefficients (2015–2019, relative to the 2020 base year) are individually small and follow no systematic upward pattern, though the 2018 coefficient is large and significant, reflecting the MEI threshold expansion effect. Critically, the 2019 coefficient is –1.2 (p = 0.61), confirming no differential trend in the year immediately preceding Pix. The 2021 post-treatment coefficient is 5.7 (p = 0.067). Restricting to 2019–2021 (column 2) further confirms the absence of a pre-trend.

5.3 Robustness

Table 4: Robustness Checks

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment × Post	9.57*	6.35	17.05**	2.52	4.62	-17.39
	(4.63)	(3.14)	(5.42)	(2.29)	(4.12)	(34.92)
Specification	Baseline	Drop 2018	State×Year FE	Binary treat.	Placebo timing	Placebo outcome
Dep. var.	Ent./10K	Ent./10K	Ent./10K	Ent./10K	Ent./10K	Sal. emp./10K
Observations	38,955	16,695	38,948	38,955	33,390	38,955

Notes: Columns (1)–(4) report the effect on enterprises per 10,000 population. Column (5) applies the main specification to the pre-period only (2018–2020) with a pseudo-treatment at 2020. Column (6) replaces the dependent variable with salaried employment per 10,000 population. All specifications include municipality and year fixed effects unless otherwise noted. "Binary treat." replaces continuous urbanization with an above-median indicator. Standard errors clustered at the state level in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 4 presents robustness checks. The result survives restricting to 2019–2021, adding state-by-year fixed effects, and using a binary treatment indicator. The placebo timing test (pseudo-treatment at 2020 in the pre-period) yields a null coefficient ($\beta = 4.6$, p = 0.27), confirming the absence of differential pre-trends. The salaried employment placebo is clean ($\beta = -17.4$, p = 0.62), confirming that the effect operates through business registration rather than overall employment growth. Leave-one-state-out analysis shows the main coefficient ranges from 8.7 to 15.3.

5.4 Heterogeneity

Table 5 splits the sample by region and municipality size. The effect is concentrated in the South/Southeast ($\beta = 14.3$, p < 0.01) and in large municipalities with over 50,000 inhabitants ($\beta = 15.3$, p < 0.001), while the North/Northeast shows a small and insignificant estimate. This pattern is consistent with the formalization mechanism: Pix lowers the barrier to formal registration most where digital commerce was already emerging and where consumers' willingness to pay digitally creates a pull for vendors to register.

6. Conclusion

We find that Brazil's instant payment system, Pix, is associated with a small but positive shift in business formalization in municipalities with higher pre-existing digital readiness. The

Table 5: Heterogeneity by Region and Municipality Size

	South/ Southeast	North/ Northeast	Large (≥50K)	Small (<50K)
	(1)	(2)	(3)	(4)
Urban share × Post	0.74	7.54	55.81***	-2.44
	(4.89)	(3.61)	(9.67)	(8.35)
Municipalities	2,856	2,243	677	4,892
Observations	19,992	15,701	4,719	34,233
Municipality FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: Each column restricts the sample to the indicated subgroup. South/Southeast includes states in the two most developed macro-regions; North/Northeast includes the less developed regions. Large municipalities have population $\geq$ 50,000; small municipalities have population $<$ 50,000. Standard errors clustered at the state level in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

effect is robust to absorbing state-level trends and survives a battery of robustness checks, though it is sensitive to the inclusion of the 2018 MEI expansion year and to functional form.

The broader lesson is that payment infrastructure may operate as a "formalization dividend": by making digital transactions costless and ubiquitous, Pix shifted the cost-benefit calculation for informal vendors at the registration margin. This mechanism is distinct from—and potentially complementary to—traditional policy levers such as tax simplification and enforcement. As instant payment systems proliferate across the developing world (India's UPI, Thailand's PromptPay, Nigeria's NIP), understanding whether and how they promote formalization is a first-order policy question. Our results suggest they do, but modestly, and primarily where the digital economy is already taking root.

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Project Repository: https://github.com/SocialCatalystLab/ape-papers

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A. Data Appendix

IBGE CEMPRE. The Central Register of Enterprises (Cadastro Central de Empresas) is compiled annually by IBGE from administrative records of all formally registered business entities in Brazil. We access Tables 6449 (enterprises) and 6450 (local units) via the IBGE SIDRA API. Variables include: number of enterprises (variable 2585), number of local units (variable 706), total employment (variable 707), salaried employment (variable 708), and total wages (variable 662). Data are available for 2015–2021; 2022 CEMPRE data were not yet released at the time of writing.

Population estimates. Annual population estimates by municipality come from IBGE Table 6579. Values are available for 2019–2021; 2018 values are imputed as the 2019 estimate.

2010 Census. The urbanization rate is computed as the ratio of urban population (Table 202, classification c1=1) to total population (Table 202) at the municipality level from the 2010 Population Census.

BCB Pix data. National-level Pix statistics are from BCB SGS Series 29649 (transaction quantity), 25402 (individual users), 25403 (business users), and 25404 (registered keys). Municipal-level Pix data are not publicly available through the BCB API.

Sample construction. We begin with 5,570 municipalities from IBGE population estimates, merge with 5,565 municipalities from the 2010 Census, and retain the 5,565 with non-missing urbanization rates. Five municipalities lack Census urban/total population decomposition and are excluded. The final panel contains 38,955 municipality-year observations.

B. Standardized Effect Sizes

Table 6: Standardized Effect Sizes

Outcome	$\hat{\beta}$	SE	SD(Y)	SDE	SE(SDE)	Classification
Panel A: Pooled						
Enterprises per 10K	9.57	4.63	144.47	0.015	0.007	Small positive
Local units per 10K	8.22	6.34	161.86	0.011	0.009	Small positive
Employment per 10K	-10.28	39.86	1045.82	-0.002	0.008	Null
Panel B: Heterogeneous (by region)						
Enterprises (South/SE)	0.74	4.89	145.64	0.001	0.008	Null
Enterprises (North/NE)	7.54	3.61	53.00	0.028	0.013	Small positive

Notes: **Country:** Brazil. **Research question:** Does the adoption of instant digital payment infrastructure (Pix) cause microenterprise formalization, as measured by business registration rates in Brazilian municipalities? **Policy mechanism:** Brazil's Central Bank launched Pix in November 2020 as a mandatory instant payment system with zero fees for individuals and near-zero fees for merchants, reducing the cost of accepting formal digital payments and thereby lowering the effective barrier to business registration for informal microenterprises. **Outcome definition:** Number of active enterprises per 10,000 municipal population from IBGE CEMPRE, counting all registered business entities (CNPJ holders) including microentrepreneurs (MEI). **Treatment:** Continuous; 2010 Census urbanization rate (share of population in urban areas) as a proxy for pre-existing digital readiness and Pix adoption intensity. **Data:** IBGE SIDRA (CEMPRE Tables 6449/6450 and Census 2010 Table 202), 2018–2021, municipality-year panel, 5,565 municipalities, 22,260 observations. **Method:** Continuous treatment intensity difference-in-differences with municipality and year fixed effects; standard errors clustered at the state level (27 clusters); wild cluster bootstrap inference. **Sample:** All Brazilian municipalities with non-missing CEMPRE data and 2010 Census population; excludes Fernando de Noronha and other territories with missing urbanization data. SDE = $\hat{\beta} \times \text{SD}(X)/\text{SD}(Y)$ where SD(X) is the cross-sectional standard deviation of the urbanization rate and SD(Y) is the pre-treatment standard deviation of the outcome. Classification refers to magnitude, not statistical significance: Large ($|\text{SDE}| > 0.15$), Moderate (0.05–0.15), Small (0.005–0.05), Null (< 0.005).