Financial Technologies, Labor Markets, and Wage Inequality: Evidence from Instant Payment Systems*

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Abstract

We study the labor market effects of instant payment systems in the context of Brazil's Pix rollout. Using matched employer–employee administrative data, we implement a triple-difference design that exploits pre-treatment variation in mobile penetration across municipalities, the differential exposure to payment frictions of small versus large establishments, and the timing of Pix's introduction. We find that wages in small establishments rise significantly relative to those in large establishments after Pix, an effect fully explained by cash-intensive sectors such as retail and services. Crucially, wage inequality declines, driven entirely by wage gains among workers in the lower half of the distribution, who are primarily hired by small, cash-intensive firms. Our evidence indicates that Pix's benefits stem from lower cash-handling costs rather than increased local consumer demand, and the pass-through to wages is amplified by local labor market frictions. A quantitative model of monopsonistic labor markets shows that while Pix's actual rollout significantly increased wage-bill and profits, a counterfactual scenario with uniform adoption–achieved by closing mobile penetration gaps–would multiply these gains by a factor of four.

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1 Introduction

The relationship between technological change and wage inequality has long been a subject of intense debate. The conventional view is that production technologies increase inequality by complementing skilled labor and substituting for routine tasks typically performed by less-educated workers (Autor et al., 2003; Acemoglu and Autor, 2011). However, the labor market and distributional effects of financial technologies remain largely unexplored, despite their rapid adoption across both developed and developing economies. This raises a fundamental question: Do financial technologies affect labor markets and wage structures similarly to production technologies, or do they follow a different pattern? Answering this question is crucial for policy makers seeking to design inclusive growth strategies in an era of rapid digital transformation.

In this paper, we contribute to this debate by examining the labor market impacts of instant payment systems, a major financial innovation adopted by over 60 countries as of 2023 (BIS, 2023), which significantly reduce transaction costs such as merchant fees and cash-handling expenses, enable immediate settlement, and generate digital transaction records to enhance financial access.[1] These features alleviate frictions particularly burdensome for small, cash-intensive businesses.

However, the impact of these technologies on wage inequality is theoretically ambiguous. Inequality could increase if instant payments complement high-skill labor, as production technologies do. In contrast, inequality could decline if they complement low-skill workers or favor low-skill intensive firms. Furthermore, even if low-skill intensive firms are disproportionally benefited, the pass-through to wages may be muted when monopsony power is considered. This occurs because as benefited firms expand, their increased labor market shares can lead to higher wage markdowns, leaving inequality unchanged or even exacerbating it. Thus, whether instant payment systems reduce wage inequality or not is an empirical question.

[1] Prior studies document several economic effects of payment systems: Ghosh et al. (2024) and Dalton et al. (2024) find improved credit access, Bachas et al. (2018) shows reduced transaction costs, and Berg et al. (2020) demonstrates how digital footprints enhance credit screening and lower defaults.

We analyze Brazil's Pix system, an instant payment platform launched by the central bank in November 2020, which reduced transaction fees to approximately one-tenth those of credit cards while achieving unprecedented adoption—67 percent of Brazil's adult population within its first year.[2] Contrary to conventional patterns of skill-biased technical change, we find that instant payment systems reduce wage inequality by raising wages in small establishments within cash-intensive sectors such as retail and services, with gains concentrated among workers in the lower half of the wage distribution and amplified in areas where low-skill labor is scarce.

We develop a conceptual framework to formalize the mechanisms through which instant payment systems affect wage inequality. Our framework incorporates two skill groups and a continuum of firms that are heterogeneous in productivity and have monopsony power in wage setting. Firms are grouped into two sectors that differ in their cash-dependence–which determines their exposure to Pix–their skill intensity, and the complementarity between the payment technology and worker skill. Our framework shows how a reduction in transaction costs from digital payment adoption boosts the labor demand of firms in cash-intensive sectors, thereby raising wages. When these firms use predominantly low-skill workers, Pix reduces inequality. The magnitude of this effect is amplified when instant payments reduce local labor market concentration, but is dampened–and can even reverse–if the technology complements high-skill or substitutes low-skill workers.

We then estimate the labor market effects of Pix using comprehensive administrative data on formal workers and firms from 2016 to 2024. Our primary identification strategy is a triple difference-in-differences (DiD) design exploiting variation in Pix's nationwide introduction timing, pre-existing mobile penetration across municipalities—which strongly predicts Pix adoption—and exposure to payment frictions captured by establishment size. We compare

[2]Pix is an instant payment system developed by Brazil's central bank to reduce cash usage and promote financial inclusion. It facilitates real-time transfers through simplified identifiers such as email addresses or phone numbers. Key institutional features include mandatory participation by large banks, zero transaction fees for individuals, and substantially reduced fees for merchants—approximately 0.22 percent per transaction compared to roughly 2.2 percent for credit cards. By early 2024, Pix had over 152 million individual users and 15 million registered businesses.

wage changes between small and large establishments within the same municipality before and after Pix adoption, isolating Pix's impact while controlling for local economic conditions and industry-specific trends. The main rationale is that small establishments, particularly in cash-intensive sectors, will benefit the most from Pix.

Our baseline triple DiD design assumes that, without Pix, wage trends in small versus large establishments would have evolved similarly across municipalities with different levels of pre-treatment mobile penetration. We provide three main pieces of evidence that support this assumption. First, we plot event study graphs showing no differential pre-trends in wages between small and large establishments prior to Pix's introduction, providing support for the parallel trends assumption. Second, a key concern is that municipalities with higher mobile penetration might differ in ways that could influence wage trends and bias our results. To address this, we include municipality-by-industry-by-year fixed effects to control for local shocks that vary by industry and municipality over time, municipality-by-size-by-industry fixed effects to absorb all time-invariant differences between establishments, and size-by-industry-by-year fixed effects to capture national-level trends specific to establishment sizes within industries. Third, we define an industry-specific measure of cash-dependence equal to the share of sales to households–a segment we assume relies more heavily on cash than other buyers like firms, government, or non-residents. This allows us to perform a placebo test by estimating our triple DiD equation in the lowest tercile of cash-intensity. Consistent with our identifying assumption, we find null effects in this group of industries.

We find that following Pix's introduction, small establishments in municipalities with higher mobile penetration experienced significant wage increases relative to large establishments within the same municipalities. Specifically, our estimates indicate that a one-standard-deviation increase in mobile penetration leads to a 0.4 percent increase in wages for small establishments (those with fewer than 20 employees).[3] Our results remain robust to

[3]This wage response, combined with the 1.7 percent employment increase for micro establishments, implies a firm-level labor supply elasticity of approximately 4, consistent with recent estimates derived from firm-specific labor demand shocks (Sokolova and Sorensen, 2021).

alternative definitions of small establishments (fewer than 5 or 10 employees) and are notably stronger in cash-intensive sectors, specifically retail (0.8 percent) and services (1.4 percent), which rely heavily on small-value, consumer-facing transactions. In contrast, we find no significant wage effects in less cash-intensive sectors such as wholesale or manufacturing, which primarily conduct larger-value, business-to-business transactions, underscoring that the wage gains are driven specifically by reductions in payment frictions associated with cash usage.

We next examine the impact of Pix adoption on wage inequality. We find that municipalities with higher mobile penetration experienced a significant decline in wage inequality following Pix's introduction, which is consistent with the larger wage effects in sectors and establishments that employ a high share of low-skill workers. A one-standard-deviation increase in mobile penetration is associated with approximately a 1 percent reduction in the Gini coefficient relative to the sample mean. This reduction is driven by wage gains among workers in the lower half of the wage distribution, with no significant effects at the top. This decline in inequality notably contrasts with the typical effects of skill-biased technological change documented in the literature. To test for such skill bias in the context of instant payments, we estimate separate wage responses for low and high-skill workers. The results show statistically equivalent wage gains: a 0.4% increase among low-skill workers and 0.5% for high-skill. This finding indicates that Pix does not exhibit the skill complementarity of other technological innovations.

A key identification challenge arises from Pix's nationwide rollout coinciding with the COVID-19 pandemic. We address this concern in several ways. First, our triple-difference design includes municipality-by-industry-by-year fixed effects, municipality-by-size-by-industry fixed effects, and size-by-industry-by-year fixed effects. These stringent controls comprehensively absorb local pandemic shocks, national industry-size-specific trends, and unobserved, time-varying factors affecting specific industries within municipalities. Second, we explicitly incorporate COVID-19 policy controls, interacting our treatment and post variables with per-capita emergency aid transfers (Auxílio Emergencial), municipal stay-at-home orders,

and cumulative COVID-19 cases per capita. Across all these robustness checks, our Pix adoption estimates remain stable and highly significant, whereas COVID-specific interactions are negligible or insignificant. Finally, the pronounced industry heterogeneity we document—significant wage effects concentrated specifically in small retail establishments and absent in manufacturing or wholesale sectors—further supports our interpretation that the observed wage increases result from Pix adoption rather than pandemic-driven digitalization. Taken together, these analyses confirm that our estimates reflect Pix's causal impact rather than confounding pandemic-related factors. Moreover, since pandemic-induced digitalization likely favored larger establishments due to their superior technological capacity, our within-municipality comparison of small versus large establishments plausibly understates the true impact of Pix.

Our evidence points to increased labor demand from small businesses as the key mechanism behind these inequality-reducing effects. These findings are consistent with our conceptual framework, which predicts that lowering transaction costs increases firm profitability and stimulates employment growth among small, cash-dependent establishments. Because these firms rely heavily on low-skill labor, the resulting increase in labor demand raises wages at the bottom of the distribution and reduces inequality.

We find four key pieces of evidence supporting this mechanism of increased small-firm profitability leading to higher labor demand. First, municipalities with higher mobile penetration experienced significant employment growth in small establishments—a 1.7 percent increase in employment among small firms—after Pix's introduction. Second, higher mobile penetration led to increased small-business entry in retail sectors. In contrast, we find no corresponding effects in small manufacturing, indicating that Pix's impact is concentrated in small, cash-intensive businesses. Third, we observe increased entry of individual micro-entrepreneurs (MEIs)—businesses with only one employee—as shown by rising MEI tax contributions, consistent with a transition toward self-employment facilitated by reduced transaction frictions. Fourth, the inequality-reducing effects of Pix are notably stronger in

areas characterized by tighter low-skill labor markets, with no significant effect in regions where low-skill workers are abundant. This heterogeneity aligns with a mechanism in which increased labor demand generates upward wage pressure where worker mobility is limited, amplifying the reductions in wage inequality.

We test two potential drivers of the underlying increased small firm profitability: lower cash-handling costs and higher local demand. First, a shift to digital payments can generate gains by mitigating cash-handling costs–e.g., risks of robbery or fraud, limited ATM availability. To test this channel, we estimate the effect of Pix on bank branch cash inventories. We find a clear decline in cash balances as Pix transactions grow, suggesting that Pix substitutes for cash transactions. Furthermore, we document that our estimated wage increases rise monotonically with the share of sales to households, our industry-specific measure of cash-dependence. Second, Pix may also boost demand by providing a safer and more convenient alternative to cash. Following Mian and Sufi 2014, we classify industries with payroll concentrated in few locations as tradable, while those with payroll dispersed nationally are considered non-tradable and more exposed to local demand shocks. We find a similar wage response across the two groups, suggesting that an increase in local demand plays a limited role in explaining small-firm gains from Pix.

While our findings point to increased labor demand and local labor market frictions as the main drivers, several alternative explanations merit consideration. First, rent-sharing—where firms share profits from reduced transaction costs with workers—is unlikely. Small retail establishments typically have low unionization and weak bargaining power. More decisively, wage gains occur exclusively in tight labor markets, whereas rent-sharing effects would not depend on local labor supply conditions. Second, although we document evidence consistent with increased formalization, particularly through rising registrations of solo entrepreneurs (MEIs), formalization alone cannot fully explain the observed wage gains. Wage increases extend to small establishments with up to 20 employees, which typically already comply with formal labor regulations, and are concentrated specifically in municipalities where low-skill

labor is scarce. Third, despite the potential for digital transaction records to improve credit access, we find no measurable increase in business lending following Pix adoption.

Motivated by our empirical results, we extend our conceptual framework to quantify the aggregate gains from Pix and simulate a counterfactual scenario where the mobile penetration gap is closed and Pix is adopted evenly across Brazilian municipalities. While our empirical analysis finds that Pix reduced wage inequality within high-adoption municipalities, the aggregate, country-wide effect is theoretically ambiguous. Cities with higher mobile penetration also tend to have higher average wages; consequently, the technology could increase between-city inequality even as it reduces within-city inequality. To assess the net effect, we extend our model in three directions. First, we incorporate four skill groups to flexibly capture the full wage distribution. Second, we endogenize wage markdowns to quantify the role of labor market competition. Third, we model 100 distinct cities, which is essential for decomposing aggregate inequality into within- and between-city components.

We calibrate the model to match key moments of the Brazilian labor market, including the sectoral skill composition, the firm-size distribution, and skill-specific average wages. We then simulate Pix as a reduction in transaction costs for small firms in the cash-intensive sector.[4] The calibrated model reproduces the increase in average wages and decline in wage inequality, and underscores three sources of welfare gains that cannot be quantified in our reduced-form framework. First, large firms also raise wages despite not being directly benefited by lower payment frictions. This general equilibrium effect is driven by intensified labor market competition resulting from the growth of small firms. Second, Pix reduces average wage markdowns. As small firms gain market share, the employment Herfindahl-Hirschman Index (HHI) declines, leading to a reduction in average firm-level monopsony power. Third, the decline of the within-city component of the variance of wages is partially offset by a rise in the between-city component.

We use the model to simulate a counterfactual scenario in which the mobile penetration

[4]We approximate mobile penetration in the model using a reduced-form linear function of city-level employment, wage bill, and number of firms, estimated from the data.

gap is fully closed and Pix is adopted evenly across municipalities. The effects of Pix are amplified along two key dimensions. First, labor market competition intensifies more sharply due to a larger increase in the wage-bill share of small firms. Second, the impact on aggregate wage inequality is stronger. Unlike the baseline scenario, closing the mobile penetration gap leads to a decline in both the within- and between-city components of the variance of wages. We quantify the aggregate welfare gains and find that, while the uneven rollout of Pix increased the total wage-bill by 0.04% and firm profits by 0.02%, closing the mobile penetration gap would generate a larger 0.21% increase in the total wage-bill and 0.03% rise in profits, relative to a world without Pix. Our counterfactual analysis indicates that while Pix provides broad benefits, its full potential for reducing inequality is achieved when access to the technology is evenly distributed.

Related Literature. Our paper contributes to several strands of literature. We first add to the emerging literature on financial technology and digital payments. While recent work has documented the effects of digital payments on risk-sharing and poverty reduction (Jack and Suri, 2014; Suri and Jack, 2016), financial inclusion (Ouyang, 2021), and economic growth (Dubey and Purnanandam, 2023), the labor market impacts of these innovations remain largely unexplored. Our work complements papers analyzing the economic effects of payment system adoption (Chodorow-Reich et al., 2020; Crouzet et al., 2023), research on how instant payment systems affect deposit competition (Sarkisyan, 2023) and the role of payment technology complementarities (Sampaio and Ornelas, 2024), and work examining how physical bank infrastructure influences digital payment adoption (Mariani et al., 2023). Additionally, we contribute to the literature on how digital financial infrastructure, such as Open Banking, affects credit access, particularly for underserved populations (Alok et al., 2024). More broadly, we contribute to the emerging literature on fintech's role in fostering inclusive growth (Beck et al., 2022; Brunnermeier et al., 2023), its effects on labor markets (Jiang et al., 2021), and its impact on small business operations (Agarwal et al., 2019, 2022; Klapper, 2023; Dalton et al., 2024; Ghosh et al., 2024; Higgins, 2024).

While prior research on instant payments has focused on adoption patterns, financial outcomes, and banking-sector implications, our paper is the first to examine how these systems affect wages and inequality. We find that Pix increases wages in small, cash-intensive establishments, which disproportionately employ low-skilled workers, thereby reducing wage inequality. Our evidence indicates that these effects are driven by increased small-business labor demand, amplified by local labor market frictions. Our findings are consistent with a novel mechanism: by reducing transaction costs and expanding revenue opportunities, instant payments spur small business expansion, boost labor demand for low-skill workers, and thereby reduce wage inequality, contrary to the conventional view that technological innovation primarily benefits skilled labor.

Second, we contribute to the extensive literature on technological change and wage inequality. The conventional view, supported by evidence from computerization and automation, posits that new technologies generally raise inequality by complementing skilled labor and substituting for routine tasks (Autor et al., 2003; Acemoglu and Autor, 2011). This includes both skill-biased technological change, which directly complements higher-skilled labor (Goldin and Katz, 1998; Bound and Johnson, 1992; Krusell et al., 2000), and routine-biased technological change, which displaces routine-task workers (Goos et al., 2014; Autor and Dorn, 2013; Michaels et al., 2014). In contrast, we show that financial technologies can exhibit markedly different distributional effects. Our results suggest that the impact of technology on wage inequality critically depends on the intersection of three factors: which specific market frictions it alleviates, the types of businesses it disproportionately affects, and the skill composition of their workforces.[5]

[5]Related work links faster payments or broader financial access to labor market outcomes. Barrot and Nanda (2020) show that the U.S. QuickPay reform raised employment for treated small contractors, while Fonseca and Matray (2024) find that expanding bank branch coverage in Brazil increased wages. We complement these studies by analyzing a nationwide instant payment platform that lowers transaction costs and delivers concentrated gains in firm entry, employment, and wage compression among cash-intensive businesses.

2 Conceptual Framework

We develop a theoretical framework to analyze the potential effects of instant payment systems on wage inequality. Our model inclides two sectors with different cash dependences, heterogeneous firms with monopsony power in labor markets, and two skill groups of workers.

2.1 Workers

The economy is populated by a continuum of workers distributed across skill groups $\mathcal{S} = \{1, 2\}$, where each group s has measure N_s such that $\sum_{s \in \mathcal{S}} N_s = 1$. A worker i in skill group $s \in \mathcal{S}$ derives utility from employment at firm j according to:

$$u_{ij}^s = A_{ij} w_{sj}$$

where w_{sj} denotes the wage paid by firm j to workers of skill type s, and A_{ij} represents an idiosyncratic amenity shock that is independently and identically distributed across workers and firms. We assume A_{ij} follows a Fréchet distribution with shape parameter η_s. Labor markets are segmented by skill group.

Under these assumptions, the labor supply faced by firm j for skill group s is given by:

$$l_{sj} = \Pr[u_{ij}^s > u_{ik}^s \text{ for all } k \neq j] = N_s \left(\frac{w_{sj}}{W_s} \right)^{\eta_s}$$

The parameter η_s governs the elasticity of labor supply for skill group s, which we allow to vary across skill categories.

2.2 Firms

The model includes a continuum of firms with total measure one, divided into two sectors: non-cash-intensive and cash-intensive, indexed by $c = \{0, 1\}$.[6] Each sector c contains a mass

[6]The non-cash sector represents industries like manufacturing, where cash usage is limited and transaction costs are consequently low. The cash-intensive sector includes activities such as retail, which traditionally

M_c of firms. Within each sector, firms are heterogeneous in productivity z, which follows a Pareto distribution with shape parameter ζ_c over the support $[\underline{z}, \overline{z}]$.

Firms produce a homogeneous, sector-specific good sold in perfectly competitive markets, with prices normalized to one for both sectors. A firm with productivity z in sector c employs labor from different skill groups according to the production technology:

$$y_c(z) = \sum_{s \in \mathcal{S}} z f_{sc}(z) l_{sc}(z)^{\alpha_{sc}}$$

where $f_{sc}(z)$ captures skill-specific complementarity with firm productivity, and α_{sc} represents the degree of decreasing returns to scale for skill group s in sector c.

Firms face transaction costs $\tau_c(z)$ per unit of revenue and operate in monopsonistic labor markets. Taking other firms' wage policies as given, the profit maximization problem is:

$$\Pi_c(z) = \max_{w_s, l_s} \; (1 - \tau_c(z)) \sum_{s \in \mathcal{S}} z f_{sc}(z) l_s^{\alpha_{sc}} - \sum_{s \in \mathcal{S}} w_s l_s$$

subject to the labor supply curve derived from worker preferences. Profit maximization implies that firms set wages below the marginal revenue product of labor as follows:

$$w_{sc}(z) = W_s \left(\frac{\eta_s}{1 + \eta_s} \frac{(1 - \tau_c(z)) \, \alpha_{sc} z f_{sc}(z) N_s^{\alpha_{sc} - 1}}{W_s} \right)^{\frac{1}{1 + \eta_s (1 - \alpha_{sc})}}$$

This framework generates a complete distribution of wages across workers, which is essential for quantifying the effects of transaction cost reductions from digital payments on wage inequality.

2.3 Comparative statics

We conduct comparative static exercises to illustrate how lower transaction costs affect wage inequality and to examine how this relationship depends on the model's primitives.

We consider an economy with two skill groups, where low-skill workers represent 80 per-

relies heavily on cash transactions and faces higher transaction costs.

cent of the workforce, matching the share of workers without tertiary education in our data. The labor supply elasticity is set to one and assumed constant across skill groups. We assign equal mass to both sectors ($M_c = 0.5$ for $c = \{0, 1\}$) and specify a smaller Pareto parameter for the non-cash sector, reflecting the prevalence of larger firms in industries like manufacturing. Production technologies exhibit identical decreasing returns across skill groups and sectors, but we allow for stronger complementarity between high-skill workers and firm productivity in the non-cash sector.[7] Finally, we assume transaction costs $\tau_c(z) = 0.05$ for small firms in the cash-intensive sector and zero otherwise, defining small firms as those in the bottom 80 percent of the productivity distribution.

Figure A2 displays the change in inequality when transaction costs are reduced to zero across all firms. The model predicts a decline in wage inequality, measured by the Gini coefficient and 90-10 wage percentile ratio. We examine two key mechanisms driving the decline in inequality predicted by our framework. First, we analyze the role of skill complementarity. In our baseline specification, the degree of complementarity between workers and firm productivity varies by both skill group and industry. Panel A of Figure A3 displays the reduction in inequality resulting from lower transaction costs in economies with different levels of low-skill complementarity in the cash-intensive sector, holding other parameters constant. The results highlight the crucial role of skill complementarity in mediating the effects of transaction costs on inequality.

Lower values of λ_{L1} indicate that low-skill workers are less complementary to cash-intensive firms' productivity relative to high-skill workers, implying that low-skill workers are predominantly employed by small firms. Consequently, they are more exposed to shocks affecting small firms, such as the reduction of transaction costs in our framework. Conversely, when low-skill workers exhibit strong complementarities with firm productivity in the cash-intensive sector (higher values of λ_{L1}), inequality may actually increase.

[7] Specifically, we define $f_{sc}(z) = z^{\lambda_{sc}} / \sum_{k \in S} z^{\lambda_{kc}}$, with $\sum_{k \in S} \lambda_{kc} = 0$, and assume $\lambda_{H0} = 0.2$ and $\lambda_{H1} = 0.01$, implying stronger complementarities in the non-cash sector. We set the Pareto parameter to 1.3 in non-cash (1.5 in cash) industry, so that the top 20 percent of firms represent around 75 (60) percent of sales.

We next analyze the role of monopsony power in low-skill labor markets. Panel B of Figure A3 presents the effect of lower transaction costs on inequality in economies with different values of low-skill labor supply elasticity η_L. When η_L is lower–indicating greater monopsony power among firms–the reduction in inequality is more pronounced. This pattern reveals a key mechanism through which transaction cost reductions affect labor markets by enabling small firms to compete more effectively with larger firms, particularly in markets that were initially less competitive. Conversely, when low-skill labor markets are more competitive (higher η_L), the benefits of lower transaction costs accrue relatively more to high-skill workers in now relatively less competitive segments of the labor market, potentially leading to increased inequality.

Overall, our model highlights the important roles of skill complementarity and firm monopsony power in shaping distributional outcomes. The decline in wage inequality is more pronounced when low-skill workers exhibit weaker complementarity with firm productivity in the cash-intensive sector, or when low-skill labor markets are less competitive.

3 Institutional Background

In November 2020, the Central Bank of Brazil launched Pix, a new instant payment technology designed to modernize the country's financial system.[8] Pix allows immediate, 24/7 transfers between individuals, businesses, and government entities. The system is accessible through banks' mobile apps or websites, making it widely available to anyone with a bank account and internet connection. Transfers are initiated using aliases such as email addresses, tax IDs, phone numbers, or QR codes.

As of early 2024, over 152 million individuals and 15 million firms have registered for Pix, with a substantial percentage using it regularly for transactions. Beyond better user experience and convenience, two other factors likely contributed to Pix's success. First, the regulation mandates the participation of large banks (defined as those with more than 500,000

[8]The Central Bank of Brazil began internal development of instant payments (leading to Pix) in 2016.

accounts). Since the Brazilian market is concentrated and dominated by a small number of large banks, this measure ensured widespread availability and interoperability.[9] Second, the regulation exempts individuals from transaction fees to foster financial inclusion.[10] Since many small firms use the owner's personal bank account for transactions, they have seen a significant reduction in fees compared to traditional methods such as credit and debit cards or TED transfers (the electronic wire transfer available before Pix). Even when firms pay fees, they are substantially smaller than those of other methods. According to Duarte et al. (2022), merchants pay an average fee of 0.22 percent per Pix transaction, compared to 2.2 percent for credit card payments.

Due to these advantages, Pix quickly gained prominence as a payment method. About a year after its launch, the number of Pix transactions surpassed those of credit and debit cards and TED transfers. Regarding the transaction value, Pix exceeded credit and debit cards just two quarters after its introduction (Figure A4 in the Online Appendix). Pix started mainly as a payment method between accounts linked to individuals. Gradually, transactions from individual-linked accounts to business-linked accounts started to grow (Appendix Figure A5).[11]

The rise in Pix coincides with a 35 percent drop in the number of cash withdrawals (Figure A6 in the Online Appendix), indicating a smaller reliance on cash. Surveys from the Central Bank of Brazil confirm a decline in cash usage. While 60.2 percent of respondents identified cash as the most common payment method in 2018, this figure dropped to 41.7 percent in 2021 and further decreased to 22 percent in 2024.[12]

As a potential replacement for cash, Pix likely played a more prominent role in cash-intensive sectors that engage in a large number of small-value transactions with final con-

[9]Banks with more than 500,000 customers accounted for more than 99 percent of the bank accounts in 2020.

[10]Financial inclusion was one of the Pix goals. See `https://www.bcb.gov.br/en/financialstability/pix_en`.

[11]Bank accounts are associated with either an individual tax ID or a business tax ID. Some accounts tied to individuals may also be used for business purposes, especially by small businesses and informal firms. Similar to other instant payment systems, adoption dynamics were gradual (e.g., Alvarez et al., 2023).

[12]The figures are from the Central Bank of Brazil's survey *O brasileiro e sua relação com o dinheiro*.

sumers. Indeed, as shown in Appendix Table A1, between 2021 and 2023, the retail sector accounted for 32.8 percent of the total number of Pix transactions, followed by the services sector with 31.6 percent. Despite representing 64.4 percent of Pix transactions, these sectors contributed 18.5 percent of GDP in 2019. In contrast, the manufacturing sector, which contributed 27.7 percent of GDP in 2019, accounted for only 3.1 percent of Pix transactions.

The rapid adoption of Pix in Brazil provides an ideal setting to study the labor market impacts of financial technology innovation. By reducing transaction costs and improving liquidity management, Pix has the potential to significantly affect business operations, particularly for small firms in cash-intensive sectors such as retail.

4 Data and Research Design

4.1 Data

We use data from multiple sources. First, we draw on data from the Central Bank of Brazil, which provides information on the number and value of Pix transactions initiated or received by firms and individuals, broken down by municipality and month.[13] Second, we use matched employer-establishment data from the Brazilian Ministry of Labor (*Relação Anual de Informações Sociais*, RAIS).[14] This dataset includes information on workers (e.g., education), job contracts (e.g., wages), and employers (e.g., size, industry) for all Brazilian formal employment records. Third, we use data on firm creation from the *Cadastro Nacional da Pessoa Jurídica*, a firm registry maintained by the Brazilian Federal Tax Authority. This dataset allows us to compute the monthly creation of micro-firms, small businesses, and large enterprises at the municipality-industry level. Finally, we collect data on municipality characteristics, such as the age profile of the population, the number of bank branches, GDP per capita, and mobile penetration from the Brazilian Institute of Geography and Statistics (IBGE), the Central Bank of Brazil, and the Telecommunications Agency (ANATEL). We

[13] Brazil has 5,570 municipalities, grouped into 26 states and one federal district.

[14] We use the RAIS confidential micro-data, which includes firm and worker identifiers.

restrict our analysis to the 2016–2024 period, providing a four-year window before and after the introduction of Pix.

Table 1 provides summary statistics of the main variables. The average municipality has a GDP per capita of 24,500 BRL (median 18,200), 4 branches (median 1), and 36,460 inhabitants (median 11,065). The average municipality has a Gini coefficient of 0.29 (median 0.28). The share of the population with access to 3G+ is 54 percent (median 53 percent).

4.2 Research Design

This paper investigates how instant payment systems affect labor markets and wage inequality. These technologies address critical payment frictions: costs of handling cash (bank deposits, security risks), high payment processing fees, and delayed settlement. We exploit Brazil's nationwide introduction of Pix, where previously 77 percent of retail transactions used cash, credit card fees averaged 2.2 percent, and settlements took multiple days. Pix reduced transaction fees to 0.22 percent and enabled instant settlement. We hypothesize that small establishments benefit disproportionately from these improvements, particularly in cash-intensive sectors like retail that heavily relied on physical currency prior to Pix.

We employ a triple difference-in-differences design leveraging variation across three dimensions. First, we exploit Pix's nationwide introduction in November 2020. Second, we use pre-existing mobile penetration across Brazilian municipalities, measured as the 2019 ratio of 3G-capable devices to population, which strongly predicts Pix adoption intensity. Third, we contrast small versus large establishments within the same municipality, hypothesizing that small establishments benefit disproportionately from reduced transaction costs and accelerated cash flow enabled by instant payments. This design identifies intention-to-treat effects of instant payment availability on establishment-level wages.

Formally, we define pre-Pix mobile penetration at the municipality level c as:

$$\text{Mobile Penetration}_c = \frac{\text{Number of cellphones with 3G or above}_c}{\text{Population}_c} \tag{1}$$

Figure 1 shows the spatial distribution of mobile penetration across municipalities, measured as the ratio of 3G-capable devices to population in 2019. The map displays considerable variation across Brazil. Using pre-Pix mobile penetration avoids endogeneity from infrastructure investments that could respond to the payment system's introduction.

Our triple difference-in-differences specification is:

$$Y_{kjct} = \beta \times (\text{Mobile Penetration}_c \times \text{Small}_k \times \text{Post}_t) + \delta_{kjc} + \delta_{ct} + \delta_{kt} + \delta_{jt} + u_{kjct} \qquad (2)$$

where Y_{kjct} is the log average wage for establishment size group k in industry j, municipality c, and year t.[15] *Mobile Penetration*$_c$ measures the pre-Pix ratio of mobile devices with 3G or higher capability to population in municipality c. *Small*$_k$ equals one for establishments with fewer than 20 employees (or fewer than 10 or 5 employees), based on 2019 employment. *Post*$_t$ equals one from November 2020 onward.

Our granular data allow a rich set of fixed effects to address potential confounders. Municipality-by-size-by-industry fixed effects (δ_{kjc}) absorb time-invariant differences across establishment types within each municipality. Municipality-by-year fixed effects (δ_{ct}) control for time-varying local economic shocks affecting all establishments in a municipality. Size-by-year fixed effects (δ_{kt}) capture national trends that differentially affect establishments of different sizes. Industry-by-year fixed effects (δ_{jt}) account for sector-specific shocks and trends at the national level. While this is our baseline specification, we also present results using more demanding fixed-effect structures as robustness checks. Standard errors are clustered at the municipality level to account for serial correlation.

The coefficient β captures the intention-to-treat effect of instant payment availability on small relative to large establishments. While our main specification contrasts all small versus large establishments, we perform heterogeneity analysis comparing cash-intensive sectors,

[15] Size bins are constructed based on the number of employees (0, up to 4, 9, 19, 49, 99, 249, 499, 999, and 1000 or more workers)

such as retail, with less cash-intensive sectors, such as wholesale and manufacturing.

The key identifying assumption underlying our triple difference-in-differences design is that, in the absence of Pix, wage trends for small and large establishments would have evolved similarly across municipalities with different levels of mobile penetration, conditional on our fixed effects. While this assumption cannot be tested directly, we provide supporting evidence by examining pre-trends.

One concern is that mobile penetration correlates with unobserved municipality characteristics affecting wages. For instance, high-penetration municipalities might have better infrastructure, biasing estimates if this differentially affects small versus large establishments.[16] Municipality-by-year fixed effects absorb such local factors, while size-by-year and industry-by-year fixed effects control for national trends. Our triple-difference estimator thus relies solely on within-municipality wage differentials between small and large establishments across varying mobile penetration.

A further concern is that mobile penetration could have enabled a stronger uptake of online platforms and digitalization, benefiting small firms through channels orthogonal to the payment frictions alleviated by Pix. To address this, we construct an industry-specific measure of cash intensity, defined as the share of sales to households–a segment we assume relies more heavily on cash than firms, government, or non-residents. This measure, computed using 2019 data, captures an industry's exposure to payment frictions and strongly predicts Pix usage in the cross-section of industries. Importantly, we find a null small-versus-large wage effect of mobile penetration in low-cash-intensity industries, serving as a placebo test that supports our identification.

Finally, Pix's introduction during the COVID-19 pandemic raises potential confounding concerns. Our triple-difference design addresses these directly: municipality-by-year fixed effects absorb local variation in pandemic severity and policy responses, while size-by-year and

[16] Figure A7 shows that while high-mobile-penetration municipalities are unconditionally more urban with higher wages (green estimates), these differences disappear within size and agricultural exposure deciles (red estimates).

industry-by-year fixed effects control for national pandemic shocks across establishment sizes and industries. For residual bias to remain, pandemic impacts would need to systematically differ between small and large establishments in a way correlated with pre-existing municipal mobile penetration. Section 5.4 presents additional robustness checks.

5 Main Results

In this section, we examine how Pix adoption affects wages. First, we explore the relationship between pre-existing mobile penetration and Pix adoption. Next, we analyze the effects of Pix on wages across establishments, focusing on differences by establishment size and industry. Finally, we investigate the implications for wage inequality, exploring whether Pix affects the wage distribution.

5.1 Pix Adoption

We begin by examining the relationship between our treatment variable, pre-existing mobile penetration at the municipality level, and subsequent Pix adoption. Figure 2 reports coefficient estimates from regressions analyzing Pix adoption and cash usage following Pix's introduction, controlling for municipality fixed effects, time fixed effects, and municipality characteristics (e.g., GDP per capita, percent of young population, and percent agriculture) interacted with time.

Panel A illustrates the per capita value of Pix transactions received by firms, households, and in total. It shows a substantial increase in Pix usage over time, particularly among firms. For example, by the third quarter of 2023, the value of Pix transactions received by firms had increased by approximately BRL 750 per capita in municipalities with higher mobile penetration. The growing magnitude of the coefficients suggests that pre-existing differences in mobile infrastructure significantly influenced the intensity of Pix adoption across municipalities. Table A2 quantifies this relationship, showing that a one-standard-deviation

increase in mobile penetration is associated with 5.8 additional transactions per capita and approximately BRL 2,073 higher transaction value per capita following Pix introduction.

Panel B presents the relationship between our measure of pre-determined cash-intensity and ex-post Pix usage in the cross-section of industries. We define cash-intensity as the industry share of sales to households from the Brazilian input-output table of 2019. We normalize the value of Pix transactions by the total wage-bill of each industry. Cash-intensity explains 30 percent of the variability of Pix adoption in the cross-section of industries.

Both panels reveal that municipalities with higher initial mobile penetration experienced significantly greater Pix adoption and industries with higher cash-dependence use Pix more intensively. Thes results confirm the strong role of pre-existing mobile infrastructure and consumer-facing transactions in shaping the intensity of Pix usage across municipalities and industries. Overall, these results support our approach of using mobile penetration as a variable to capture differential exposure to Pix adoption.

5.2 Wage Effects

This section analyzes the impact of Pix adoption on wages in Brazil using a triple difference-in-differences framework. Our approach exploits variation across municipalities in mobile penetration and establishment size. Table 2 reports the primary estimates, with the dependent variable defined as the log of average monthly wages. The triple interaction term (Mobile Penetration $\times$ Small $\times$ Post) captures Pix's wage effect by comparing small and large establishments across municipalities with differing mobile penetration before and after Pix's rollout. Small establishments are defined as those with fewer than 20 employees.

Panel A of Table 2 presents estimates across alternative sets of fixed effects to address potential confounders. Column (1) includes municipality-by-size-bin-by-industry fixed effects to absorb all time-invariant differences between firms, as well as municipality-by-year, size-by-year, and industry-by-year fixed effects. This specification controls for any general time-varying local shocks (e.g., a city-wide lockdown or demand shock) and national-level trends

affecting all small firms or all firms within an industry. The triple interaction coefficient is 0.003, indicating that a one-standard-deviation increase in mobile penetration leads to a 0.3 percent (approximately BRL 8.08, equivalent to USD 2.05 in 2019 terms) monthly wage increase for small establishments relative to large ones post-Pix.

In Column (2), we replace the separate municipality-by-year and industry-by-year fixed effects with the more demanding municipality-by-industry-by-year fixed effects. These new fixed effects absorb any unobserved, time-varying shocks that are specific to an industry within a given municipality, such as localized COVID-19 restrictions on retail, or a local demand shock that disproportionately affects the service sector. This rigorous control ensures the comparison is not driven by these localized, industry-specific trends. The estimate remains similar (0.4 percent) and highly significant.

Finally, Column (3), our preferred specification, replaces the size-by-year control with size-by-industry-by-year fixed effects. This fully saturated model additionally controls for any national-level trends, policies, or economic shocks that affect firms differently based on both their size and industry (e.g., a federal relief program targeted only at small service-sector businesses). The estimate remains similar (0.4 percent) and highly significant, demonstrating that our finding is robust to this comprehensive set of controls for time-varying local conditions, industry-specific local shocks, and national size-by-industry trends.[17]

Panel B further decomposes these effects by worker skill level. For each skill category (high- or low-skill), we restrict the data, aggregate observations to municipality $\times$ industry $\times$ establishment-size $\times$ year cells, and apply our main specification. The positive wage effects of Pix adoption are significant for both low-skill (0.4 percent) and high-skill workers (0.5 percent), consistent with both skill groups benefiting from reduced transaction frictions in cash-intensive sectors.[18]

Figure 3 plots dynamic effects from our triple difference specification based on establish-

[17] A potential concern is that our estimates may be confounded by the COVID-19 pandemic. In Section 5.4, we present a comprehensive set of robustness tests.

[18] Note that column 3 has fewer observations because some cells lack high-skill workers; this also occurs occasionally for low-skill workers.

ment size, with coefficients normalized to 2020 as the baseline. Small establishments are defined as those with fewer than 20 employees. Pre-Pix coefficients (2016–2019) are small, statistically insignificant, and exhibit no evidence of differential pre-trends, supporting the parallel trends assumption. After Pix's introduction, wages in small establishments within municipalities characterized by higher mobile penetration increase steadily, reaching approximately 0.8 percent by 2024. These results indicate that Pix adoption significantly increased wages in smaller establishments, particularly in municipalities with higher mobile penetration.

Finally, Table 3 examines robustness across alternative definitions of small establishments (fewer than 5, 10, 20, and 50 employees). The results remain consistently stable, significant, and robust for establishments defined with fewer than 5, 10, and 20 employees, but are insignificant for establishments with fewer than 50 employees. All significant results have coefficients of 0.004. These additional robustness checks further validate Pix's positive impact on wages in smaller establishments rather than larger establishments, which are the type of businesses that benefit the most from this technology.

5.2.1 Industry Heterogeneity Analysis

Our central hypothesis is that Pix boosts wages by reducing transaction frictions ($\tau_c(z)$) that are particularly costly for small, cash-intensive firms. A key implication of this mechanism is that the wage effect should not be uniform across the economy. Instead, wage effects should be concentrated primarily in industries heavily reliant on in-person, small-value, business-to-consumer (B2C) transactions. Conversely, we should observe minimal or no effects in sectors that are not cash-intensive, such as capital-intensive or business-to-business (B2B) industries.

To test this critical prediction, we disaggregate our preferred triple-difference specification (Panel A of Table 2, Column (3)) and re-estimate it separately for different industries. This provides a robust test against alternative explanations, such as a general non-Pix-related technology shock, which might affect all industries broadly rather than specifically targeting

the cash-intensive sectors identified by our mechanism.

Table 4 presents these results, which strongly support our proposed transaction-cost mechanism. Column (1) of Panel A presents pooled results for all industries, closely replicating our main findings. Column (2) shows results specifically for Retail, where we find a large and statistically significant coefficient (0.008), double the magnitude of the pooled effect. In contrast, in Wholesale (Column (3)) and Manufacturing (Column (4))—both primarily B2B sectors—the estimated effects are small and statistically insignificant. This null finding is particularly insightful. While Pix can also facilitate B2B transfers, its marginal benefit is largest when replacing high-friction payment methods like physical cash or high-fee credit cards (common in B2C retail). For B2B firms, Pix primarily replaces existing, low-cost bank transfers (like TED), offering a comparatively smaller efficiency gain. The absence of wage effects in these B2B sectors thus suggests our results are not driven by general efficiency improvements, but rather by the transformative reduction of high-friction, cash-based transactions.

Similarly, within service industries (Panel B), we observe the largest effect in "Other Services" (e.g., barber shops, Column (4)), with a coefficient of 0.014, while more formal service sectors like Hotels (Column (2)) show no significant effect. This pronounced heterogeneity—large, positive effects in cash-intensive consumer-facing sectors and null effects in B2B or formal sectors—provides compelling evidence that wage gains result specifically from reducing payment frictions faced by small businesses that previously relied heavily on cash transactions.

5.3 Effects on Wage Inequality

Having established that Pix adoption led to significant wage gains concentrated in small establishments, particularly within the retail sector, we now explore the broader implications for wage inequality. Our theoretical model (Section 2) provides a clear framework: a reduction in transaction frictions ($\tau_c(z)$) can either compress or widen wage inequality depending on

(i) the skill–productivity complementarities (λ_{kc}) across sectors and (ii) the elasticity of labor supply η_s that governs wage markdowns under monopsony. A crucial precondition for a reduction in inequality is that the firms experiencing the largest wage gains must disproportionately employ low-skill labor.

We examine this condition in Figure 4, which plots the share of payroll allocated to low-skill workers for the key industries analyzed previously.

The figure provides compelling evidence supporting an inequality-reducing channel. Small retail establishments are particularly intensive in low-skill labor, allocating over 91 percent of their total payroll to low-skill workers, compared to only 58 percent in large retail establishments. This contrasts with small manufacturing firms, which have a notably lower low-skill payroll share (around 75 percent).

Given this specific workforce composition, our model predicts that as Pix reduces transaction frictions for small retail firms, the resulting increase in labor demand should disproportionately benefit low-skill workers, thereby compressing the wage distribution. We next examine whether this mechanism translates into observable reductions in wage inequality at the municipality level.

To test this prediction, we use a municipality-level difference-in-differences specification, regressing our measure of inequality, the Gini coefficient, on standardized mobile penetration while controlling for municipality fixed effects, region-by-year fixed effects, and municipality characteristics interacted with year.

Figure 5 supports our model's prediction using the Gini coefficient of wages, calculated from the distribution of average monthly wages across all establishments within each municipality-year and multiplied by 100. This approach isolates the effect of Pix adoption on wage inequality while accounting for time-invariant municipality characteristics and local time-varying shocks. The estimates show no differential trends prior to Pix's introduction, consistent with our identifying assumption. Following Pix adoption, we observe a significant decline in the Gini coefficient in municipalities with higher mobile penetration relative to

those with lower mobile penetration. This reduction in wage inequality emerges gradually, starting in 2021, and becomes more pronounced through the end of our sample.

Column (1) in Panel A of Table 5 quantifies this effect, showing that a one-standard-deviation increase in mobile penetration is associated with a statistically significant 0.270-point decline in the Gini coefficient (scaled by 100) following Pix adoption. Relative to the sample mean of 29 (corresponding to an unscaled Gini of 0.29), this represents a 0.9 percent reduction in wage inequality.

Figure 6 further unpacks these results by examining wage dynamics separately for different segments of the wage distribution. Panel A of Figure 6 reveals a noticeable increase in wages for workers in the bottom 50% of the distribution following Pix adoption. In contrast, Panel B shows no significant wage changes for workers in the top 50% of the distribution. The regression results in Table 5 (Columns (2) and (3)) confirm that the bottom 50% experiences a significant 0.6 percent increase in wages, while the top 50% experiences no significant effect. This decomposition clearly highlights that the observed reduction in wage inequality is driven by wage growth at the bottom of the distribution, rather than wage compression at the top.

The decline in wage inequality is particularly notable given the canonical literature on skill-biased technical change, which suggests that new technologies typically increase wage inequality by raising the productivity and wages of skilled workers (Autor et al., 1998; Acemoglu and Autor, 2011). Our findings show that financial technologies can have markedly different distributional effects. By reducing frictions in cash-intensive sectors that disproportionately employ low-skill workers, digital payment technologies can generate more inclusive patterns of wage growth.

5.4 Challenges to Identification: COVID-19

Before proceeding, we consider potential alternative explanations arising from the concurrent timing of Pix's nationwide rollout and the COVID-19 pandemic. Specifically, one concern is that municipalities with higher pre-existing mobile penetration might have been better

prepared to adapt digitally during the pandemic, potentially driving differential economic recoveries unrelated to Pix.

We address this identification concern in several ways. First, our primary specification (Table 2, Column (3)) includes municipality-by-size-by-industry fixed effects to absorb time-invariant differences across firm types; size-by-industry-by-year fixed effects to capture national-level trends affecting specific sectors and sizes; and, most critically, municipality-by-industry-by-year fixed effects. This final set of controls is particularly stringent, absorbing any time-varying shocks (such as local pandemic severity or demand shocks) affecting a specific industry within a specific municipality. Additionally, we verify the absence of differential pre-trends across all specifications, further supporting the parallel trends assumption.

Second, in Table 6, we augment our baseline specification by explicitly incorporating direct COVID-19 policy controls into this preferred, fully saturated specification. Column (1) interacts per capita transfers from Brazil's emergency aid program (Auxílio Emergencial) with the small-establishment and post indicators. While the transfer interaction itself is positive and significant (0.004), our main Pix coefficient remains stable and highly significant (0.005), confirming that pandemic relief does not drive our observed wage effects. Columns (2) and (3) further control for municipal stay-at-home orders and cumulative COVID-19 cases per capita, respectively. In both specifications, the main Pix coefficient remains stable and significant (0.004), whereas the interactions with lockdown policies and case severity are negligible and statistically insignificant.

Third, the pronounced industry heterogeneity of our main findings (Table 4) provides further evidence that our documented effects are not driven by a general pandemic-related shock. If differential digital adaptation were the true driver, we might expect wage gains for small firms across all sectors, including manufacturing. The fact that our effect is large and significant for small retail but insignificant for small manufacturing supports the interpretation that the documented effects result from Pix adoption rather than from a general, pandemic-driven digitalization effect.

Fourth, to the extent that pandemic-induced digitalization occurred, it likely biases our estimates downward. Globally, larger firms weathered COVID-19 better than smaller ones: in the U.S., small offline firms experienced losses of around 40 percent, compared to only 10 percent for large online firms (Bloom et al., 2021); similarly, SMEs in Latin America faced steeper declines and greater liquidity constraints relative to larger firms (Cerda et al., 2023). Because our analysis compares small to large establishments within municipalities, any COVID-related advantages favoring large firms in high-mobile areas would attenuate our estimated effects, making our positive estimates conservative.

Taken together, these robustness checks reinforce our interpretation that the observed effects reflect Pix's causal impact rather than confounding pandemic-related factors.

6 Mechanisms

In this section, we examine the mechanisms underlying our findings. We first analyze how reduced transaction costs from Pix adoption affect labor demand and entrepreneurship in small, cash-intensive businesses. Next, we assess how local labor market frictions, particularly low-skill labor scarcity, could amplify these effects. Finally, we evaluate alternative explanations, including formalization-driven compliance, rent-sharing, and credit access.

6.1 Labor Demand Effects

Our main results indicate that higher mobile penetration increases wages in small establishments, especially within retail, disproportionately benefiting low-skill workers and compressing wage inequality. According to our model, reductions in transaction frictions increase firm profitability and stimulate labor demand, particularly in cash-intensive sectors that heavily rely on low-skilled labor.

We test this hypothesis by examining employment growth using a triple difference-in-differences approach comparing small versus large establishments. Figure 7 illustrates the

dynamic effects on job growth for the smallest establishments (fewer than 5 employees). The estimates show no significant pre-trends and a clear increase after Pix's introduction in November 2020. Table 7 quantifies these effects, using the logarithm of active jobs as the dependent variable. We find a positive and significant effect of 0.017 for the smallest firms (N<5, Column 1). Slightly larger definitions of "small" (N<10, Column 2; N<20, Column 3) yield smaller, insignificant estimates.

Given that employment growth could result either from existing firms expanding or from new firm entry, we next analyze firm creation directly. Our model predicts that reduced transaction costs enhance entrepreneurial incentives, particularly benefiting smaller, consumer-facing firms. Figure 8 presents entry patterns by sector and firm size. After Pix's introduction, municipalities with higher mobile penetration show a significant increase in small retail firm entry (Panel A). In contrast, entry rates for small manufacturing firms remain unchanged (Panel B), consistent with our earlier findings. Table 8 quantifies these results, showing that a one-standard-deviation increase in mobile penetration raises small retail firm entry per 1,000 residents by 0.004, with no significant effect in small manufacturing.

We further examine entrepreneurship using municipal MEI-ICMS data. The Micro-Empreendedor Individual (MEI) tax charges a fixed R$1 monthly ICMS fee regardless of sales volume, making per-capita MEI-ICMS receipts a direct measure of entrepreneur counts.

Figure A8 plots the dynamic effects of mobile penetration on MEI–ICMS receipts per 1,000 residents. The estimates show no significant pre-trends, then rise after Pix's introduction in November 2020 for high-mobile-penetration municipalities. Table 9 quantifies this effect: a one-standard-deviation increase in mobile penetration raises MEI–ICMS receipts by BRL 1.417 per 1,000 residents.

This MEI expansion following Pix adoption is consistent with reduced transaction costs, facilitating micro-enterprise entry (or formalization). Combined with our evidence on small retail firm entry, these results indicate that Pix expands entrepreneurship at the extensive

margin, particularly among cash-intensive sole proprietors.[19]

These findings on employment and firm entry reveal an important pattern in how Pix affects labor markets.

6.2 Local Labor Market Frictions

While increased labor demand can explain higher wages in an environment with search frictions or imperfect labor mobility, standard models with a perfectly elastic labor supply would predict no wage effects. To test whether labor market frictions explain the observed decline in wage inequality, we compare the Gini coefficient across areas with scarce versus abundant low-skill labor.

Table 5, Panel B, quantifies how Pix adoption affects wage inequality under varying labor market conditions by interacting the treatment with an indicator for tight labor markets. We define tight markets as municipalities where the share of low-skill workers is below the population-weighted median, indicating relative scarcity of low-skill labor. Column (1) shows that a one-standard-deviation increase in mobile penetration reduces the Gini coefficient by an additional 0.323 points in tight labor markets. When examining wage components, the differential effect on Bottom 50% wages in tight markets (Column 2) is positive but imprecisely estimated. These findings suggest Pix's inequality-reducing effects are concentrated in areas where low-skill labor is relatively scarce.

These heterogeneous effects, driven by local labor market scarcity, help explain both the magnitude and distribution of wage gains. In areas where low-skill workers are scarce, firms—particularly small establishments—must offer higher wages to attract workers, resulting in more pronounced declines in wage inequality. This finding aligns with search and matching models, which predict that wage effects are amplified in tight labor markets (Pis-

[19]While employment growth is primarily concentrated in the smallest firms (N<5) and new entrants, wage effects are robust across all small establishments (N<20). This pattern suggests a local labor market equilibrium effect. The aggregate increase in labor demand from micro-firms and new entrepreneurs raises outside options for low-skill workers. Consequently, slightly larger small businesses are compelled to increase wages as well, to retain and compete for labor, despite limited or no headcount expansion of their own.

sarides, 2000).

6.3 Small Firm Profitability

We test two potential drivers of the underlying increased small firm profitability: lower cash-handling costs and higher local demand. First, a shift to digital payments can generate gains by mitigating cash-handling costs–e.g., risks of robbery or fraud, limited ATM availability. Notice that this is not necessarily the case. Pix might not reduce cash usage if it instead expands overall payment volume without substituting for cash.

To test this channel, we estimate the effect of Pix on bank branch cash inventories. Figure 9 presents the impact on the logarithm of cash balances, measured as the stock of cash held by bank branches in each municipality and year. Municipalities with higher mobile penetration experienced a pronounced and statistically significant decline in cash usage. The reduction intensifies over time, suggesting that Pix adoption substantially substituted for cash transactions. To link this directly to our firm-level results, we estimate the wage response for industries with different levels of cash-intensity as measured by their share of sales to households. Our results are reported in Table 10. Column (1) shows null effects on low-cash industries, while columns (2) and (3) show that our estimated wage increases rise monotonically with cash-dependence.

Second, Pix may also boost demand by providing a safer and more convenient alternative to cash. To test whether increasing demand is a main driver of Pix's gains, we split industries into tradable and non-tradable categories based on their payroll geographical concentration. Following Mian and Sufi 2014, we classify industries with payroll concentrated in few locations as tradable, while those with payroll dispersed nationally are considered non-tradable. If local demand were a key mechanism, we would expect a larger wage increase in non-tradable industries located in high-mobile-penetration municipalities. Table 11 shows our estimation results for non-tradable industries in column (1), and tradable sectors in column (2). We exclude low-cash sectors from our analysis as they were unaffected by Pix. We find a similar

wage response across the two groups, suggesting that an increase in local consumer demand was not the major factor explaining small-firm gains from Pix.

Overall, our results indicate that reduced cash-handling costs are a primary source of Pix's gains for small firms.

6.4 Alternative Mechanism

The evidence presented in this paper indicates that Pix adoption reduced transaction costs for cash-intensive businesses, stimulating labor demand, encouraging entry among small establishments, and also potentially facilitating formalization. These demand shifts translated into significant wage gains, particularly where local labor markets faced constraints in low-skill labor supply. We now examine how this labor-demand mechanism compares with three alternative explanations: formalization effects, rent-sharing, and credit access expansion.

The Role of Formalization. Our findings indicate that Pix spurred formalization, particularly the registration of solo entrepreneurs (MEIs), as evidenced by increased MEI tax revenue. This formalization can contribute to wage gains in administrative data through increased compliance with minimum wage laws. If previously informal workers or off-the-books payments are formalized, reported wages may increase.

However, two empirical patterns indicate that formalization alone cannot be the primary driver of observed wage increases. First, wage effects remain stable across different size thresholds, with identical effects for firms with fewer than 5, 10, and 20 employees. Since firms approaching 20 employees are substantially more likely to already comply with labor regulations, the persistence of wage gains in this group suggests generalized labor demand increases rather than formalization-driven compliance effects.

Second, pure compliance effects would generate uniform wage increases toward the regulatory minimum, independent of local labor market conditions. Instead, we find inequality and wage effects concentrated precisely where low-skill labor is scarce. This heterogeneity

demonstrates that increased labor demand, interacting with constrained labor supply, drives the results.

We therefore interpret formalization as a complementary channel that may amplify wage gains by improving compliance, while the primary mechanism is increased labor demand from cash-intensive businesses interacting with local labor-market frictions.

Rent-Sharing. An alternative explanation is rent-sharing, whereby firms that become more profitable from Pix adoption—through both cost savings and productivity gains—share these benefits with workers due to bargaining power or efficiency wage considerations (Card et al., 2018). However, this channel is inconsistent with the empirical patterns we document. Rent-sharing predicts that firms share efficiency gains irrespective of external labor market conditions, as pass-through is governed by firm-specific bargaining parameters rather than workers' outside options.

In contrast, we find that wage increases are concentrated precisely in municipalities with tight labor markets and negligible in areas where low-skill labor is abundant. This marked geographic heterogeneity strongly indicates that market-level competition for scarce low-skill workers, rather than within-firm bargaining, drives the wage gains. Moreover, these effects are most pronounced among small retail and service establishments, sectors typically characterized by minimal unionization and limited worker bargaining power, making rent-sharing an unlikely primary mechanism.

Credit Access Channel. Pix might affect labor markets through improved credit access, as digital transaction records reduce information asymmetries between lenders and small firms (Ouyang, 2021; Alok et al., 2024; Ghosh et al., 2024; Cramer et al., 2024).

We test this channel using municipality-level business lending data. Figure A9 plots the dynamic effects of mobile penetration on log per-capita business loans, showing no differential trends before Pix's introduction and no significant increase afterward.

The absence of aggregate credit expansion indicates that improved digital payment records

did not generate detectable increases in business lending during our sample period.[20] In addition, wage gains are concentrated in small, consumer-facing sectors (retail and services) and in the bottom half of the distribution, unlike the pattern expected from a broad credit supply shock. Together, the absence of credit expansion and the sectoral/distributional concentration support an interpretation of reduced payment frictions that increase demand for low-skill labor, rather than one centered on improved credit access.

Overall, the wage gains we document are primarily driven by reductions in transaction costs. Cash-intensive establishments benefit most from Pix adoption through increased labor demand, with wage effects amplified precisely in municipalities where low-skill labor supply is constrained. While formalization contributes by improving compliance and wage reporting, it cannot fully explain the observed geographic heterogeneity, as pure compliance-driven effects would not concentrate exclusively in tight labor markets. The absence of measurable credit expansion and the inconsistency of our results with rent-sharing predictions further confirm transaction-cost reduction as the fundamental mechanism.

7 Quantitative Analysis

We consider a set of $c = 1, \ldots, C$ cities, each containing M_c firms. A fixed share γ_k of firms operates in sector k, which can be retail, wholesale, or manufacturing. Workers are grouped into four skill categories $s = \{1, \ldots, 4\}$, each with mass H_s, where $\sum_s H_s = 1$.

A worker i of skill s derives the following utility from working at firm j located in city c:

$$u_{ijc} = \log(w_{sjc}) + \xi_{ijc}$$

where w_{sjc} is the wage offered by firm j in city c to workers of skill s, and ξ_{ijc} is a worker-

[20] This null is consistent with Brazil's consent-based Open Finance, introduced after Pix and still scaling, which makes lenders' access to transaction histories contingent on customer authorization. By contrast, India's UPI operates within a mature data-sharing stack (Account Aggregator and Credit Line on UPI), and loan-level evidence shows sizable credit expansions there (Alok et al., 2024). Our local design may also mask compositional shifts.

specific taste shock for firm j. These shocks are i.i.d. across individuals and follow the nested logit distribution:

$$F(\xi_{1,1},\ldots,\xi_{M_c,C}) = \exp\left[-\sum_{c=1}^{C}\left(\sum_{j=1}^{M_c} e^{-(1+\eta)\xi_{jc}}\right)^{\frac{1+\theta}{1+\eta}}\right],$$

where η and θ govern within-city and between-city substitution elasticities, respectively.

Given this preference structure, the labor supply to firm j in city c for skill s is given by:[21]

$$n_{sjc} = \left(\frac{w_{sjc}}{W_{sc}}\right)^{\eta}\left(\frac{W_{sc}}{W_s}\right)^{\theta} N_s. \tag{3}$$

Firm j in industry k and city c uses a decreasing-returns technology that combines the four types of labor additively. Its profit function is given by:

$$\Pi_{jkc} = \sum_s (1-\tau_{jc}) A_s A_c z_j f_{ks}(z_j) n_{jsc}^{\alpha} - \sum_s w_s\left(n_{jsc}, N_{sc}(n_{jsc}, n_{(-j)sc}), N_s, W_s\right) n_{jsc}$$

where A_s and A_c are skill- and city-specific productivity terms, and τ_{jc} is a transaction cost. The function $f_{ks}(z_j)$ captures sector-specific skill complementarities and is defined as

$$f_{ks}(z) = \frac{z^{\lambda_{ks}}}{\sum_{q\in S} z^{\lambda_{kq}}}, \qquad \sum_{q\in S}\lambda_{kq} = 0.$$

The wage function $w_s\left(n_{jsc}, N_{sc}, N_s, W_s\right)$ is the inverse of the labor-supply relation given in equation 3. For each skill group s, firms internalize their impact on N_{sc}, but take as given the country level values N_s and W_s, as well as their competitors' strategies. Profit

[21] The aggregate indices are defined as: $N_s = \left[\sum_{c=1}^{C} N_{sc}^{\frac{\theta+1}{\theta}}\right]^{\frac{\theta}{\theta+1}}$, $W_s = \left[\sum_{c=1}^{C} W_{sc}^{\theta+1}\right]^{\frac{1}{\theta+1}}$, $N_{sc} = \left[\sum_{j=1}^{M_c} n_{jsc}^{\frac{\eta+1}{\eta}}\right]^{\frac{\eta}{\eta+1}}$, and $W_{sc} = \left[\sum_{j=1}^{M_c} w_{jsc}^{\eta+1}\right]^{\frac{1}{\eta+1}}$.

maximization yields the optimal wage for skill s offered by firm j operating in city c:

$$w_{jsc} = \frac{1}{1 + \left[s_{jsc}/\theta + (1 - s_{jsc})/\eta\right]} \alpha(1 - \tau_{jc}) A_s A_c z_j f_{ks}(z_j) n_{jsc}^{\alpha-1}, \tag{4}$$

where s_{jsc} denotes the firm's wage-bill market share in city c for skill group s. Thus, a firm with a larger market share s_{jsc} sets a larger markdown, i.e., pays a lower wage relative to marginal product, if and only if $\theta < \eta$.

We solve the model through the following steps. First, following Berger et al. (2022), market shares satisfy the fixed-point condition

$$s_{js} = \frac{\mu_{js}\, s_{js}^{\frac{\alpha\eta}{1+\eta}}\, (1 - \tau_j)\, z_j\, f_{k(j)s}(z_j)}{\sum_\ell \mu_{\ell s}\, s_{\ell s}^{\frac{\alpha\eta}{1+\eta}}\, (1 - \tau_\ell)\, z_\ell\, f_{k(\ell)s}(z_\ell)},$$

where $\mu_{jsc} = 1\Big/\Big(1 + [s_{jsc}/\theta + (1 - s_{jsc})/\eta]\Big)$ is the wage markdown. This system of equations determines the equilibrium vector of firm market shares.

Second, given the resulting markdowns μ_{jsc}, equilibrium wages and labor supply are computed directly from equations 3 and 4. Finally, equilibrium requires that the market clears for each skill group $\sum_{j,c} n_{jsc} = H_s$ for all s.

7.1 Calibration

Our calibration distinguishes between two sets of parameters: those that are predetermined, based either on external evidence or on observable moments that are perfectly matched, and those that are calibrated internally to match specific moments of the data.

Predetermined Parameters. We standardize the number of cities to $C = 100$, skill groups to $S = 4$, and sectors to $K = 3$. We group Brazilian cities evenly into 100 bins. The number of firms M_c is such that the smallest bin has $x_m = 695$ firms, corresponding to the empirical minimum; and for the remaining bins, the number of firms is drawn from a Pareto distribution with shape parameter $\alpha_c = 1.24$. This parameterization ensures that the largest

10% of cities (the top 10 bins) account for 64% of all firms, matching the empirical concentration of firms across cities. Skill groups are defined by educational attainment: primary education, secondary education, some college, and college graduates. Their population shares H_s are set to match the empirical distribution of workers. The three sectors–manufacturing, retail, and wholesale–have shares γ_k calibrated to the observed number of firms in each sector.

We set the within-city and between-city labor supply elasticities to $\eta = 7$ and $\theta = 0.5$, respectively, following Berger et al. (2022). The decreasing-returns parameter is $\alpha = 0.7$. Transaction costs τ are set to 5% for small retailers–defined as firms with productivity below the 90th percentile of the productivity distribution, which in our data have less than 19 employees–and zero otherwise.[22] All predetermined parameters are summarized in Table 12.

Calibrated parameters. A second set of parameters is calibrated to match key moments of the Brazilian labor market. The sector-skill complementarity parameters λ_{ks} target the skill composition of employment in each sector k. The Pareto shape parameters α_k for the firm productivity distribution are chosen to match the employment share of the top 10% of firms in each sector. Finally, skill-specific productivity levels A_s are calibrated to replicate the observed skill premium relative to the least educated group ($s = 1$). Table 13 lists these 15 calibrated parameters and their corresponding empirical targets.

Our calibrated model successfully reproduces key features of the Brazilian labor market. As illustrated in Table 14, the model captures fairly well the skill composition of each sector. Retail is the least skill-intensive sector, with around 10 percent of its workers holding a bachelor's degree. In contrast, manufacturing and wholesale are more skill-intensive, with college graduate shares of 15 and 22 percent, respectively. Table 14 shows that the model also matches the aggregate employment distribution across sectors. Retail and manufacturing each account for approximately 40 percent of total employment, while wholesale employs about 10 percent of the workforce. Finally, the bottom panel of Table 14 confirms that

[22]This structure can be rationalized by a technology adoption decision: firms draw a potential productivity and decide whether to pay a fixed cost to adopt a technology that avoids transaction costs (Ulyssea, 2018). Then, bigger firms are more likely to adopt the technology. Pix eliminates this fixed cost, thereby reducing transaction costs to zero for all firms.

the skill-specific average wages generated by the model align closely with their empirical counterparts.

7.2 Counterfactual Analysis

We use our model to quantify the aggregate gains from Pix and to simulate a counterfactual economy where the mobile penetration gap declines to zero and Pix is evenly adopted across municipalities.

Pix Introduction. We study Pix's implementation through the lens of our calibrated model. Consistent with our empirical findings, we model Pix as a reduction in transaction costs for small firms in the retail sector as follows:

$$\tau^{\text{new}} = \tau^{\text{old}} \times \Big(1 - \omega(\text{MP}_c)\Big),$$

where $\omega : [0,1] \times [0,1]$ is a strictly increasing function and MP_c denotes mobile penetration. Given that our model does not include mobile penetration, we define it in a reduced-form way as a linear function of city-level variables such as the number of firms, total wage-bill, and employment. We estimate the corresponding coefficients β in the data and define mobile penetration in the model as $\text{MP}_c = \hat{\beta}_0 + \hat{\beta}_1 \ln \text{Wage-bill}_c + \hat{\beta}_3 \ln \text{Employment}_c$. Our estimation results imply that small firms in cities with high average wages and number of firms experience a larger reduction in transaction costs. Finally, we define ω as a linear function whose minimum value is zero and maximum value is one. Thus, we choose $\tau^{\text{old}} = 5\%$ as described above to match the effect of one standard deviation higher mobile penetration on average wages of small relative to large firms in the retail sector.

We first quantify the wage response and report our results in Figures 10 and 11. Average wages increase by 0.23% in small firms and by 0.04% in large firms. While large firms are not directly affected by the transaction cost reduction, they face increased labor market competition from expanding small firms. Because small firms predominantly employ low-

skill workers, the wage gains differ substantially across skill groups. Workers in skill groups 1 and 2 experience average wage increases of 0.12% and 0.22%, respectively, while workers in groups 3 and 4 see changes of 0.01% and nearly zero, respectively.

To assess whether Pix increased competition, we compute changes in the wage-bill share of small firms and the Herfindahl–Hirschman Index (HHI). As shown in Figure 12, the wage-bill share of small firms rises by 0.09 percentage points, while HHI falls by 0.16%. Both findings are consistent with Pix fostering greater competition in local labor markets.

Given that low-skill workers experience larger wage gains, one might expect wage inequality to decline after Pix. However, the transaction cost reduction is stronger in larger cities. If pre-Pix wages were already higher in these cities, overall inequality could remain unchanged or even increase. Figure 13 confirms that average wages are indeed higher in cities with more firms, highlighting the potential for opposing spatial and skill-based effects on inequality. Therefore, the net impact on overall wage inequality is an empirical question that depends on the relative strength of these two forces.

To quantify the net effect, we decompose the change in wage inequality into within-city and between-city components using the variance of log wages. We find a net decline of 0.04% in overall wage variance. As shown in Figure 14, this result is driven entirely by a contraction in within-city inequality, which is partially offset by a rise in between-city inequality. This pattern indicates that while Pix compresses wage differentials among workers within the same city, it simultaneously amplifies wage differences across cities.

Closing the Mobile Penetration Gap. We next compute the effects of closing the mobile penetration gap entirely. In this scenario, Pix reduces transaction costs to zero for all small firms nationwide, corresponding to $\omega(\text{MP}_c) = 1$ for every city c. The impact of Pix in this case differs from the baseline simulation in two key dimensions.

First, the effects on labor market competition are stronger. The wage-bill share of small firms increases by 0.7 percentage points, leading to a 1.2% decline in the Herfindahl–Hirschman Index (HHI). Consequently, the average wage increase is larger, with gains

concentrated among low-skill workers: skill groups 1 and 2 experience average wage increases of 0.8% and 1.5%, respectively.

Second, the effect on wage inequality is more pronounced. As reported in Figure 15, the variance of log wages declines by 0.6%. In contrast to the baseline scenario, this reduction is explained by contributions from both within-city and between-city components. This indicates that equalizing mobile access not only intensifies within-city wage compression but also mitigates the spatial inequality that arose from the uneven initial uptake of Pix payment system.

Finally, we compute the aggregate welfare gains from closing the mobile penetration gap under Pix. The initial implementation of Pix with the observed, uneven mobile penetration increases the total wage bill by 0.04% and total firm profits by 0.02%. However, fully closing the mobile penetration gap would generate significantly larger gains: a 0.21% increase in the total wage bill and a 0.03% increase in profits, relative to a baseline scenario without Pix.

These wage-bill gains are highly concentrated among low-skill workers. The bottom skill groups (1 and 2) see their total wage-bill rise by only 0.19% under the observed rollout, but by a substantial 1.3% when mobile access is equalized. This highlights that while Pix provides broad benefits, its full potential is achieved when access to the technology is evenly distributed.

Overall, our quantitative analysis shows that, by reducing transaction costs, Pix boosts competition in local labor markets and raises wages, particularly for low-skill workers. The policy also reduces overall wage inequality, primarily by compressing within-city wage inequality. Critically, we find that closing the mobile penetration gap would not only amplify the positive wage and competition effects but also ensure that the benefits of digital financial inclusion are shared more equally across regions and skill groups.

8 Conclusion

Our findings provide novel evidence on how financial technology adoption shapes labor markets and wage inequality. While the canonical skill-biased technical change hypothesis argues that technological innovation increases inequality by disproportionately benefiting skilled workers, we show that digital payment technologies can instead generate more inclusive wage growth. Using data from Brazil's nationwide adoption of instant payments (Pix), we document larger wage increases for low-skilled workers, particularly in small retail establishments, resulting in significant reductions in inequality.

These distributional effects arise because Pix substantially reduced transaction costs in cash-intensive sectors, which predominantly employ low-skill labor. Lower transaction costs increased labor demand among small businesses, driving wages upward. Moreover, local labor market frictions amplified these wage gains, making them particularly pronounced in areas with scarce low-skill labor. Our quantitative analysis highlights the key role of local labor market competition and general equilibrium effects in shaping the aggregate impact of Pix. We show that while Pix's actual rollout significantly increased wage-bill and profits, a counterfactual scenario with uniform adoption–achieved by closing mobile penetration gaps–would multiply these gains by a factor of four.

These results have important implications for both economic theory and policy. First, they demonstrate that financial innovation can complement low-skilled labor by alleviating frictions in sectors where these workers are predominantly employed, thereby reducing inequality rather than exacerbating it. Second, they indicate that investments in digital payment infrastructure could effectively complement traditional inclusive growth policies by improving the economic environment for small businesses and generating broad-based wage gains. Ultimately, the distributional consequences of new technologies depend critically on the specific market frictions they alleviate: instant payment systems reduce inequality by removing constraints faced by low-skill-intensive firms, in contrast to automation technologies that typically widen inequality by displacing routine labor.

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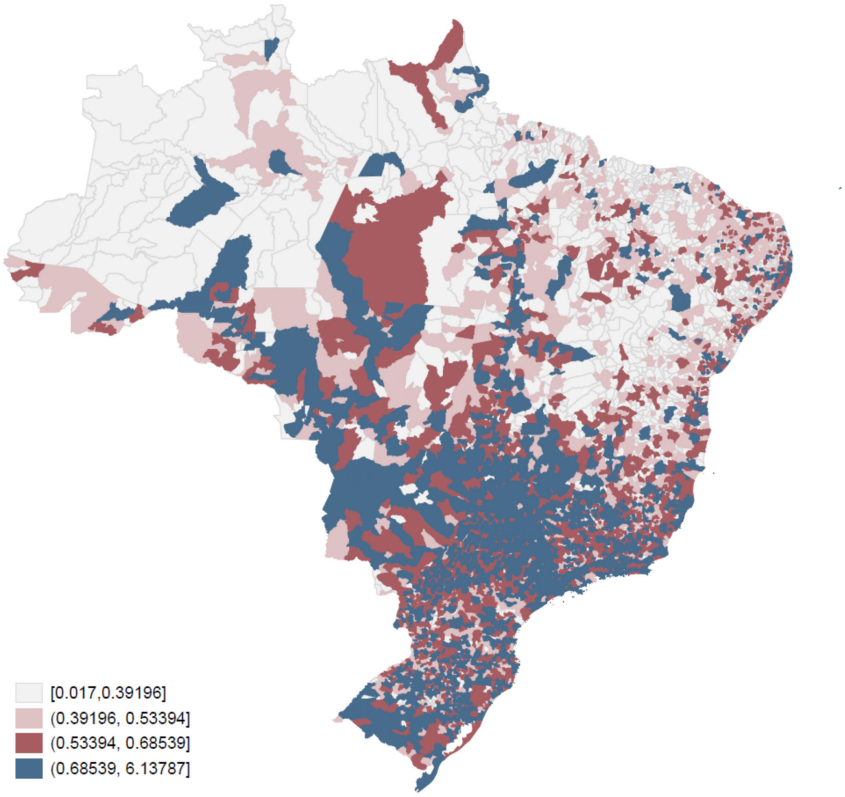
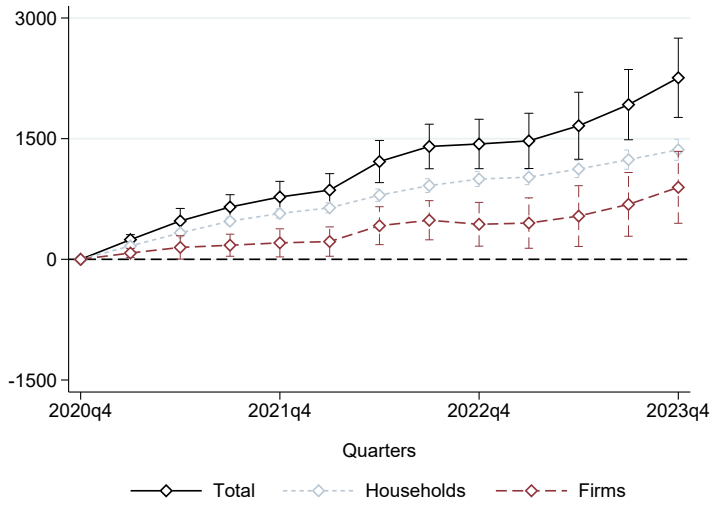
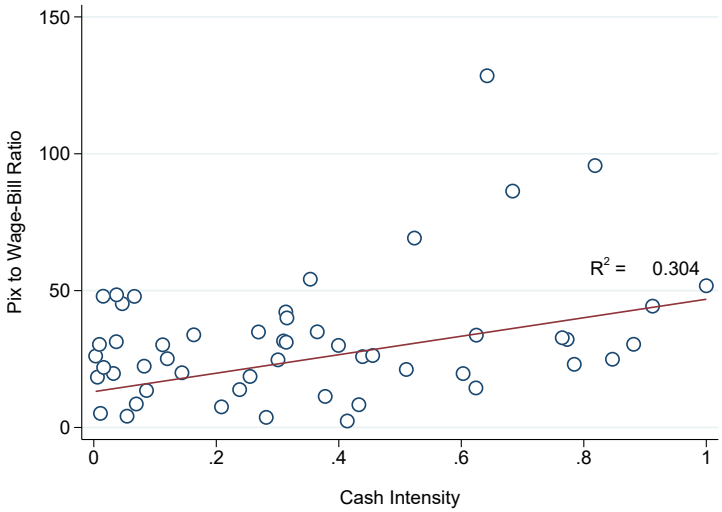


Figure 1 Geographic Distribution of Mobile Technology Penetration

This figure displays the spatial variation in mobile technology penetration across Brazilian municipalities as of 2019. Mobile penetration is defined as the ratio of mobile devices with 3G or higher capability to the total population in each municipality. The map uses four color categories to represent different levels of penetration. These ranges correspond to quartiles of the mobile penetration distribution across municipalities. The data combine telecommunications infrastructure information from ANATEL (Agência Nacional de Telecomunicações) with population estimates from IBGE (Instituto Brasileiro de Geografia e Estatística).



Panel A. Pix Value Per Capita



Panel B. Pix Usage and Cash-Intesity

Figure 2 Effect of Mobile Penetration and Cash-Intensity on Pix Value

Panel (a) presents the estimated coefficient from municipality-level regressions examining the effect of standardized mobile penetration on Pix transaction value and cash usage around the introduction of Pix in November 2020. The dependent variable is the value of Pix transactions per capita received by firms and households, measured using the municipality's 2019 population. Panel B plots the relationship between industry Pix usage divided by wage-bill as of 2022 and cash-intensity measured by the share of sales to households in the input-output table of 2019. Panel (a) includes municipality fixed effects, time fixed effects, and municipality characteristics interacted with time fixed effects. Municipality characteristics include deciles of GDP per capita, percentage of young population, and percentage of value added in agriculture. The dashed lines represent 95% confidence intervals constructed using robust standard errors. Mobile penetration is defined as the ratio of mobile devices with 3G or higher capability to total municipal population, standardized to have unit variance. Data are from the Central Bank of Brazil.

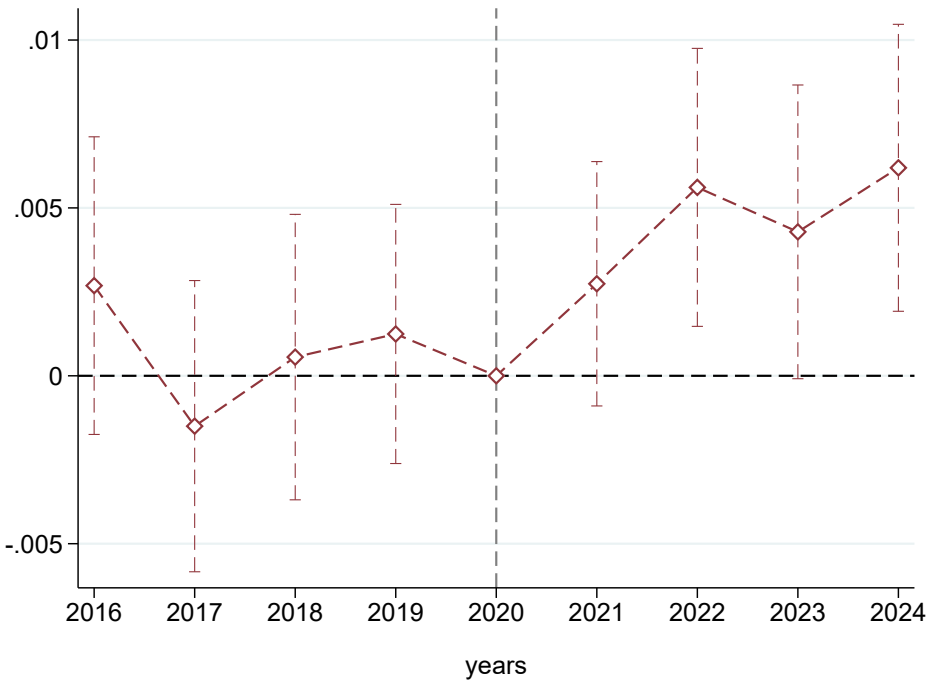


Figure 3 Effect of Mobile Penetration on Wages by Small Establishments

This figure plots the estimated yearly coefficients from a triple difference-in-differences specification that measures the differential effect of mobile penetration on the logarithm of average wages between small and large establishments around the introduction of Pix in late 2020. Small establishments are defined as those with fewer than 20 employees. The dependent variable is the logarithm of average monthly wages. The regression specification includes fixed effects for municipality-by-industry-by-year, municipality-by-size-by-industry, and size-by-industry-by-year. The dashed lines represent 95% confidence intervals constructed using robust standard errors clustered at the municipality level. A vertical dashed line marks the introduction of Pix in 2020. Mobile penetration is defined as the ratio of mobile devices with 3G or higher capability to total municipal population, standardized to have unit variance and winsorized at the 1% level.

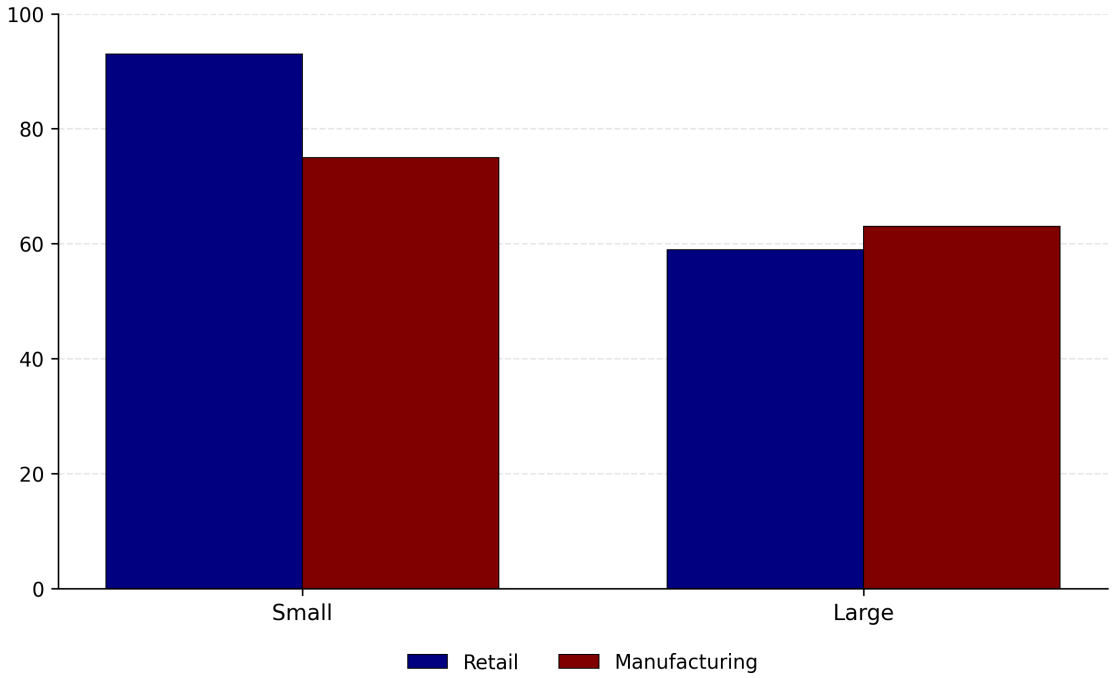


Figure 4 Skill Composition by Industry and Firm Size

This figure plots the share of low-skill payroll as a percentage of total payroll for small and large establishments in the retail and manufacturing industries. Small firms are defined as having fewer than 20 employees. The data are from RAIS employer-employee matched data for 2019. The bars display results separately for the retail (blue) and manufacturing (maroon) sectors across various firm size categories.

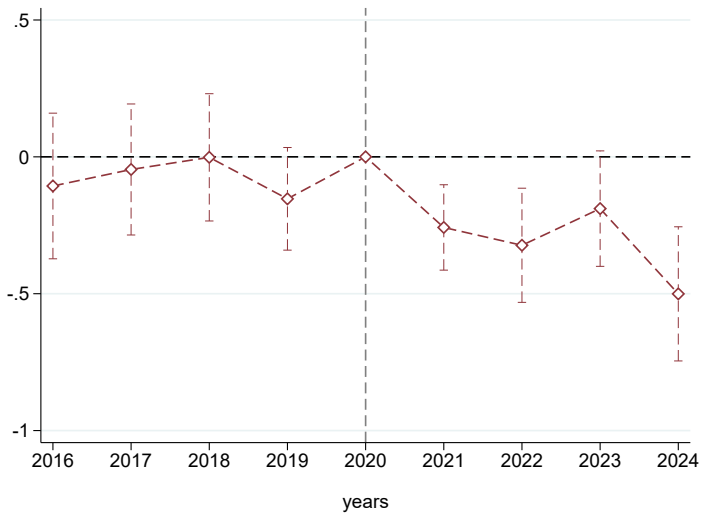
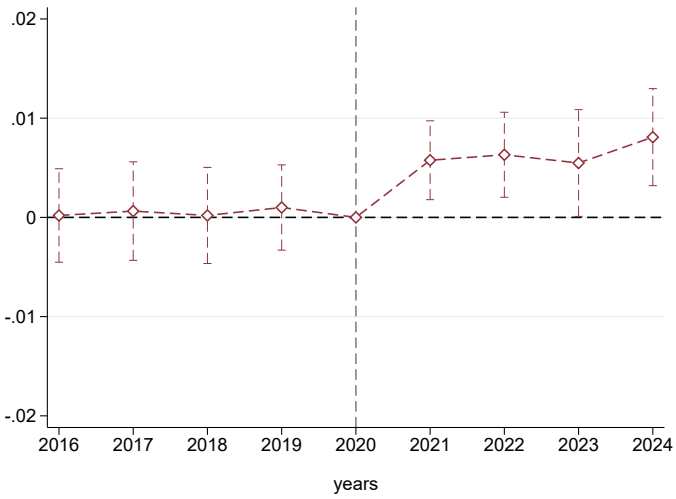
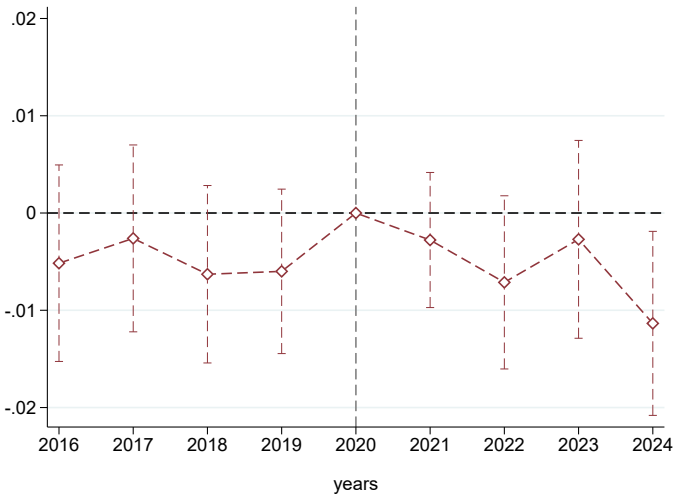


Figure 5 Effect of Mobile Penetration on Wage Inequality

This figure presents the estimated yearly coefficients from municipality-level difference-in-differences regressions examining the effect of standardized mobile penetration on the Gini coefficient of wages around the introduction of Pix in November 2020. The dependent variable is the Gini coefficient calculated from the distribution of average monthly wages across all establishments within each municipality-year, multiplied by 100. The regression specification includes municipality fixed effects, time fixed effects, and municipality characteristics interacted with time fixed effects. Municipality characteristics include deciles of GDP per capita, percentage of young population, and percentage of value added in agriculture. The dashed lines represent 95% confidence intervals constructed using robust standard errors clustered at the municipality level. A vertical dashed line marks the introduction of Pix in 2020. Mobile penetration is defined as the ratio of mobile devices with 3G or higher capability to total municipal population, standardized to have unit variance and winsorized at the 1% level.



Panel A. Workers' Wages Bottom 50%



Panel B. Workers' Wages Top 50%

Figure 6 Effect of Mobile Penetration on Wages Across the Wage Distribution

This figure presents the estimated yearly coefficients from municipality-level difference-in-differences regressions examining the effect of standardized mobile penetration on the logarithm of average wages across different segments of the wage distribution around the introduction of Pix in November 2020. Panel A plots coefficient estimates for workers in the bottom 50% of the wage distribution within each municipality-year. Panel B plots coefficient estimates for workers in the top 50% of the wage distribution. The wage distribution is calculated separately for each municipality-year based on individual worker wages. The regression specification includes municipality fixed effects, time fixed effects, and municipality characteristics interacted with time fixed effects. Municipality characteristics include deciles of GDP per capita, percentage of young population, and percentage of value added in agriculture. The dashed lines represent 95% confidence intervals constructed using robust standard errors clustered at the municipality level. A vertical dashed line marks the introduction of Pix in 2020. Mobile penetration is defined as the ratio of mobile devices with 3G or higher capability to total municipal population, standardized to have unit variance and winsorized at the 1% level.

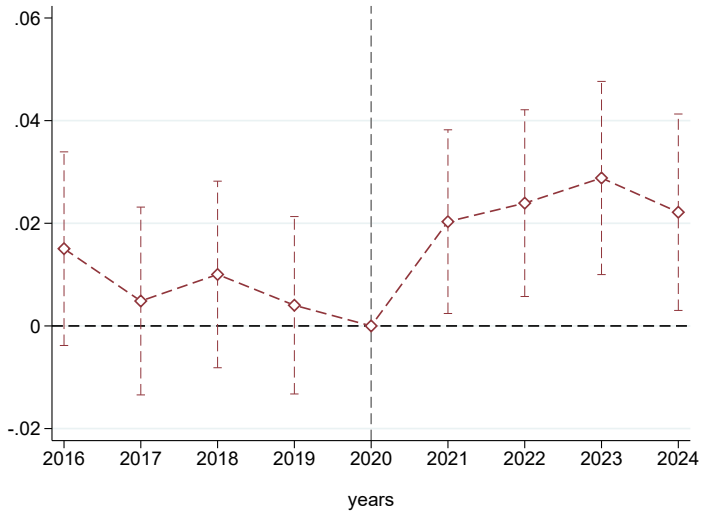
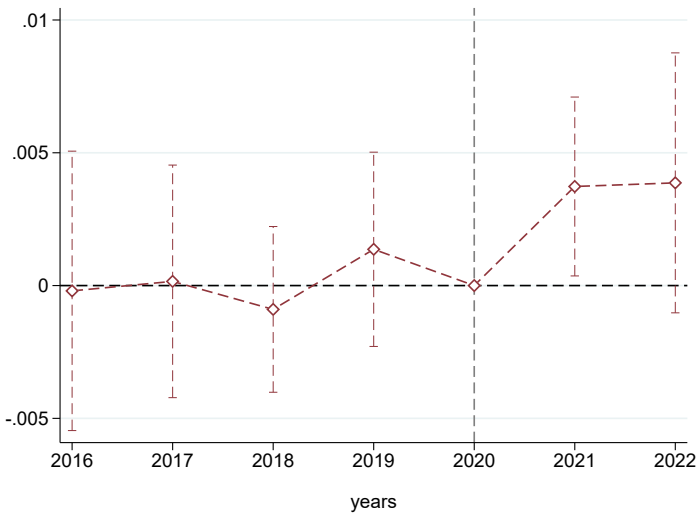
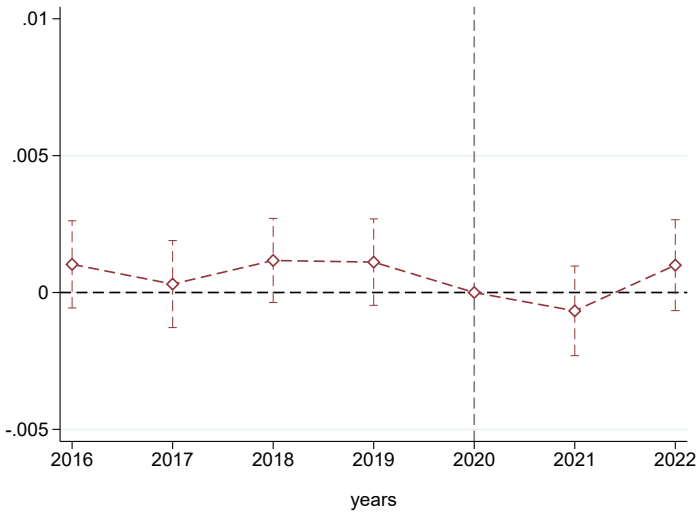


Figure 7 Effect of Mobile Penetration on Active Jobs in Small Establishments

This figure presents the estimated yearly coefficients from a triple difference-in-differences specification examining the differential effect of standardized mobile penetration on the logarithm of the number of active jobs in small establishments relative to large establishments around the introduction of Pix in November 2020. Small establishments are defined as those with fewer than 5 employees. The dependent variable is the logarithm of active jobs. The regression specification includes fixed effects for municipality-by-industry-by-year, municipality-by-size-by-industry, and size-by-industry-by-year. The dashed lines represent 95% confidence intervals constructed using robust standard errors clustered at the municipality level. A vertical dashed line marks the introduction of Pix in 2020. Mobile penetration is defined as the ratio of mobile devices with 3G or higher capability to total municipal population, standardized to have unit variance and winsorized at the 1% level.



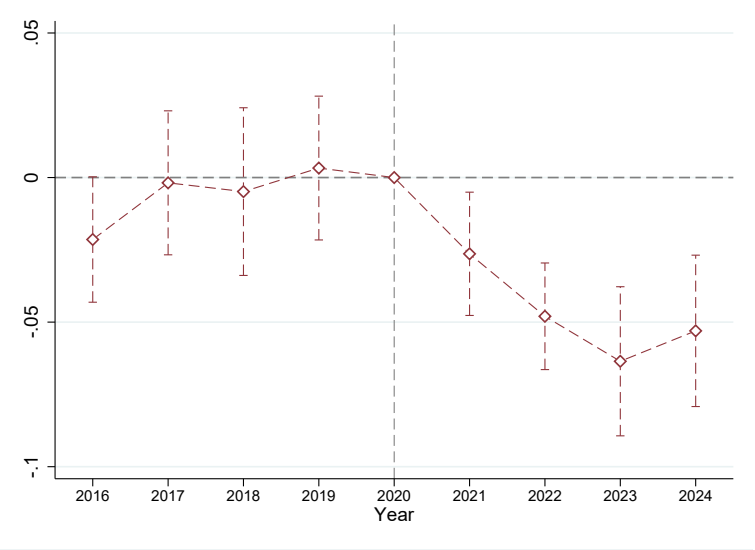
Panel A. Small Retail



Panel B. Small Manufacturing

Figure 8 Effect of Mobile Penetration on Firm Entry by Industry and Size

This figure presents the estimated yearly coefficients from municipality-level difference-in-differences regressions examining the effect of standardized mobile penetration on the number of firm entrants per 1,000 population around the introduction of Pix in November 2020, estimated separately for small retail and small manufacturing firms. Small firms are defined as those with annual sales between USD 70,000 and USD 970,000. The regression specification includes municipality fixed effects, time fixed effects, and municipality characteristics interacted with time fixed effects. Municipality characteristics include state membership, deciles of GDP per capita, percentage of young population, and percentage of value added in agriculture. The dashed lines represent 95% confidence intervals constructed using robust standard errors clustered at the municipality level. A vertical dashed line marks the introduction of Pix in 2020. Mobile penetration is defined as the ratio of mobile devices with 3G or higher capability to total municipal population, standardized to have unit variance and winsorized at the 1% level.



Log Cash

Figure 9 Effect of Mobile Penetration on Bank Branch Cash Inventories

This figure presents the estimated coefficient from municipality-level regressions examining the effect of standardized mobile penetration on cash usage around the introduction of Pix in November 2020. The dependent variable is the logarithm of cash, measured as the stock of cash held by bank branches in each municipality and year. Our specification includes municipality fixed effects, time fixed effects, and municipality characteristics interacted with time fixed effects. Municipality characteristics include deciles of GDP per capita, percentage of young population, and percentage of value added in agriculture. The dashed lines represent 95% confidence intervals constructed using robust standard errors. Mobile penetration is defined as the ratio of mobile devices with 3G or higher capability to total municipal population, standardized to have unit variance. Data are from the Central Bank of Brazil.

Table 1 Summary Statistics

This table presents summary statistics for average municipality-level characteristics in 2019. Wage values are measured in Brazilian reais (BRL). The number of bank branches is sourced from the ESTBAN database. Wages and skill composition measures are derived from the RAIS employer–employee dataset. Local GDP per capita, population, and the shares of agriculture and services in local value added are obtained from the Brazilian Institute of Geography and Statistics (IBGE). Mobile penetration (Share Mobile) is defined as the ratio of mobile devices with 3G or higher capability to the total municipal population. Low-skill workers are those without a college degree, while high-skill workers hold at least a college degree. The average wage is the mean monthly wage across all workers in the municipality.

	(1) Mean	(2) Median	(3) SD	(4) N
GDP per capita (in 1,000 BRL)	24.5	18.2	25.6	5,570
Share services	0.35	0.32	0.14	5,570
Share agriculture	0.18	0.14	0.15	5,570
Num. branches	4	1	35	5,570
Population	36,460	11,065	206,519	5,570
Share mobile	0.54	0.53	0.20	5,570
Share young	0.43	0.43	0.03	5,570
Avg. monthly wage	2,020	1,946	443	5,570
Low-skill avg. wage	1,697	1,649	355	5,570
High-skill avg. wage	3,312	3,148	1,009	5,570
Gini coefficient	0.29	0.28	0.06	5,570
Wage Top 50%	2,607.19	2,383.79	980.29	5,524
Wage Bottom 50%	1,109.32	1,074.68	171.85	5,524

Table 2 Effect of Mobile Penetration on Average Wages in Small Establishments

This table presents triple difference-in-differences estimates examining the differential effect of standardized mobile penetration on average wages in small establishments relative to large establishments following the introduction of Pix in November 2020. The dependent variable is the logarithm of average monthly wages. Small establishments are defined as those with fewer than 20 employees. The key coefficient of interest, Mobile Penetration × Small × Post, measures how the effect of mobile penetration on wages varies with establishment size after Pix introduction. Panel A examines robustness across different fixed effects specifications. Panel B examines the effects separately for all workers, low-skill workers, and high-skill workers, using the specification from Panel A Column (3). Low-skill workers are those without a college degree and high-skill workers are those with at least a college degree. Standard errors clustered at the municipality level are reported in parentheses. Mobile penetration is defined as the ratio of mobile devices with 3G or higher capability to total municipal population, standardized to have unit variance and winsorized at the 1% level. ***p<0.01, **p<0.05, *p<0.1.

Panel A: Alternative Fixed Effects Specifications

	(1)	(2)	(3)
Mobile Penetration × Small × Post	0.003***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)
Observations	1,529,548	1,529,548	1,529,548
Municipality × Size × Industry	✓	✓	✓
Municipality × Industry × Year	✗	✓	✓
Size × Year	✓	✓	✗
Industry × Year	✓	✗	✗
Municipality × Year	✓	✗	✗
Size × Industry × Year	✗	✗	✓

Panel B: Effects by Worker Skill Level

	(1)	(2)	(3)
	All	Low-Skill	High-Skill
Mobile Penetration × Small × Post	0.004***	0.004***	0.005*
	(0.001)	(0.001)	(0.003)
Observations	1,586,407	1,569,418	1,005,200
Municipality × Size × Industry	✓	✓	✓
Municipality × Industry × Year	✓	✓	✓
Size × Industry × Year	✓	✓	✓

Table 3 Effect of Mobile Penetration on Average Wages in Small Establishments: Alternative Size Definitions

This table presents triple difference-in-differences estimates examining the differential effect of standardized mobile penetration on average wages in small establishments relative to large establishments following the introduction of Pix in November 2020, with robustness checks across alternative definitions of small establishments. The dependent variable is the logarithm of average monthly wages. The key coefficient of interest, Mobile Penetration × Small × Post, measures how the effect of mobile penetration on wages varies with establishment size after Pix introduction. Columns vary the threshold for small establishments: fewer than 5, 10, 20, and 50 employees. All specifications include municipality-by-size-by-industry fixed effects, municipality-by-industry-by-year fixed effects, and size-by-industry-by-year fixed effects. Standard errors clustered at the municipality level are reported in parentheses. Mobile penetration is defined as the ratio of mobile devices with 3G or higher capability to total municipal population, standardized to have unit variance and winsorized at the 1% level. ***p<0.01, **p<0.05, *p<0.1.

	(1)	(2)	(3)	(4)
	$N < 5$	$N < 10$	$N < 20$	$N < 50$
Mobile Penetration × Small × Post	0.004***	0.004***	0.004***	0.001
	(0.001)	(0.001)	(0.001)	(0.002)
Observations	1,529,548	1,529,548	1,529,548	1,529,548
Municipality × Size × Industry	✓	✓	✓	✓
Municipality × Industry × Year	✓	✓	✓	✓
Size × Industry × Year	✓	✓	✓	✓

Table 4 Effect of Mobile Penetration on Average Wages in Small Establishments by Industry

This table presents triple difference-in-differences estimates examining the differential effect of standardized mobile penetration on average wages in small establishments relative to large establishments across different industries following the introduction of Pix in November 2020. The dependent variable is the logarithm of average monthly wages. Small establishments are defined as those with fewer than 20 employees. The key coefficient of interest, Mobile Penetration × Small × Post, measures how the effect of mobile penetration on wages varies with establishment size after Pix introduction, estimated separately for each industry. Panel A presents results disaggregated by industry. Column (1) presents the pooled estimate across all industries, replicating Column (3) from Panel A of Table 2. Columns (2)-(5) present results for retail, wholesale, manufacturing, and all other industries. Panel B presents results for service industry subsectors: restaurants, hotels, household services, and other services. All specifications include municipality-by-size-by-industry fixed effects, municipality-by-industry-by-year fixed effects, and size-by-industry-by-year fixed effects. Standard errors clustered at the municipality level are reported in parentheses. Mobile penetration is defined as the ratio of mobile devices with 3G or higher capability to total municipal population, standardized to have unit variance and winsorized at the 1% level. ***p<0.01, **p<0.05, *p<0.1.

Panel A: All Industries, Retail, Wholesale, Manufacturing, and Other

	(1)	(2)	(3)	(4)	(5)
	All	Retail	Wholesale	Manuf.	Other Ind.
Mobile Penetration × Small × Post	0.004***	0.008***	-0.009	-0.000	0.001
	(0.001)	(0.002)	(0.006)	(0.002)	(0.003)
Observations	1,529,548	122,242	71,142	476,797	289,488
Municipality × Size × Industry	✓	✓	✓	✓	✓
Municipality × Industry × Year	✓	✓	✓	✓	✓
Size × Industry × Year	✓	✓	✓	✓	✓

Panel B: Service Industry Subsectors

	(1)	(2)	(3)	(4)
	Restaurants	Hotel	House Serv.	Other Serv.
Mobile Penetration × Small × Post	0.002	-0.002	0.001	0.014***
	(0.004)	(0.005)	(0.011)	(0.003)
Observations	64,406	41,582	45,554	456,773
Municipality × Size × Industry	✓	✓	✓	✓
Municipality × Industry × Year	✓	✓	✓	✓
Size × Industry × Year	✓	✓	✓	✓

Table 5 Effect of Mobile Penetration on Wages Across the Wage Distribution

This table presents difference-in-differences estimates examining the effect of standardized mobile penetration on the logarithm of average wages across different segments of the wage distribution and wage inequality following the introduction of Pix in November 2020. The dependent variable in Column (1) is the Gini coefficient of wages, calculated from the distribution of average monthly wages across all establishments within each municipality-year multiplied by 100. The dependent variable in Columns (2) and (3) is the logarithm of average monthly wages for each group. The wage distribution is calculated separately for each municipality-year based on individual worker wages. Panel A presents estimates for the Gini coefficient (Column (1)), workers in the bottom 50% of the wage distribution (Column (2)), and workers in the top 50% of the wage distribution (Column (3)). Panel B extends the analysis by interacting the mobile penetration treatment with an indicator for tight low-skill labor markets. Tight labor markets are defined as municipalities where the ratio of low-skill workers to total workers is below the population-weighted median. The key coefficient Mobile Penetration × Post in Panel A measures the average effect of mobile penetration on each outcome, while Mobile Penetration × Post × Tight in Panel B measures the differential effect in municipalities with tight low-skill labor markets. All specifications include municipality fixed effects, region-by-year fixed effects, and municipality characteristics interacted with year fixed effects. Panel B additionally includes Tight-by-time fixed effects. Standard errors clustered at the municipality level are reported in parentheses. Mobile penetration is defined as the ratio of mobile devices with 3G or higher capability to total municipal population, standardized to have unit variance and winsorized at the 1% level. ***p<0.01, **p<0.05, *p<0.1.

Panel A: Average Effect Across Wage Distribution

	(1)	(2)	(3)
	Gini	Bottom 50%	Top 50%
Mobile Penetration × Post	-0.270**	0.006**	-0.002
	(0.085)	(0.002)	(0.004)
Observations	23,331	23,331	23,331
Municipality	✓	✓	✓
Region × Year	✓	✓	✓
Controls × Year	✓	✓	✓

Panel B: Heterogeneous Effects by Low-Skill Labor Market Scarcity

	(1)	(2)	(3)
	Gini	Bottom 50%	Top 50%
Mobile Penetration × Post	-0.142	0.005***	0.001
	(0.089)	(0.002)	(0.004)
Mobile Penetration × Post × Tight	-0.323***	0.003	-0.007
	(0.122)	(0.002)	(0.005)
Observations	23,331	23,331	23,331
Municipality	✓	✓	✓
Region × Year	✓	✓	✓
Controls × Year	✓	✓	✓
Tight × Time	✓	✓	✓

Table 6 Effect of Mobile Penetration on Average Wages in Small Establishments: Robustness to COVID-19

This table presents triple difference-in-differences estimates examining the differential effect of standardized mobile penetration on average wages in small establishments relative to large establishments following the introduction of Pix in November 2020, with additional robustness controls for the effect of COVID-19. The dependent variable is the logarithm of average monthly wages. The key coefficient of interest, Mobile Penetration × Small × Post, measures how the effect of mobile penetration on wages varies with establishment size after Pix introduction. Small establishments are defined as those with fewer than 20 employees. Column (1) includes controls for government transfers per capita (Auxílio Emergencial) interacted with small and post-period indicators. Column (2) includes controls for COVID-19 isolation policies using municipal-level isolation policy indicators. Column (3) controls for COVID-19 severity by including cumulative COVID cases per capita at the municipality level, interacted with small and post-period indicators. All specifications include municipality-by-size-by-industry fixed effects, municipality-by-industry-by-year fixed effects, and size-by-industry-by-year fixed effects. Standard errors clustered at the municipality level are reported in parentheses. Mobile penetration is defined as the ratio of mobile devices with 3G or higher capability to total municipal population, standardized to have unit variance and winsorized at the 1% level. ***p<0.01, **p<0.05, *p<0.1.

	(1)	(2)	(3)
Mobile penetration × Small × Post	0.005***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)
Transfers × Small × Post	0.004***		
	(0.001)		
Isolation × Small × Post		-0.008	
		(0.009)	
COVID cases per capita × Small × Post			-0.001
			(0.001)
Observations	1,529,548	1,529,548	1,529,548
Municipality × Size × Industry	✓	✓	✓
Municipality × Industry × Year	✓	✓	✓
Size × Industry × Year	✓	✓	✓

Table 7 Effect of Mobile Penetration on Active Jobs in Small Establishments

This table presents triple difference-in-differences estimates examining the differential effect of standardized mobile penetration on the logarithm of the number of active jobs in small establishments relative to large establishments following the introduction of Pix in November 2020. The dependent variable is the logarithm of the number of active jobs. The key coefficient of interest, Mobile Penetration × Small × Post, measures how the effect of mobile penetration on active jobs varies with establishment size after Pix introduction, estimated separately for alternative definitions of small establishments. Small establishments are defined with varying thresholds across columns: fewer than 5, 10, and 20 employees. All specifications include municipality-by-size-by-industry fixed effects, municipality-by-industry-by-year fixed effects, and size-by-industry-by-year fixed effects. Standard errors clustered at the municipality level are reported in parentheses. Mobile penetration is defined as the ratio of mobile devices with 3G or higher capability to total municipal population, standardized to have unit variance and winsorized at the 1% level. ***p<0.01, **p<0.05, *p<0.1.

	(1)	(2)	(3)
	$N < 5$	$N < 10$	$N < 20$
Mobile Penetration × Small × Post	0.017***	0.007	-0.005
	(0.006)	(0.006)	(0.007)
Observations	122,199	122,199	122,199
Municipality × Size × Industry	✓	✓	✓
Municipality × Industry × Year	✓	✓	✓
Size × Industry × Year	✓	✓	✓

Table 8 Effect of Mobile Penetration on Entry of Small Establishments by Industry

This table presents difference-in-differences estimates examining the effect of standardized mobile penetration on the number of small firm entrants per 1,000 population following the introduction of Pix in November 2020, estimated separately for small retail firms and small manufacturing firms. Small firms are defined as those with annual sales between USD 70,000 and USD 970,000. The dependent variable is the number of firm entrants per 1,000 population. The key coefficient of interest, Mobile Penetration × Post, measures how mobile penetration affects small firm entry after Pix introduction. Column (1) presents estimates for small retail firms, while Column (2) presents estimates for small manufacturing firms. All specifications include municipality fixed effects, region-by-year fixed effects, and municipality characteristics interacted with year fixed effects. Standard errors clustered at the municipality level are reported in parentheses. Mobile penetration is defined as the ratio of mobile devices with 3G or higher capability to total municipal population, standardized to have unit variance and winsorized at the 1% level. ***p<0.01, **p<0.05, *p<0.1.

	(1)	(2)
	Small Retail	Small Manufacturing
Mobile Penetration × Post	0.004***	-0.001
	(0.001)	(0.001)
Observations	18,445	18,445
Municipality	✓	✓
Region × Year	✓	✓
Controls × Year	✓	✓

Table 9 Effect of Mobile Penetration on Micro-entrepreneur Entry

This table presents difference-in-differences estimates examining the effect of standardized mobile penetration on the entry of individual micro-entrepreneurs (MEI) following the introduction of Pix in November 2020. The dependent variable is the municipal tax revenue from the Tax on the Circulation of Goods and Services (Imposto sobre Circulação de Mercadorias e Serviços, ICMS) per 1,000 population paid by MEI firms. The ICMS fee for MEIs is a fixed amount of one Brazilian real (BRL 1.00), predominantly paid by retailers. The key coefficient of interest, Mobile Penetration × Post, measures how mobile penetration affects MEI entry after Pix introduction. The specification includes municipality fixed effects, region-by-year fixed effects, municipality characteristics interacted with year fixed effects, and pre-Pix MEI levels interacted with year fixed effects. Standard errors clustered at the municipality level are reported in parentheses. Mobile penetration is defined as the ratio of mobile devices with 3G or higher capability to total municipal population, standardized to have unit variance and winsorized at the 1% level. **p<0.05, *p<0.1.

	(1)
Mobile penetration × Post	1.417**
	(0.571)
Observations	23,562
Municipality	✓
Region × Year	✓
Controls × Year	✓
Pre-MEI × Year	✓

Table 10 Effect of Mobile Penetration on Entry of Small Establishments by Industry Cash-Intensity

This table presents triple difference-in-differences estimates examining the differential effect of standardized mobile penetration on average wages in small establishments relative to large establishments across different groups of industries following the introduction of Pix in November 2020. We define an industry-specific measure of cash-intensity equal to the share of sales to households. Low-cash industries are in the bottom tercile of the cash-intensity distribution, medium-cash are in the middle tercile, and high-cash are at the top tercile. The dependent variable is the logarithm of average monthly wages. Small establishments are defined as those with fewer than 20 employees. The key coefficient of interest, Mobile Penetration × Small × Post, measures how the effect of mobile penetration on wages varies with establishment size after Pix introduction, estimated separately for each group of industries. Column (1) presents the estimate for low-cash industries, column (2) for medium-cash, and column (3) for high-cash. All specifications include municipality-by-size-by-industry fixed effects, municipality-by-industry-by-year fixed effects, and size-by-industry-by-year fixed effects. Standard errors clustered at the municipality level are reported in parentheses. Mobile penetration is defined as the ratio of mobile devices with 3G or higher capability to total municipal population, standardized to have unit variance and winsorized at the 1% level. ***p<0.01, **p<0.05, *p<0.1.

	(1)	(2)	(3)
	Low-Cash	Medium-Cash	High-Cash
Mobile Penetration × Small × Post	0.001	0.006**	0.008***
	(0.003)	(0.003)	(0.002)
Observations	438,395	474,332	374,534
Municipality × Size × Industry	✓	✓	✓
Municipality × Industry × Year	✓	✓	✓
Size × Industry × Year	✓	✓	✓

Table 11 Effect of Mobile Penetration on Entry of Small Establishments by Industry Tradability

This table presents triple difference-in-differences estimates examining the differential effect of standardized mobile penetration on average wages in small establishments relative to large establishments across different groups of industries following the introduction of Pix in November 2020. We define an industry-specific measure of tradability equal to the geographical concentration of wage-bill defined by the Herfindahl Hirschman Index (HHI). We exclude low-cash sectors and classify industries as non-tradable if they are in the bottom half of the HHI distribution, and as tradable if they are in the top half. The dependent variable is the logarithm of average monthly wages. Small establishments are defined as those with fewer than 20 employees. The key coefficient of interest, Mobile Penetration × Small × Post, measures how the effect of mobile penetration on wages varies with establishment size after Pix introduction, estimated separately for each group of industries. Column (1) presents the estimate for non-tradable industries and column (2) for tradable industries. All specifications include municipality-by-size-by-industry fixed effects, municipality-by-industry-by-year fixed effects, and size-by-industry-by-year fixed effects. Standard errors clustered at the municipality level are reported in parentheses. Mobile penetration is defined as the ratio of mobile devices with 3G or higher capability to total municipal population, standardized to have unit variance and winsorized at the 1% level. ***p<0.01, **p<0.05, *p<0.1.

	(1)	(2)
	Non-Tradable	Tradable
Mobile Penetration × Post	0.007***	0.007**
	(0.002)	(0.003)
Observations	436,015	412,851
Municipality × Size × Industry	✓	✓
Municipality × Industry × Year	✓	✓
Size × Industry × Year	✓	✓

Table 12 Pre-Determined Model Parameters

Parameter	**Description**	**Value**
C	Number of cities	100
S	Number of skill groups	4
K	Number of sectors	3
α_c and x_m	Num. cities: shape (1.24) and min. (695)	Share of firms in 10% bigger cities
H_s	Skill group masses	[8.3%, 16.3%, 61.8%, 13.6%]
γ_k	Sector shares	[19%, 14%, 67%]
η and θ	Within and between-city LS elasticity	7 and 0.5 (Berger et al., 2022)
α	Labor share	0.7
τ	Transaction costs	5%

Table 13 Calibrated Parameters

Parameter	**Description and Value**	**Target**
λ_{ks}	Sector-skill productivity parameters	Skill-specific labor share of:
$k = 1$	$[-0.45, -0.63, 0.33, 0.75]$	– Sector 1
$k = 2$	$[-1.125, -1.425, 1.02, 1.53]$	– Sector 2
$k = 3$	$[-2.9, -2.1, 2.3, 2.7]$	– Sector 3
α_k	Pareto shape by sector [1.1, 1.3, 1.6]	Sector-specific labor share
A_s	Skill productivity [1, 1.37, 0.208, 0.054]	Skill-specific average wage

Table 14 Model Fit of the Brazilian Labor Market

Moment	**Data**	**Model**
I. College Graduate Labor Share by Sector		
Manufacturing	15.5	14.5
Wholesale	22.2	22.0
Retail	10.1	10.1
II. Sectoral Labor Share		
Manufacturing	43.9	43.0
Wholesale	11.3	13.7
Retail	44.8	43.4
III. Skill-Specific Average Wages, relative to $s = 1$		
Skill Group 2 (Secondary)	1.00	0.99
Skill Group 3 (Some College)	1.12	1.12
Skill Group 4 (College Graduates)	2.99	3.01

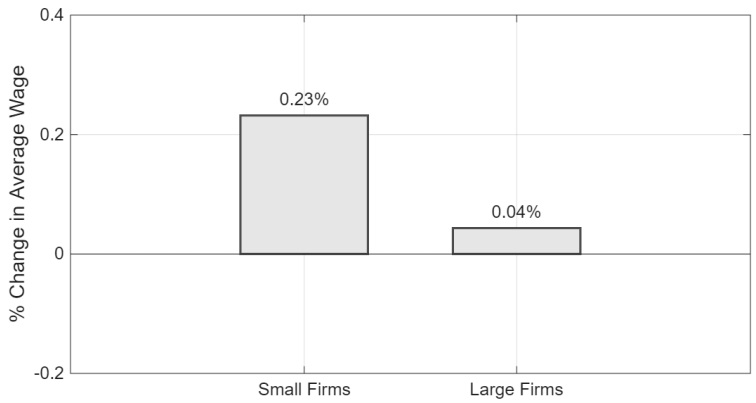


Figure 10 Change in Average Wage by Firm Size after Pix Implementation

This figure shows the percentage change in average wages following Pix, comparing small firms directly affected by the transaction cost reduction (left bar) and large firms affected indirectly through increased labor market competition (right bar). Wage change is defined as a percentage respect to the baseline equilibrium with transaction costs.

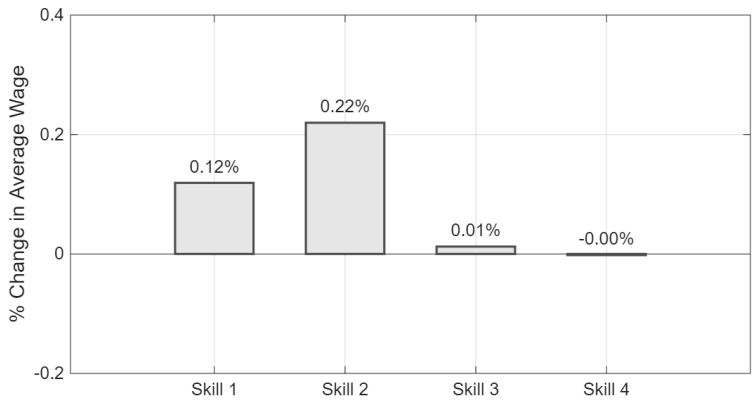


Figure 11 Change in Average Wage by Skill Group after Pix Implementation

This figure shows the percentage change in average wages following Pix for the four skill groups (1: primary education, 2: secondary education, 3: some college, 4: college graduates). Wage change is defined as a percentage respect to the baseline equilibrium with transaction costs.

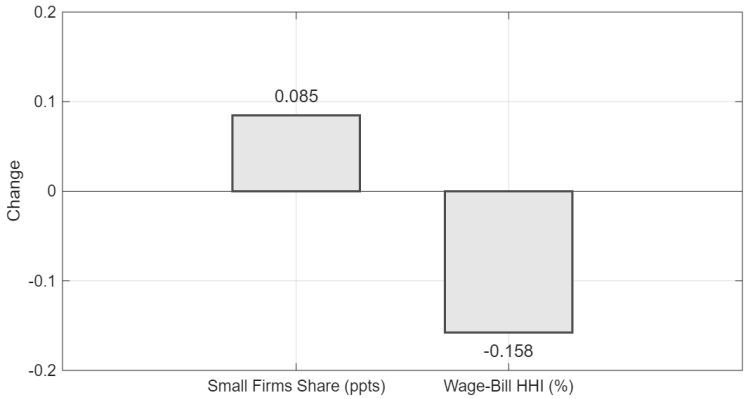


Figure 12 Wage-Bill: Small Firm Share and HHI

This figure shows the change in the wage-bill share of small firms (left bar) and the percentage change in the wage-bill Herfindahl–Hirschman Index (HHI) for local labor markets (right bar) following the implementation of Pix.

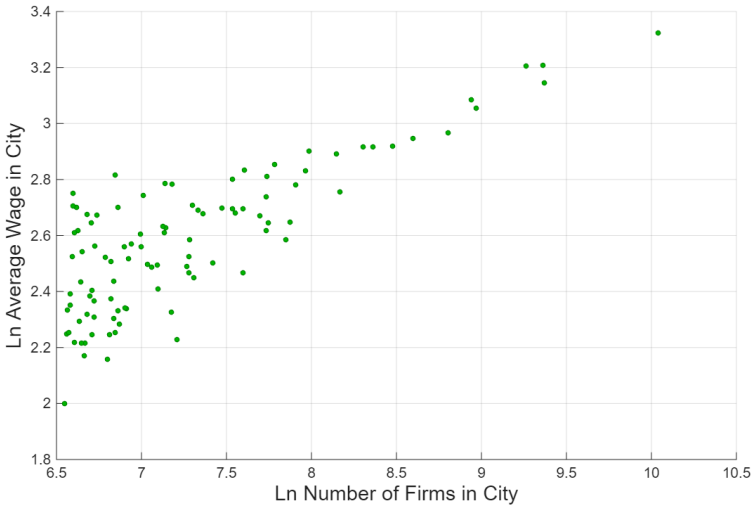


Figure 13 Average Wage and Number of Firms across Cities

This figure shows the relationship between the log of number of firms in a city (horizontal axis) and the city's average wage in logs (vertical axis) in the baseline model, prior to the implementation of Pix.

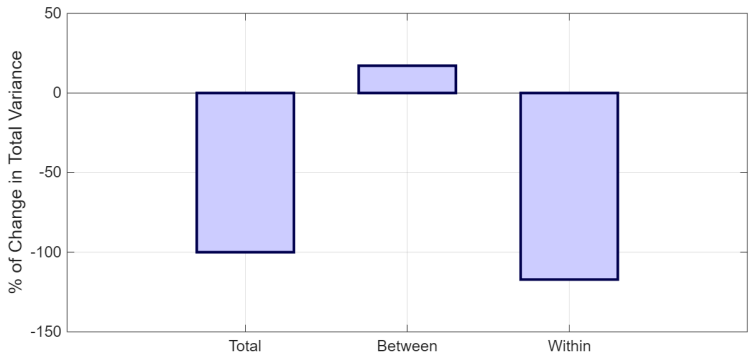


Figure 14 Decomposition of Change in Variance of Wages after Pix

This figure decomposes the decline in the total variance of log wages into contributions from changes within cities and between cities following the implementation of Pix. The left far corresponds to the total decline in variance (100%), the middle bar corresponds to the between component change divided by the change in total variance, and the right bar corresponds to the within component change divided by the total variance change.

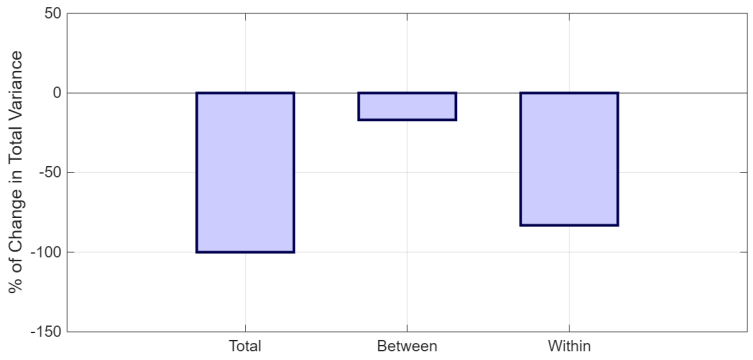
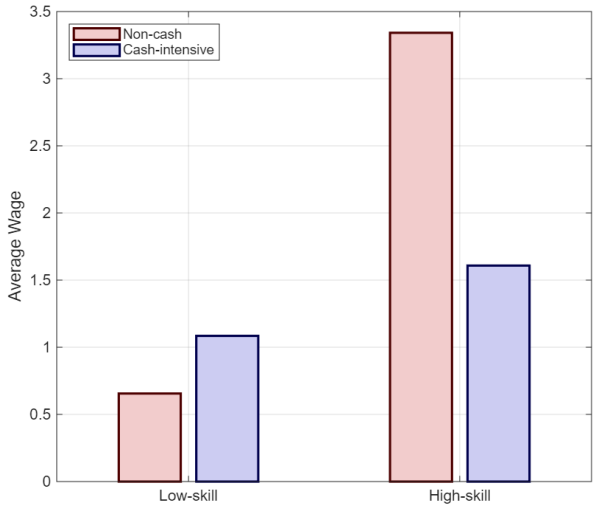


Figure 15 Decomposition of Change in Variance of Wages after Closing Mobile Gap

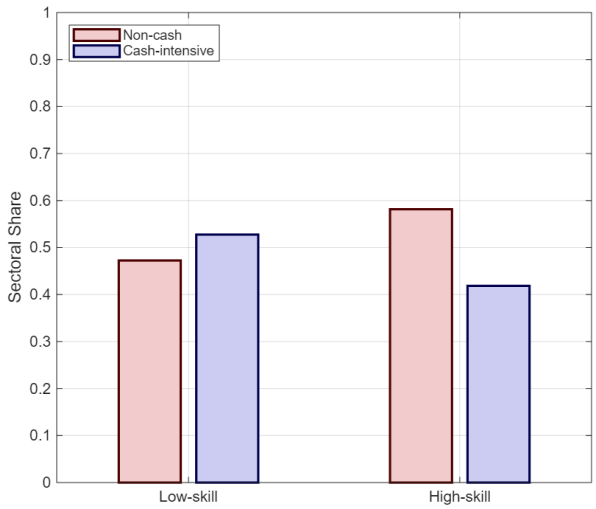
This figure decomposes the decline in the total variance of log wages into contributions from changes within cities and between cities following the equalization of mobile access. The left far corresponds to the total decline in variance (100%), the middle bar corresponds to the between component change divided by the change in total variance, and the right bar corresponds to the within component change divided by the total variance change.

Online Appendix

A1 Theoretical Framework



Panel A. Average Wage



Panel B. Employment Share

Figure A1 Baseline Model Equilibrium Wages and Employment Shares by Sector

This figure presents average wages and employment shares by skill group and industry in the baseline model equilibrium. Panel A displays average wages, while Panel B shows the sectoral distribution of employment within each skill group. The baseline calibration uses the following parameters: transaction costs $\tau_c(z) = 0.05$ for small firms in the cash-intensive sector ($c = 1$) and zero otherwise, low-skill share $N_L = 0.8$, sector masses $M_c = 0.5$, Pareto shape parameters $\zeta_0 = 1.3$ and $\zeta_1 = 1.5$, skill complementarity parameters $\lambda_{H0} = 0.2$ and $\lambda_{H1} = 0.01$, and a labor supply elasticity of one.

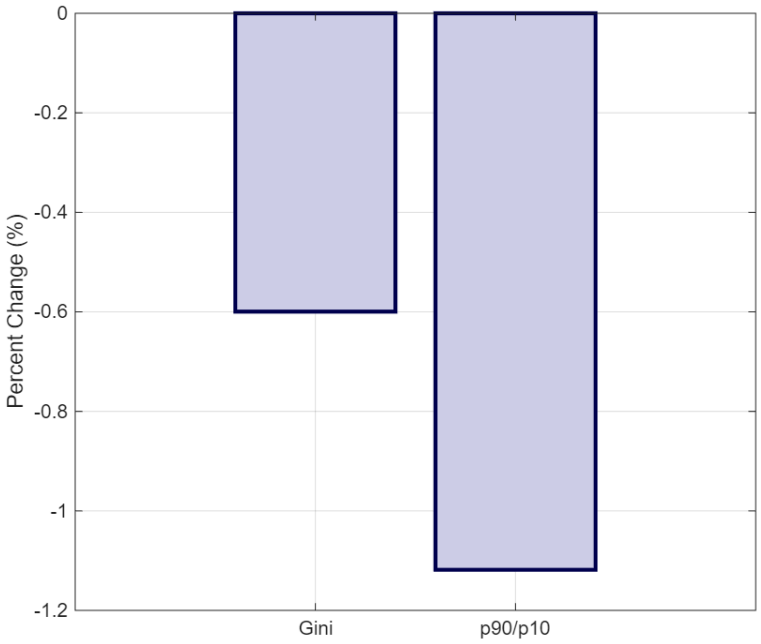
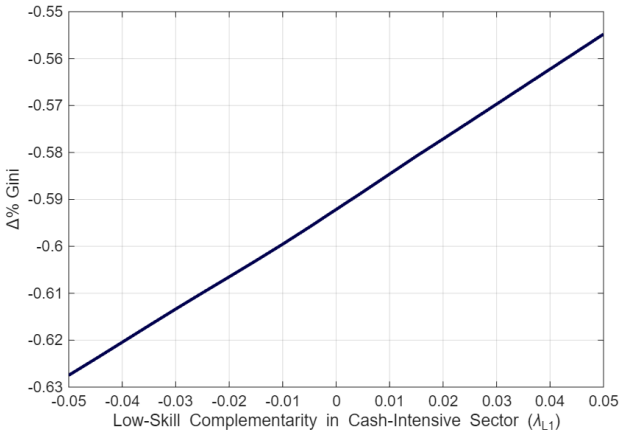
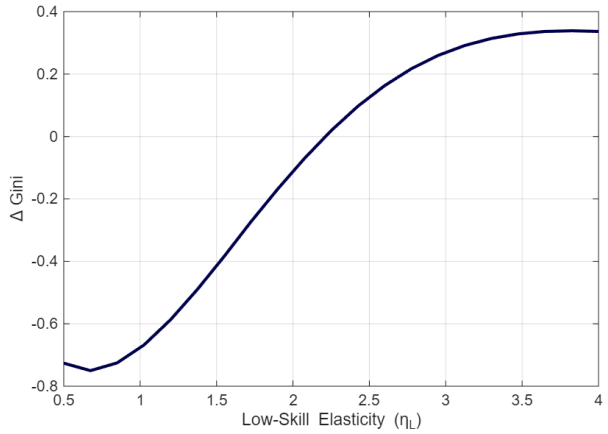


Figure A2 Effect of Lowering Transaction Cost on Wage Inequality

This figure displays the percentage change in inequality resulting from reducing transaction costs to zero for all firms, using the Gini coefficient and the 90-10 percentile ratio as inequality measures. The simulation employs the following baseline parameters: low-skill share $N_L = 0.8$, sector masses $M_c = 0.5$, Pareto shape parameters $\zeta_0 = 1.3$ and $\zeta_1 = 1.5$, skill complementarity parameters $\lambda_{H0} = 0.2$ and $\lambda_{H1} = 0.01$, and a labor supply elasticity of one.



Panel A. Skill-Complementarity

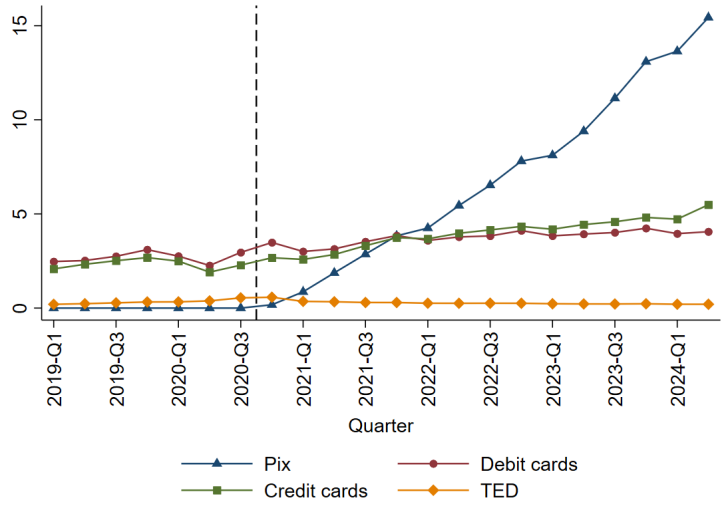


Panel B. Supply Elasticity

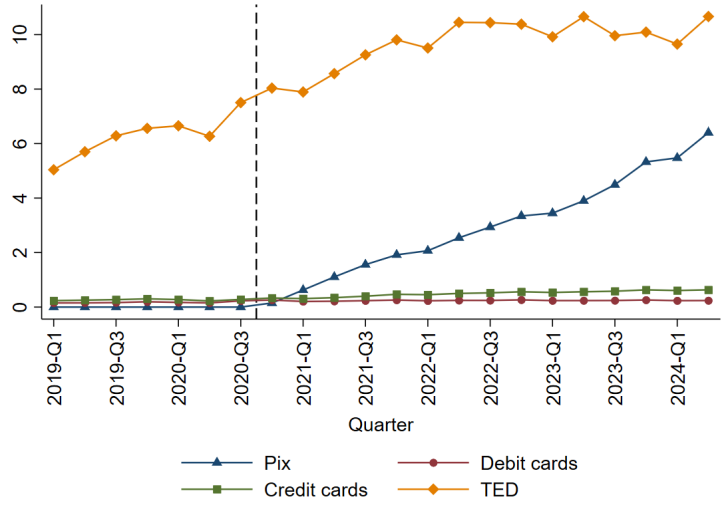
Figure A3 Drivers of Change in Inequality

This figure presents the percentage change in inequality, measured by the Gini coefficient, across different scenarios. Panel A varies the degree of low-skill complementarity in the cash-intensive sector (λ_{L1}), while Panel B examines different values of low-skill labor supply elasticity (η_L). All other parameters follow the baseline calibration: low-skill share $N_L = 0.8$, sector masses $M_c = 0.5$, Pareto shape parameters $\zeta_0 = 1.3$ and $\zeta_1 = 1.5$, skill complementarity parameters $\lambda_{H0} = 0.2$ and $\lambda_{H1} = 0.01$, and a labor supply elasticity of one.

A2 Additional Figures and Tables



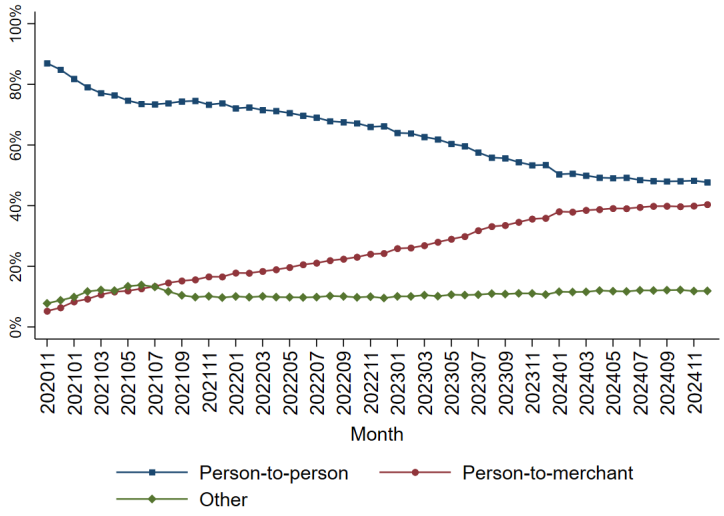
Panel A. Quantity of Transactions



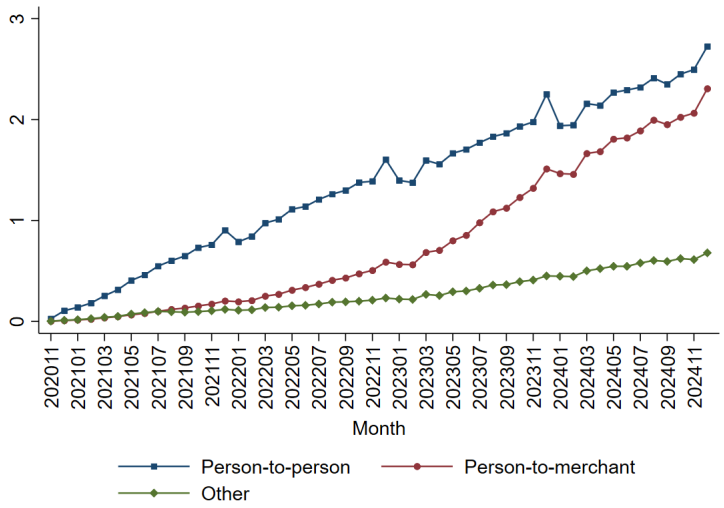
Panel B. Value of Transactions

Figure A4 Evolution of Payment Methods

This figure shows the evolution of different payment methods in Brazil from 2019 to 2024. Panel A plots the quarterly volume of transactions in billions across different payment methods. Panel B displays the quarterly value of transactions in Brazilian Reais (BRL) trillions. The vertical dashed line indicates the introduction of Pix in November 2020. Data are from the Central Bank of Brazil.



Panel A. Share of transaction types



Panel B. Quantity of transactions (in billions)

Figure A5 Evolution of different types of Pix transactions

This figure displays the evolution of Pix transactions between accounts linked to individuals (*person-to-person*), transactions from accounts linked to individuals to accounts linked to businesses (person-to-merchant), and others. The data are sourced from the Central Bank of Brazil.

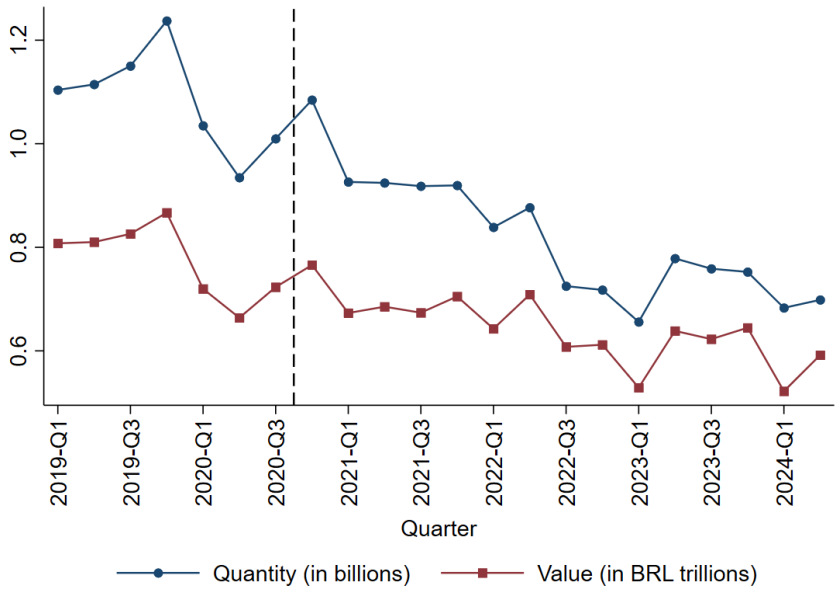


Figure A6 Evolution of Cash Withdrawals

This figure shows the evolution of cash withdrawals in Brazil from 2019 to 2024. Data from the Central Bank of Brazil. The dashed line indicates the introduction of Pix. The data are sourced from the Central Bank of Brazil.

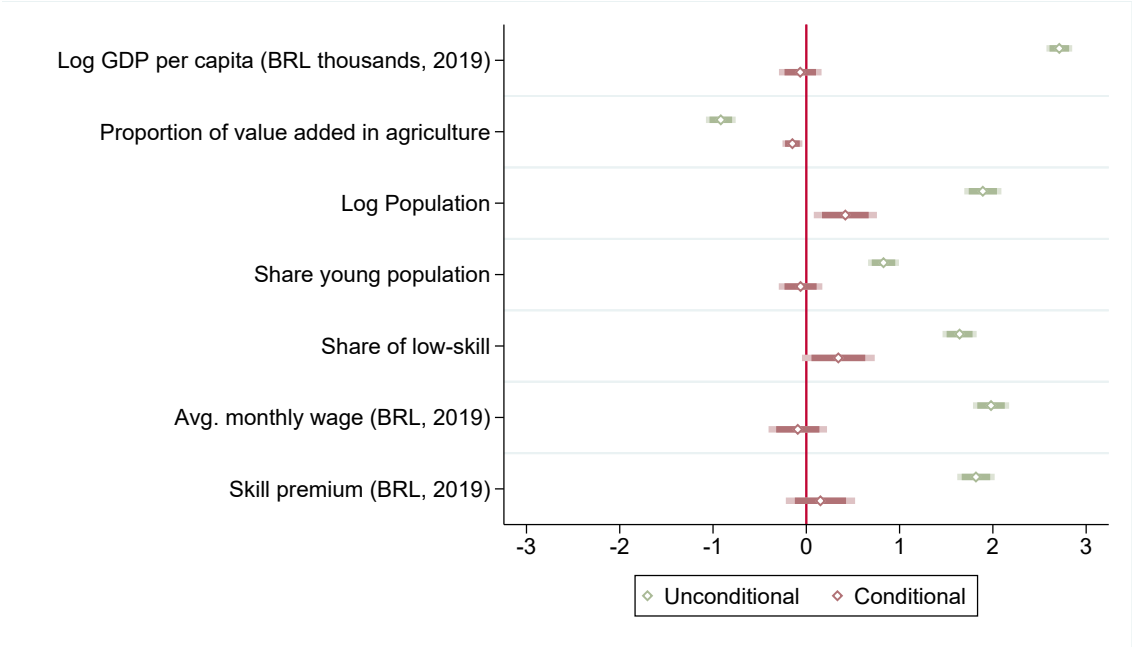


Figure A7 Balance of Covariates

This figure shows coefficient estimates and 95% (darker bars) and 99% (lighter bars) confidence intervals of one standard deviation higher mobile penetration for different variables. All variables are normalized to have a mean of zero and a standard deviation of one. "Unconditional" refers to comparing differently treated cities without conditioning on any fixed effects. "Conditional" indicates that cities are within the same region, size decile measured by GDP per capita, agriculture share decile measured by the share of GDP in the agriculture sector, and share of young individuals decile, measured by individuals between 20 and 50 years old. Skill premium refers to the difference between wages of college and non-college educated workers.

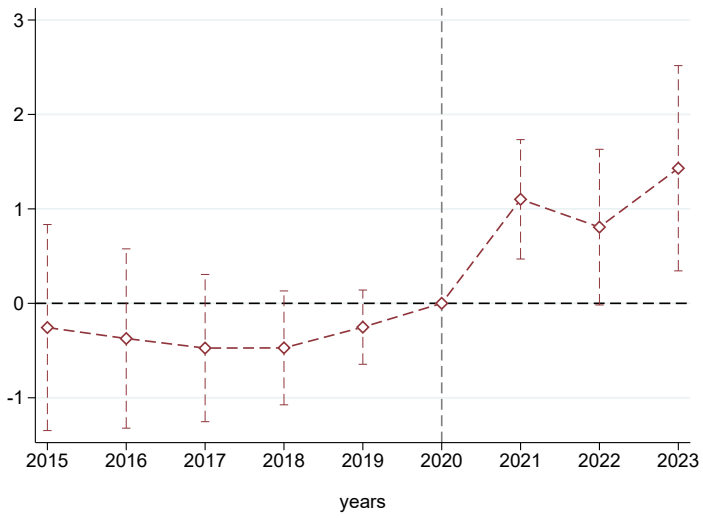


Figure A8 Effect of Mobile Penetration on Micro-entrepreneur Entry

This figure presents the estimated yearly coefficients from municipality-level difference-in-differences regressions examining the effect of standardized mobile penetration on the entry of individual micro-entrepreneurs (MEI) around the introduction of Pix in November 2020. The dependent variable is the municipal tax revenue from the Tax on the Circulation of Goods and Services (Imposto sobre Circulação de Mercadorias e Serviços, ICMS) per 1,000 population paid by MEI firms. The ICMS fee for MEIs is a fixed amount of one Brazilian real (BRL 1.00), predominantly paid by retailers. The regression specification includes municipality fixed effects, region-by-year fixed effects, and municipality characteristics interacted with year fixed effects. Municipality characteristics include deciles of GDP per capita, percentage of young population, and percentage of value added in agriculture. The dashed lines represent 95% confidence intervals constructed using robust standard errors clustered at the municipality level. A vertical dashed line marks the introduction of Pix in 2020. Mobile penetration is defined as the ratio of mobile devices with 3G or higher capability to total municipal population, standardized to have unit variance and winsorized at the 1% level.

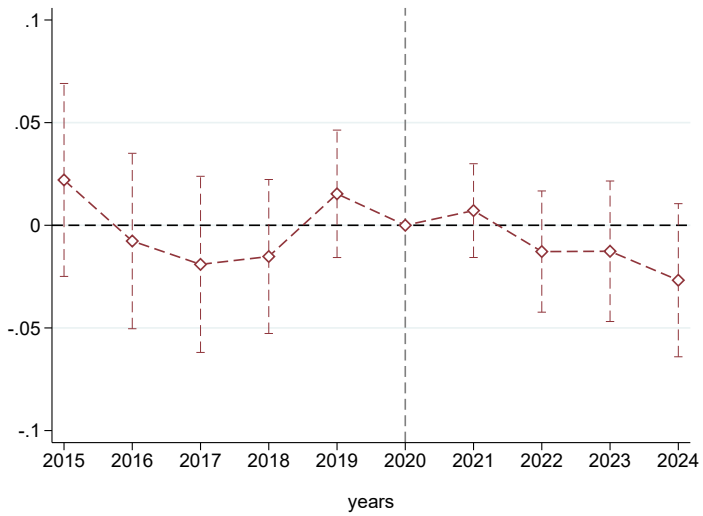


Figure A9 The Effect of Mobile Penetration on Log of Business Loans

This figure presents the estimated yearly coefficients from municipality-level difference-in-differences regressions examining the effect of standardized mobile penetration on business loans per capita around the introduction of Pix in November 2020. The dependent variable is business loans, defined as all formal lending to business entities at the municipality level. The regression specification includes municipality fixed effects, region-by-year fixed effects, and municipality characteristics interacted with year fixed effects. Municipality characteristics include deciles of GDP per capita, percentage of young population, and percentage of value added in agriculture. The dashed lines represent 95% confidence intervals constructed using robust standard errors clustered at the municipality level. A vertical dashed line marks the introduction of Pix in 2020. Mobile penetration is defined as the ratio of mobile devices with 3G or higher capability to total municipal population, standardized to have unit variance and winsorized at the 1% level.

Table A1 Share of Pix Transactions and GDP by Industry (%)

This table presents the participation of selected industries in the total quantity and value of Pix transactions from 2021 to 2023. The GDP figures correspond to the year 2019. The Pix data come from the Central Bank of Brazil and the GDP data come from the Brazilian Institute of Geography and Statistics (IBGE).

	Quantity	Value	GDP
Retail	32.8	37.1	10.1
Services (excluding financial, health, education, food)	31.6	14.7	8.4
Financial services	10.9	10.6	5.4
Accommodation and Food Services	7.3	1.8	2.6
Information	6.7	3.1	3.3
Manufacturing	3.1	16.0	27.7
Arts, Entertainment, and Recreation	1.6	0.4	0.4
Education	1.1	1.0	4.1
Health	0.9	1.9	4.2
Other	4.1	13.3	33.8

Table A2 Effect of Mobile Penetration on Pix Transactions (%)

This table presents regression estimates of the impact of mobile penetration on Pix adoption following its introduction in late 2020. The dependent variables are the number of Pix transactions per capita (Column (1)) and the value of Pix transactions per capita (Column (2)). The interaction term Mobile penetration × Post captures the differential effect of mobile penetration on Pix adoption after its introduction, representing the average quarterly effect across the post-period. The specification includes municipality fixed effects, region-by-year fixed effects, and municipality characteristics interacted with year fixed effects. Standard errors clustered at the municipality level are reported in parentheses. Mobile penetration is defined as the ratio of mobile devices with 3G or higher capability to total municipal population, standardized to have unit variance and winsorized at the 1% level. ***p<0.01, **p<0.05, *p<0.1.

	Number of Transactions per Capita (1)	Value of Transactions per Capita (2)
Mobile penetration × Post	5.779***	2,072.738***
	(0.638)	(265.207)
Observations	72,371	72,371
Municipality × Year	✓	✓
Region × Year	✓	✓
Controls × Year	✓	✓