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

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Abstract

While technological innovations typically increase wage inequality by favoring skilled workers, we show that instant payment systems instead reduce it. We study the labor market effects of instant payment systems in the context of Brazil's Pix rollout. Using matched employer-employee data, we implement a triple-difference design that exploits pre-Pix mobile penetration across municipalities, the differential benefits of Pix for small versus large establishments, and the timing of Pix. We find that wages in small establishments rise significantly relative to large establishments after Pix. These gains are concentrated in cash-intensive sectors such as retail and services, with no effects in wholesale or manufacturing. Crucially, wage inequality declines, driven by wage gains in the lower half of the distribution, with no effect at the top. Our evidence points to increased small-firm labor demand, consistent with lower payment frictions. These effects are amplified where low-skill labor is scarce. A calibrated monopsony model implies that uniform Pix adoption would reduce both the within- and between-municipality components of wage dispersion, amplifying the aggregate inequality reduction.

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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?

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). Instant payment systems reduce transaction costs such as merchant fees and cash-handling expenses, enable immediate settlement, and generate digital transaction records that expand financial access. These features alleviate frictions that are 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 benefit disproportionately, the pass-through to wages may be muted under monopsony. As these firms expand, their growing labor market shares increase wage markdowns, potentially leaving inequality unchanged or even widening it. Thus, whether instant payment systems reduce wage inequality is an empirical question.

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.[1] Contrary to conventional patterns of skill-biased technical change, we find that

[1]Pix is an instant payment system developed by Brazil's central bank to reduce cash usage and promote

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. The framework features heterogeneous firms with monopsony power in two sectors that differ in cash-dependence and skill intensity. A reduction in transaction costs boosts labor demand in cash-intensive firms, reducing inequality when these firms employ predominantly low-skill workers. The magnitude of this effect can be amplified when instant payments reduce local labor market concentration. However, the effect is weaker 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 administrative data on formal workers and establishments from 2016 to 2024. Our identification strategy is an intention-to-treat triple difference-in-differences (DiD) design exploiting Pix's nationwide launch in November 2020, pre-existing mobile penetration across municipalities, and the differential benefits of Pix for small versus large establishments. We compare wage changes between small and large establishments within the same municipality before and after Pix. We interact this contrast with pre-Pix mobile penetration, which strongly predicts Pix adoption intensity, and control for local economic conditions and industry-specific trends. The rationale is that small establishments, particularly in cash-intensive sectors, stand to gain 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, event-study estimates show no differential pre-trends in wages between

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.

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).[2] Our results remain robust to 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.

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. 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

[2]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).

distribution, with no significant effects at the top.[3]

A key question is whether our estimates capture the effect of Pix adoption or faster non-Pix digital adaptation during the COVID-19 period. Because Pix launched nationwide, our design identifies an intention-to-treat effect of pre-Pix mobile penetration on the post-2020 small-versus-large wage gap, where mobile penetration predicts Pix adoption intensity. We address the COVID digital-adaptation alternative in several ways. Our preferred fixed effects absorb municipality-by-industry-by-year shocks and national size-by-industry trends, so a digital-adaptation explanation would require size-specific pandemic impacts correlated with pre-Pix mobile penetration. We augment the specification with direct measures of pandemic intensity interacted with *Small* and *Post*, including per-capita emergency aid transfers, municipal stay-at-home orders, and cumulative COVID-19 cases per capita. Across these specifications, the Pix triple interaction remains stable, while COVID-related interactions are small or statistically insignificant. We also find sharp heterogeneity that is hard to reconcile with broad digitalization: effects concentrate in cash-intensive consumer-facing sectors and are larger in physical services than in delivery-capable services including restaurants. Finally, the dynamic effects grow over time rather than attenuate, consistent with continued merchant adoption 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 three key pieces of evidence supporting this mechanism. First, municipalities with higher mobile penetration experienced significant employment growth in small establishments (a 1.7 percent increase) after Pix's introduction. Second, higher mobile penetration led to increased small-business entry in retail sectors, with no corresponding effects in man-

[3]Separately, we estimate wage responses for low- and high-skill workers and find similar gains (0.4% and 0.5%, respectively), suggesting that the wage effects are not strongly skill-biased.

ufacturing, indicating that Pix's impact is concentrated in cash-intensive businesses. Third, 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 greater wage pressure in tighter local labor markets, amplifying the reductions in wage inequality.

We evaluate two potential drivers of the underlying increase in small-firm profitability: reductions in cash-handling costs and variation in merchant payment fees and bargaining power. Pix primarily substitutes for cash rather than credit cards, reducing the need to store, transport, and safeguard physical currency. Consistent with this channel, we document declines in bank-branch cash inventories in higher-exposure municipalities after Pix and stronger wage effects in high-crime settings where cash holding is costlier. We also find that wage gains are larger for small establishments embedded in small firms that face higher merchant fees.

While our findings point to increased labor demand as the main driver, we evaluate alternative explanations. Formalization or wage reporting alone cannot fully explain the wage gains. Formal employment is costly in Brazil, and prior reductions in formalization costs have generated limited and short-lived changes in registration (Cavalcante, 2020; Rocha et al., 2018). Moreover, incentives to formalize due to fear of tax enforcement are limited, as Pix transactions remain subject to banking secrecy and tax authorities do not observe transaction-level payer or payee identifiers. Wage increases also extend to small establishments with up to 20 employees, which typically already comply with formal labor regulations. We find no differential wage effects based on municipalities' pre-Pix share of informal workers, and worker composition is unchanged with null effects on gender, skill, tenure, and age. Effects are also stronger where low-skill labor is scarce, which is difficult to reconcile with a pure compliance or reporting channel. Improved credit access is also unlikely: despite the potential for digital transaction records to expand lending, we detect no measurable increase in business lending after Pix adoption.

Motivated by our empirical results, we extend our conceptual framework to quantify the aggregate gains from Pix and to simulate uniform adoption across municipalities. While our empirical analysis finds that Pix reduced wage inequality within high-adoption municipalities, the aggregate effect is theoretically ambiguous. Cities that adopted Pix more intensively also tend to have higher average wages, so uneven adoption could increase between-city inequality even as it reduces within-city inequality. We calibrate the model to match key moments of the Brazilian labor market and simulate Pix as a transaction-cost reduction for small, cash-intensive firms. The calibrated model reproduces the reduced-form wage and inequality patterns and reveals two sources of welfare gains not captured by the empirical design. First, as small firms gain market share, the employment HHI declines and average wage markdowns fall. Second, the decline of the within-city component of wage variance is partially offset by a rise in the between-city component. A counterfactual that closes the adoption gap amplifies these effects: unlike the baseline, uniform adoption reduces both the within- and between-city components of wage variance. The uneven rollout of Pix increased the total wage-bill by 0.04%, while uniform adoption would generate a 0.21% increase, relative to a world without Pix.

Related Literature. Our paper contributes to the literature on financial technology and digital payments. Prior work has studied the effects of digital payments on risk-sharing and poverty reduction (Jack and Suri, 2014; Suri and Jack, 2016), financial inclusion (Ouyang, 2021), economic growth (Dubey and Purnanandam, 2023), and small business outcomes (Agarwal et al., 2019, 2022; Klapper, 2023; Dalton et al., 2024; Higgins, 2024), as well as credit access via cashless payment records (Ghosh et al., 2024), but the effects of instant payment systems on wages and wage inequality remain largely unexplored. We also contribute to the payments literature studying adoption and banking outcomes, including cash disruptions and payment-technology adoption dynamics (Chodorow-Reich et al., 2020; Crouzet et al., 2023), deposit competition (Sarkisyan, 2023), payment technology complementarities (Sampaio and Ornelas, 2024), and the role of physical bank infrastructure in digital payment adoption (Mariani et al., 2023).

To our knowledge, our paper is the first to examine the effects of an instant payment system on wages and wage inequality using matched employer-employee data. We show that Pix raises wages in small, cash-intensive establishments, compressing the wage distribution from below. Our findings are consistent with a novel mechanism: by lowering transaction costs, instant payments increase labor demand among small, cash-intensive firms, with larger wage effects where low-skill workers are scarce. This contrasts with the conventional view that technological innovation primarily benefits skilled labor. We use a calibrated monopsony model to map these reduced-form estimates into aggregate implications and show that uniform adoption would reduce both within- and between-city components of wage dispersion, amplifying the aggregate gains relative to the observed uneven rollout.[4]

We also contribute to the large 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 (Goldin and Katz, 1998; Bound and Johnson, 1992; Krusell et al., 2000) and routine-biased technological change (Goos et al., 2014; Autor and Dorn, 2013; Michaels et al., 2014). In contrast, we show that financial technologies 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.

2 Conceptual Framework

We develop a theoretical framework to analyze the potential effects of instant payment systems on wage inequality. Our model includes two sectors with different cash dependences,

[4]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 reduces payment frictions and delivers concentrated wage gains and inequality compression among cash-intensive businesses.

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 $c = \{0, 1\}$.[5] Each sector c contains a mass M_c of firms.[6] 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,

[5] 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 relies heavily on cash transactions and faces higher transaction costs.

[6] In this section, c indexes sectors (cash vs non-cash). In Sections 4 onward, c indexes municipalities.

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 percent of the workforce, matching the share of workers without a college degree 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.

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

[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.

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

On November 16, 2020, the Central Bank of Brazil launched Pix, an instant payment system.[8] Pix enables immediate, 24/7 transfers between individuals, businesses, and government entities. Users initiate transfers through banks' mobile apps or websites using aliases (e.g., tax IDs, phone numbers) or QR codes.

Two design choices are relevant for adoption and for our empirical strategy.[9] First, participation is mandatory for large banks (those with more than 500,000 accounts), which covered more than 99 percent of bank accounts in 2020. This ensured widespread availability and interoperability from launch. Second, Pix transfers are free for individuals.[10] Since many small firms use the owner's personal bank account for business transactions, they pay zero or near-zero fees. Even when firms pay through business accounts, Pix fees are substantially lower than those of other methods: merchants pay an average fee of 0.22 percent per Pix transaction, compared to 2.2 percent for credit card payments (Duarte et al., 2022).

Pix quickly became a major payment method. About a year after launch, the number of Pix transactions surpassed those of credit and debit cards and TED transfers, and Pix exceeded credit and debit cards in transaction value two quarters after introduction (Ap-

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

[9] As of early 2024, over 152 million individuals and 15 million firms had registered for Pix.

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

pendix Figure B.1). Pix initially grew through transfers between individual-linked accounts and then expanded to transfers from individual-linked to business-linked accounts (Appendix Figure B.2).[11]

The rise in Pix coincides with a 35 percent drop in the number of cash withdrawals (Appendix Figure B.3), consistent with reduced reliance on cash.[12]

Pix adoption is concentrated in cash-intensive sectors. Between 2021 and 2023, retail accounted for 32.8 percent of Pix transactions and services for 31.6 percent, while manufacturing accounted for only 3.1 percent (Appendix Table B.1).[13] This concentration motivates our sectoral heterogeneity tests in the empirical analysis.

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.[14] Second, we use matched employer-establishment data from the Brazilian Ministry of Labor (*Relação Anual de Informações Sociais*, RAIS).[15] 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.[16] 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

[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] Central Bank of Brazil surveys show the decline: cash was identified as the most common payment method by 60.2 percent of respondents in 2018, 41.7 percent in 2021, and 22 percent in 2024 (*O brasileiro e sua relação com o dinheiro*).

[13] Despite representing 64.4 percent of Pix transactions, retail and services contributed 18.5 percent of GDP in 2019. Manufacturing contributed 27.7 percent of GDP.

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

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

[16] RAIS records wages for formal employment relationships reported by employers and excludes independent contractors and informal work.

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).[17] We restrict our analysis to the 2016–2024 period.

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

[17] We also use pre-Pix municipal homicide rates per 100,000 residents from the Ministry of Health Mortality Information System (SIM/DATASUS) for 2019.

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:

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

where Y_{kjct} is the log average wage for establishment size group k in industry j, municipality c, and year t.[18] *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 for $t \geq 2021$ (post-Pix) and zero otherwise.[19]

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. Standard errors are clustered at the municipality

[18] 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)

[19] Pix launched on November 16, 2020. Because we measure outcomes at the annual level, we code 2020 as the last pre-treatment year.

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, 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.[20] 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 natural question is whether mobile penetration captures broader digital adoption that benefits small firms through channels unrelated to payment frictions. To assess this, we construct an industry-specific measure of cash-intensity, defined as the share of sales to households, and estimate our baseline specification separately by cash-intensity tercile. We find null effects in low-cash-intensity industries, which is difficult to reconcile with a broad digital-adoption channel that does not vary with cash dependence. Section 6.3 examines these patterns in detail.

Because Pix launched during the COVID-19 pandemic, an alternative interpretation is that mobile penetration proxies for faster pandemic-era digital adoption that differentially

[20]Figure B.4 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).

benefited small establishments. Three pieces of evidence weigh against this alternative. First, augmenting our specification with direct measures of pandemic intensity (e.g., per-capita emergency aid transfers, stay-at-home orders) leaves the triple interaction unchanged. Second, effects concentrate in cash-intensive sectors and are larger in in-person services (e.g., barber shops, auto repair) than in delivery-capable services (e.g., restaurants), a pattern difficult to reconcile with broad digital adoption. Third, the dynamic effects grow over time rather than attenuate, consistent with continued merchant adoption of Pix rather than a transitory pandemic shock. Section 5.4 presents these tests in detail.

5 Main Results

5.1 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. Appendix Table B.2 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. These results highlight 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

Table 2 reports triple difference-in-differences estimates of Pix's wage effects by establishment size. The dependent variable is 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.

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.[21]

Figure 3 plots dynamic effects from our triple difference specification based on establishment 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,

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

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 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 important. 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 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—is consistent with wage gains reflecting reduced payment frictions faced by small businesses that previously relied heavily on cash transactions.

5.3 Effects on Wage Inequality

Section 2 implies that a reduction in transaction frictions compresses wages when the firms with the largest wage gains employ relatively more low-skill labor, with the magnitude shaped by the skill–productivity complementarities (λ_{kc}) across sectors and the elasticity of labor supply η_s that governs wage markdowns under monopsony.

Appendix Figure B.5 shows that this condition holds most strongly in retail. 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).

Motivated by this composition, we test whether wage inequality declines more after Pix in municipalities with higher pre-Pix mobile penetration. We employ 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 4 supports our model's prediction using the Gini coefficient of wages, calculated from the distribution of individual worker wages within each municipality-year and multiplied by 100.[22] This approach isolates the effect of Pix adoption on wage inequality while

[22]We exclude government employees from this calculation.

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 5 further unpacks these results by examining wage dynamics separately for different segments of the wage distribution. Panel A of Figure 5 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)) show that the bottom 50% experiences a significant 0.6 percent increase in wages, while the top 50% experiences no significant effect. This decomposition indicates 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 Alternative Interpretations: COVID and Digital Readiness

Pre-trend evidence supports the parallel trends assumption of our triple-difference design (Figure 3). The remaining question is which mechanism drives our estimates. Under the Pix hypothesis, lower payment frictions reduce costs for small establishments and raise labor demand. Alternatively, higher pre-Pix mobile penetration might capture faster non-Pix digital adaptation during COVID-19, disproportionately benefiting small establishments. We test this alternative in four ways.

COVID intensity. Our preferred specification includes municipality-by-industry-by-year fixed effects, which absorb any time-varying shock that affects all establishments in an industry within a municipality (e.g., local COVID severity, local demand changes). The remaining concern is size-specific COVID shocks correlated with pre-Pix mobile penetration. We therefore augment the specification with direct measures of pandemic intensity interacted with *Small* and *Post* (Table 6). Column (1) adds per-capita emergency aid transfers, Column (2) adds municipal stay-at-home orders, and Column (3) adds cumulative COVID cases per capita. In all three columns, the triple interaction of interest remains stable at 0.004–0.005. Lockdown and case interactions are small and insignificant. The transfer interaction is positive and significant, but the triple interaction remains unchanged. Following Altonji et al. (2005), this stability suggests that selection on unobservables would need to be large relative to selection on observed COVID proxies to explain our estimate.

Sectoral and within-services heterogeneity. Sectoral and within-services heterogeneity. If Pix operates through reduced payment frictions, effects should concentrate in cash-intensive sectors where Pix substitutes for costly payment methods. A digital-readiness alternative would predict positive wage effects across a broader set of sectors. Table 4 shows a significant effect in retail (0.8%), but no significant effects in wholesale or manufacturing. More directly, we split industries by their pre-Pix cash intensity, measured as the share of sales to households. The wage effect is close to zero in the lowest cash-intensity tercile and rises monotonically across terciles (Table 9; see Section 6.3 for details).

A more specific alternative is that delivery platforms (e.g., iFood, Rappi) raised wages

in small consumer-facing establishments. If delivery platforms drive our results, the effects should be strongest in delivery-oriented services such as restaurants. Under the Pix mechanism, effects should be relatively larger in in-person services where payment frictions were more salient. Appendix Table B.3 shows a small and statistically insignificant estimate for delivery-capable services such as restaurants (0.2%), while physical services (e.g., barber shops, auto repair) show a significant 1.9% increase. This within-services pattern is harder to reconcile with delivery platforms as the primary driver.[23]

Post-period dynamics. A COVID digital-adaptation channel would plausibly attenuate as acute disruptions fade. Under the Pix mechanism, effects should grow with merchant adoption. Figure 3 shows that the dynamic triple-interaction coefficients rise from approximately 0.3% in 2021 to 0.8% by 2024, with no sign of attenuation. This time path is more consistent with the continued expansion of person-to-merchant Pix transactions (Appendix Figure B.2) than with a transitory pandemic shock.

Cash-at-risk and merchant fees. We next exploit two predictions specific to payment-friction savings. First, if Pix reduces cash-handling costs, wage gains should be larger where cash is riskier to handle. Splitting municipalities by pre-Pix homicide rates (2019), we find effects concentrated in high-homicide areas (Figure 8, Table 10). This pattern is harder to reconcile with a generic digital-readiness channel. Second, if Pix substitutes for card payments, wage gains should be larger for small establishments in small firms, which face higher negotiated merchant discount rates ex ante. Consistent with this, the quadruple-difference event-study coefficients are near zero before Pix and turn positive after 2020 (Figure 9). Further details on these tests are in Section 6.3.

Taken together, the evidence aligns more closely with Pix operating through payment frictions than with a broad post-2020 digital-readiness channel.

[23]Delivery couriers in Brazil operate as independent contractors (typically MEIs) and are not recorded in RAIS, which covers only formal employment contracts (CLT).

6 Mechanisms

We examine why wages rise after Pix. First, we estimate effects on employment and new firm creation. Next, we test if wage effects are larger where labor markets are tighter. Finally, we examine the sources of small firm profitability gains and evaluate alternative explanations.

6.1 Labor Demand Effects

Our main results indicate that higher mobile penetration increases wages in small establishments, especially within retail, and compresses 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 6 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. Appendix Figure B.6 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 annual per-capita MEI-ICMS receipts proportional to the number of active MEIs.

Appendix Figure B.7 plots the dynamic effects of mobile penetration on annual 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. Appendix Table B.4 quantifies this effect: a one-standard-deviation increase in mobile penetration raises annual 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. Employment growth concentrates in micro-firms (N<5) and new entrants, while wage effects extend to all small establishments (N<20). This pattern is consistent with Figure A5 in our model. Micro-firm expansion raises outside options for workers, pushing up wages at slightly larger establishments even without headcount growth.

6.2 Labor Market Tightness and Wage Amplification

The evidence above shows that Pix increases labor demand for low-skill workers through employment growth and new firm entry. Whether this demand shift translates into wage gains depends on local labor supply conditions. If low-skill labor is abundant, firms can expand without raising wages. If low-skill labor is scarce, the same demand shift bids up wages and compresses inequality.

Table 5, Panel B, tests this prediction by interacting the treatment with an indicator for tight labor markets, defined as municipalities where the share of low-skill workers is below the population-weighted median. 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 results indicate that Pix's inequality-reducing effects concentrate where low-skill labor is relatively scarce, consistent with a labor demand channel amplified by local labor market tightness.

6.3 Small Firm Profitability

We examine three channels through which Pix may increase small-firm profitability: reductions in cash-handling costs, variation in merchant payment fees, and higher local demand. The first two also speak to the digital-readiness alternative discussed in Section 5.4.

Payment Frictions and Cash-Handling Costs. If Pix substitutes for cash rather than expanding overall payment volume, it can reduce the costs firms incur from storing, transporting, and safeguarding physical currency. We estimate the effect of Pix on bank branch cash inventories. Figure 7 shows that municipalities with higher mobile penetration experienced a statistically significant decline in cash balances held by bank branches. The reduction intensifies over time, suggesting that Pix adoption substituted for cash transactions.

We estimate the wage response for industries with different levels of cash-intensity, measured by their share of sales to households (Table 9). Wage effects are null in low-cash industries (Column 1) and rise monotonically with cash-intensity (Columns 2–3).

Cash dependence is more costly in high-crime environments because firms must store, transport, and safeguard physical currency, increasing losses from theft and security expenditures. We split municipalities by their 2019 homicide rate into above- and below-median groups and re-estimate the baseline specification for each (Figure 8, Table 10). In high-homicide municipalities, wages in small establishments rise by approximately 0.6 percent per one-standard-deviation increase in mobile penetration. In low-homicide municipalities, effects are small and imprecise.

Merchant Fees and Bargaining Power. When customers pay by card, merchants pay a merchant discount rate (MDR), the share of the transaction value retained by the acquiring chain. MDR comprises interchange fees set by card networks, scheme fees, and the acquirer's

processing margin. Only part of this bundle is negotiable: larger merchants with greater volume and bargaining power can typically secure lower processing margins and better contract terms, even if interchange and scheme fees are uniform. Small merchants face higher effective MDR because they are less able to negotiate discounts. In Brazil, average merchant costs on Pix are substantially lower than the average MDR faced by merchants on card transactions.

If negotiated MDR differs by firm size, switching to Pix should lower payment costs more for small establishments in small firms than for small establishments in larger firms. We estimate a quadruple difference-in- differences specification. Figure 9 plots the event- study coefficients of the interaction Mobile Penetration $\times$ Small Establishment $\times$ Small Firm $\times$ Post. The coefficients are close to zero prior to Pix and become positive after 2020.

Local Demand. Pix may also boost demand by providing a safer and more convenient alternative to cash. We split industries into tradable and non-tradable categories based on payroll geographical concentration, following Mian and Sufi (2014).[24] If local demand were a key mechanism, non-tradable industries in high-adoption municipalities should show larger wage gains. Wage responses are similar across the two groups (Appendix Table B.5). Local demand does not appear to be the primary driver.

These results are consistent with cash-handling costs being an important component of Pix's gains for small firms.

6.4 Alternative Mechanisms

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 and credit access expansion.

[24] Industries with payroll concentrated in few locations are classified as tradable; those dispersed nationally as non-tradable. We exclude low-cash sectors, which were unaffected by Pix.

Formalization and wage reporting. A natural alternative interpretation of our wage results is that Pix increased formalization or improved wage reporting, rather than changing labor market conditions. This concern matters because our main wage outcomes come from administrative data on formal employment. A formalization-driven channel predicts that wage effects should be larger where baseline informality is higher, and that the observed composition of formal workers should shift toward worker types that are overrepresented in informal employment.

Our findings indicate that Pix spurred some formalization, particularly the registration of solo entrepreneurs (MEIs). Several institutional and empirical patterns, however, make formalization unlikely to be the main driver of observed wage increases.

First, total mandated employer costs in Brazil exceed the contractual salary by more than 50 percent (Cavalcante, 2020). Even large, targeted reductions in formalization costs have produced only limited and transitory effects on firm registration,[25] making a formalization-only explanation of the wage results unlikely.

Second, Pix transactions remain covered by bank secrecy. Tax authorities do not observe transaction-level origin or destination details, limiting the scope for Pix to increase enforcement exposure and trigger formalization.

Third, 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.[26]

Fourth, pure compliance effects would generate uniform wage increases toward the regulatory minimum, independent of local labor market conditions. Instead, we find wage effects concentrated where low-skill labor is scarce. This pattern is consistent with increased labor demand interacting with constrained labor supply.

[25] The MEI program halved monthly taxes for micro-firms but increased registration by only 1.9 percentage points from a 20 percent baseline, with the effect dissipating after six months (Rocha et al., 2018).

[26] Ulyssea (2018) documents that informality declines sharply with firm size in Brazil, reaching near-zero levels well below 20 employees.

Fifth, if formalization drives our results, wage effects should be larger in municipalities with higher baseline informality, where there is greater scope to formalize previously informal employment. We split municipalities by a pre-Pix informality measure constructed from the 2010 Census and estimate our baseline triple-difference specification separately for each group. Appendix Table B.6 shows that wage effects are identical across the two groups. This pattern is inconsistent with a compliance or reporting channel, which predicts larger wage increases where initial informality was higher.

Sixth, we test directly for shifts in the composition of formal workers. If wage gains reflect formalization, we should see significant changes in the characteristics of formal employees after Pix. In Appendix Table B.7, we re-estimate our baseline specification using worker observables as outcomes: gender, skill, tenure, and age. These estimates are uniformly close to zero. The null results are informative because informal workers differ sharply from formal workers along these dimensions in the 2010 Census (Appendix Table B.8). A substantial inflow from informal employment into formal jobs would produce detectable shifts in administrative data.

Finally, we use PNAD, IBGE's household sample survey, to measure informality directly. Because PNAD identifies informality only at the state level, this test has limited power relative to our municipality-level design. Appendix Figure B.8 reports a state-level DiD for the share of informal workers. The estimates are small and imprecise, and we find no change in the informality rate following Pix.

Overall, Pix may have contributed to some formalization, but the available evidence does not support a formalization-only explanation for the wage results. We interpret formalization as a complementary channel that can amplify measured wage gains, while the primary mechanism operates through increased labor demand in cash-intensive businesses interacting with local labor-market frictions.

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

expansion using municipality-level business lending data. Appendix Figure B.9 plots the dynamic effects of mobile penetration on log per-capita business loans, showing no differential trends before Pix and no significant increase afterward.[27] Our test captures aggregate lending volume and may not detect shifts in borrower composition or lending terms. We do not find evidence that credit expansion is a primary driver of the wage effects we document.

Taken together, the evidence points to reductions in transaction costs as the main channel through which Pix raises wages in small establishments. Formalization contributes as a complementary channel but cannot account for the concentration of wage effects in tight low-skill labor markets. Finally, we find no evidence of aggregate credit expansion.

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-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.

[27] In Brazil, third-party lenders can access Pix transaction histories only with explicit customer authorization under the Open Finance framework, which launched after Pix and was still scaling during our sample period. Evidence from India documents that digital payment histories can expand credit access where data-sharing infrastructure is more mature (Alok et al., 2024; Ghosh et al., 2024). We do not detect aggregate credit expansion in our data, but credit effects may emerge as Open Finance adoption deepens.

Given this preference structure, the labor supply to firm j in city c for skill s is given by:[28]

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

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 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

[28] 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 $W_{sc} = \left[\sum_{j=1}^{M_c} w_{jsc}^{\eta+1}\right]^{\frac{1}{\eta+1}}$.

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

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.[29] All predetermined parameters are summarized in Appendix Table A1.

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 ($s = 1$). Appendix Table A2 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 Appendix Table A3, 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. Appendix Table A3 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 Appendix Table A3 confirms that the skill-specific average wages generated by the model align closely with their empirical counterparts.

7.2 Counterfactual Analysis

We use the calibrated model to quantify the aggregate effects of Pix and to simulate a counterfactual in which Pix adoption is uniform 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

[29] 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.

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 $\omega : [0,1] \to [0,1]$ is a strictly increasing function and MP_c denotes mobile penetration. Because the model does not include mobile penetration directly, we impute it using fitted values from a linear projection of observed mobile penetration on city-level aggregates: $\text{MP}_c = \hat{\beta}_0 + \hat{\boldsymbol{\beta}}' \mathbf{X}_c$, where $\mathbf{X}_c$ collects city-level aggregates (for example, log employment and log wage bill). Cities with higher imputed mobile penetration experience a larger reduction in transaction costs. We define ω as a linear function of MP_c, rescaled to lie in $[0,1]$. 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 Appendix Figures A5 and A6. In the model, average wages increase by 0.23% in small firms and by 0.04% in large firms, with the differential reflecting the direct effect of lower transaction costs on small-firm labor demand. 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 10, 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 wage gains are concentrated below the median, 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. Appendix Figure A4 shows that average wages are higher in cities with more firms.

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 Panel A of Figure 11, this result is driven entirely by a contraction in within-city inequality, which is partially offset by a rise in between-city inequality.

Uniform Adoption. We next compute the effects of uniform Pix adoption across all municipalities. 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 Panel B of Figure 11, 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 uniform adoption intensifies within-city wage compression and also mitigates the spatial inequality that arose from the uneven initial uptake of Pix.

We compute the aggregate wage and profit changes from uniform adoption under Pix. The initial implementation of Pix under the observed, uneven adoption increases the total wage bill by 0.04% and total firm profits by 0.02%. However, uniform adoption would generate 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% under uniform adoption.

Overall, our quantitative analysis shows that, by reducing transaction costs, Pix increases 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. We find that uniform adoption would amplify the wage and competition effects and reduce inequality more equally across regions and skill groups.

8 Conclusion

We study how instant payment adoption affects labor markets and wage inequality. Using Brazil's rollout of Pix, we find that wages in small, cash-intensive establishments increase relative to large establishments. Wage inequality falls, driven by gains below the median. The patterns we document are consistent with lower payment frictions raising labor demand among small firms, with larger effects on inequality where low-skill labor is scarce. These findings show that, in contrast to production technologies that prior work associates with rising inequality, financial technology can compress it by alleviating frictions in sectors that disproportionately employ low-skill labor.

Cash-intensive firms rely heavily on low-skill labor, so the wage gains we document concentrate in sectors that employ lower-wage workers. Our quantitative model implies that under the observed, uneven rollout, the within-city component of wage dispersion falls but the between-city component rises, partially offsetting the aggregate compression. Under uniform adoption, both components fall, so more even access amplifies the inequality-reducing potential of instant payments.

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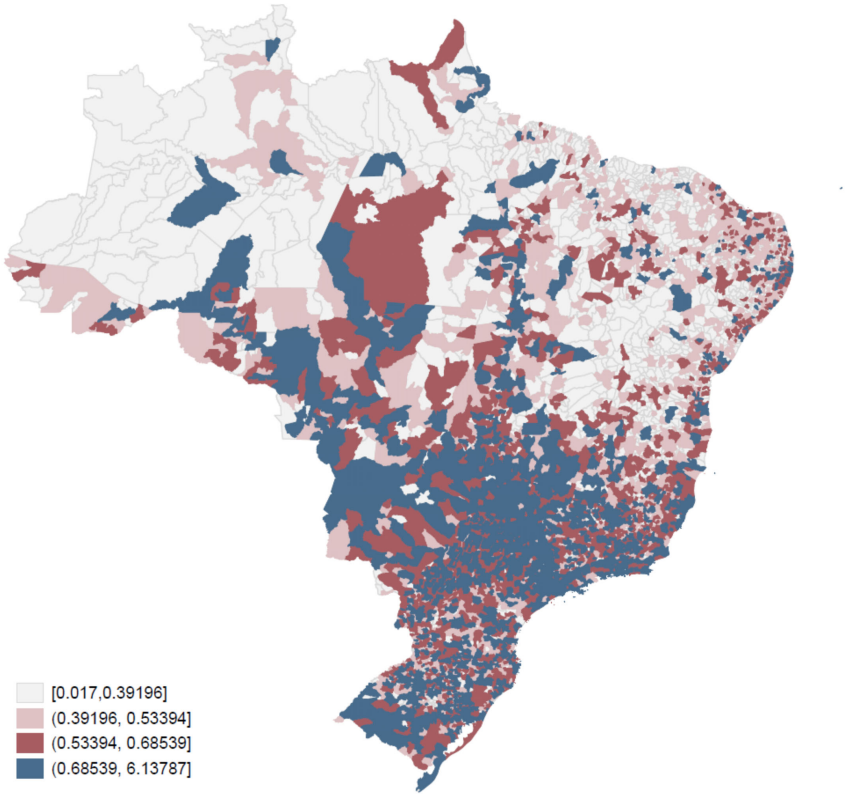
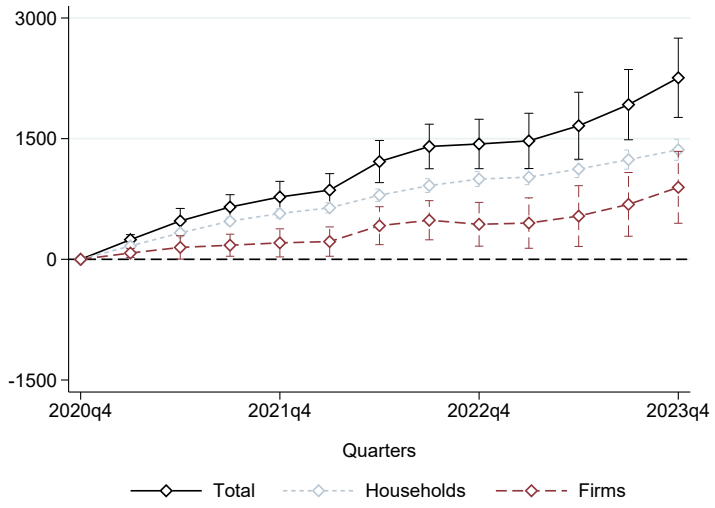
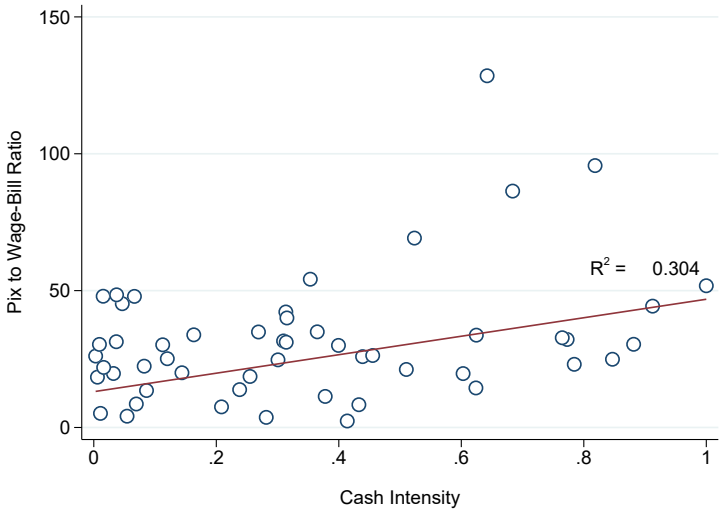


Figure 1 Geographic Distribution of Mobile Technology Penetration

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 Intensity

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 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 based on robust standard errors clustered at the municipality level. Mobile penetration is defined as the ratio of mobile devices with 3G or higher capability to the total municipal population, standardized to have unit variance and winsorized at the 1% level. Data are from the Central Bank of Brazil.

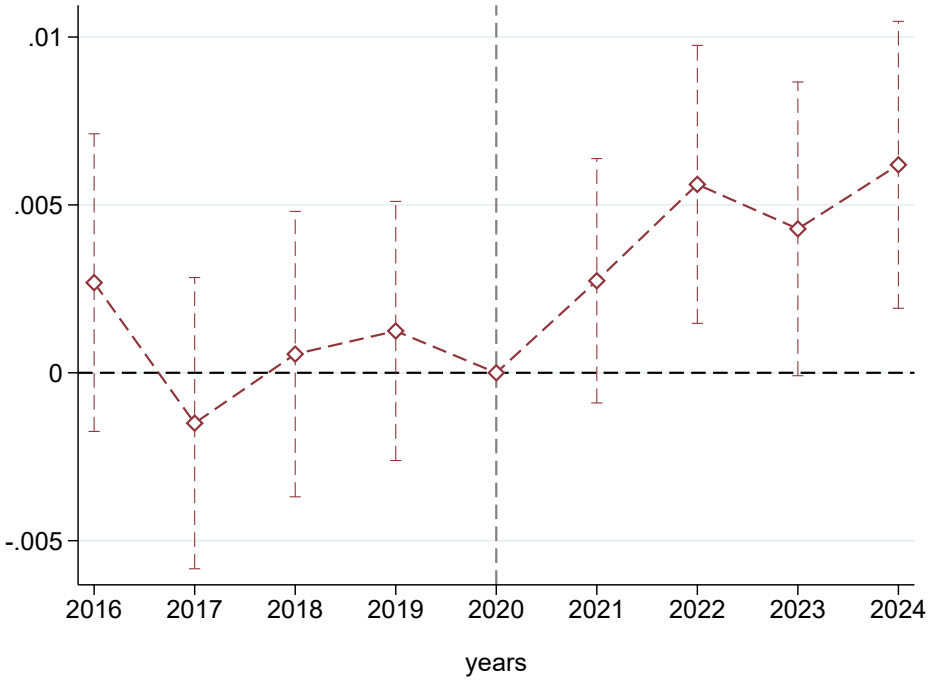


Figure 3 Effect of Mobile Penetration on Wages by Small Establishments

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.

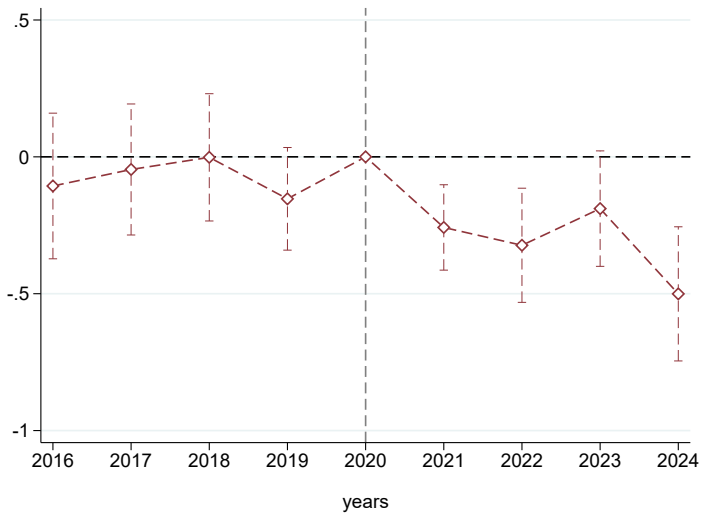
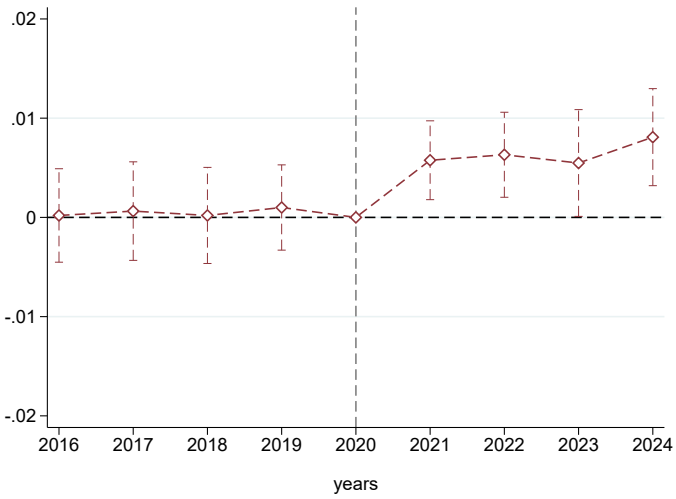
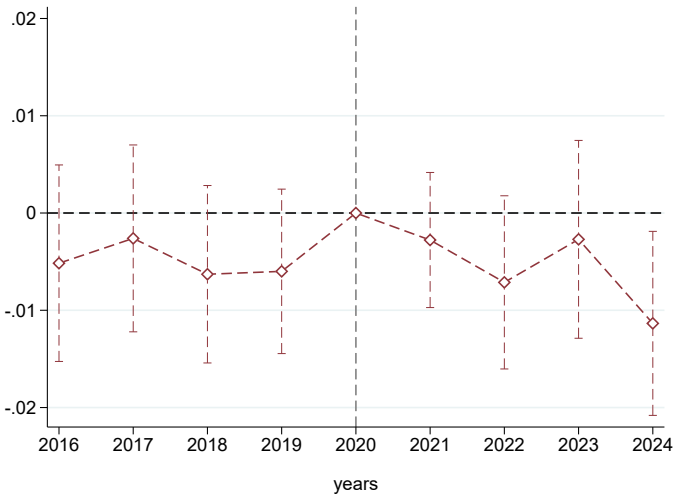


Figure 4 Effect of Mobile Penetration on Wage Inequality

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 individual worker wages within each municipality-year, multiplied by 100. 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.



Panel A. Workers' Wages Bottom 50%



Panel B. Workers' Wages Top 50%

Figure 5 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, 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.

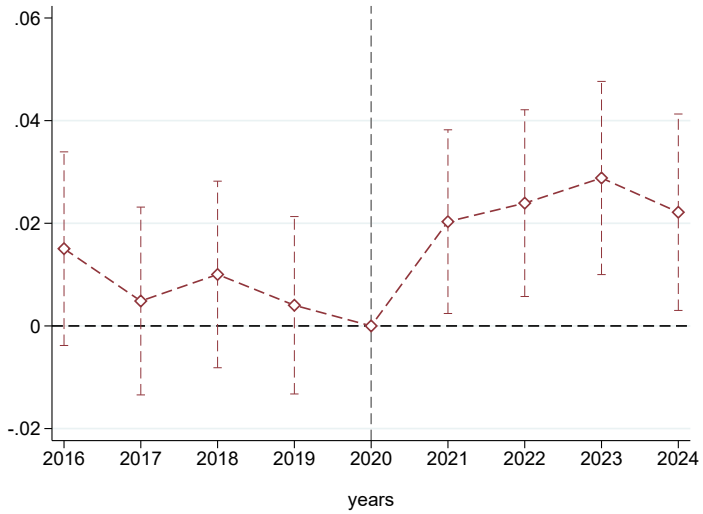
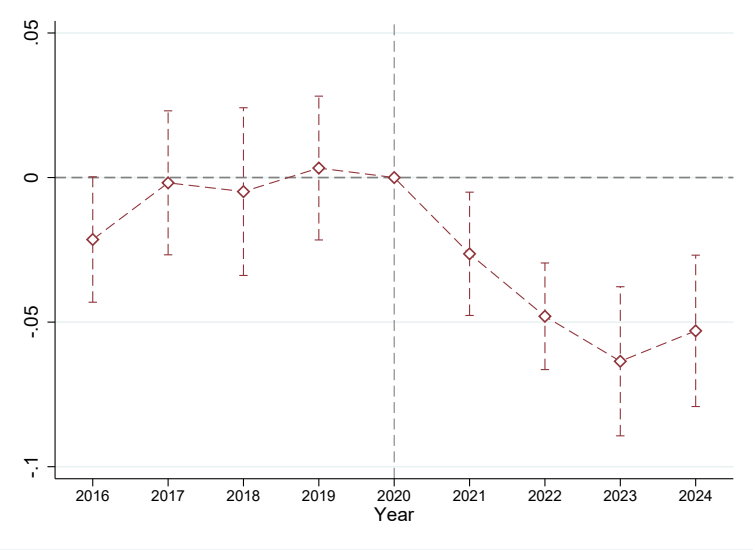


Figure 6 Effect of Mobile Penetration on Employment Growth in Small Establishments

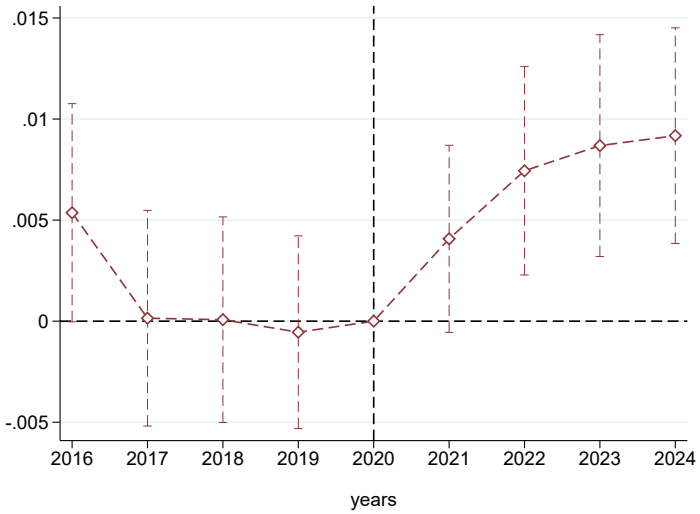
This figure presents the estimated yearly coefficients from a triple difference-in-differences specification examining the differential effect of standardized mobile penetration on the logarithm of the number of active jobs in small establishments relative to large establishments around the introduction 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.



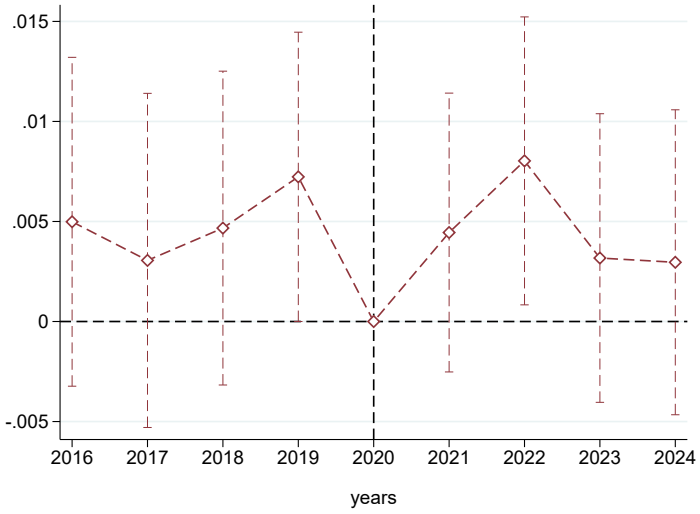
Log Cash

Figure 7 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 and winsorized at the 1% level. Data are from the Central Bank of Brazil.



Panel A. Above-Median Homicide Rate



Panel B. Below-Median Homicide Rate

Figure 8 Effect of Mobile Penetration on Wages by Small Size and Homicide Rate

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, splitting the sample by pre-Pix municipal homicide rate (measured in 2019). Panel A restricts the sample to municipalities with above-median homicide rates and Panel B to below-median. Small establishments are defined as those with fewer than 20 employees. The regression specification includes fixed effects for municipality-by-size-by-industry, municipality-by-size-by-year, and size-by-industry-by-year. Dashed lines represent 95% confidence intervals from standard errors clustered at the municipality level. 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.

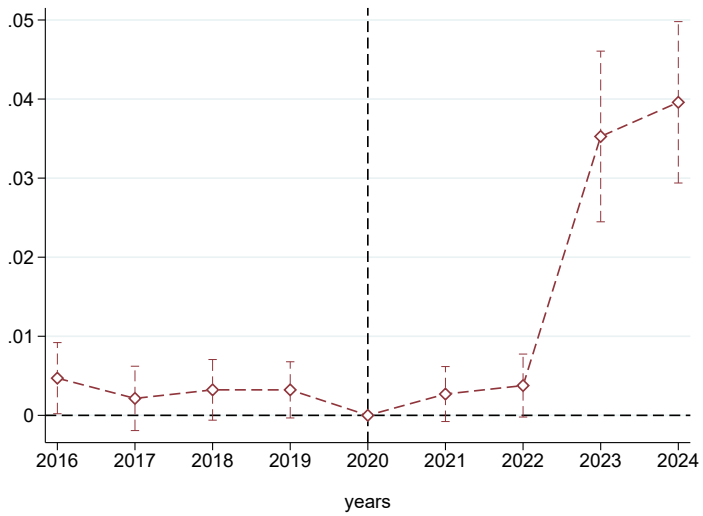


Figure 9 Effect of Mobile Penetration on Wages by Establishment and Firm Size

This figure plots the estimated yearly coefficients from a quadruple difference-in-differences specification that measures the differential effect of mobile penetration on the logarithm of average wages across establishment size and firm size around the introduction of Pix in late 2020. Small establishments and small firms 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-firm-by-industry, and firm-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.

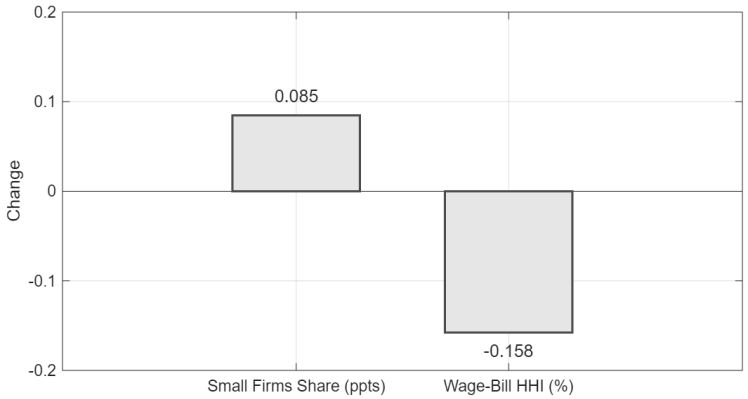
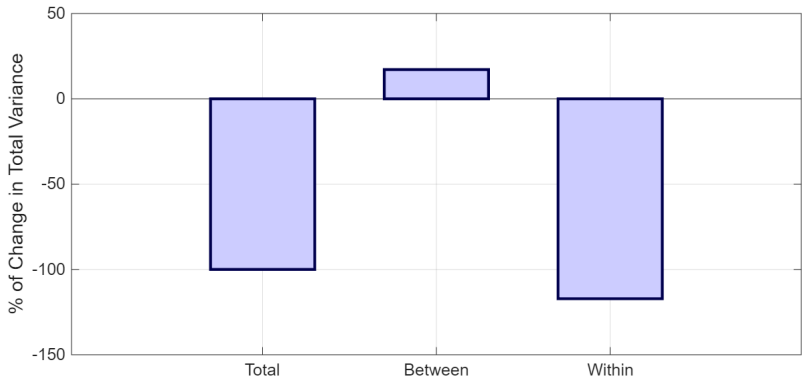
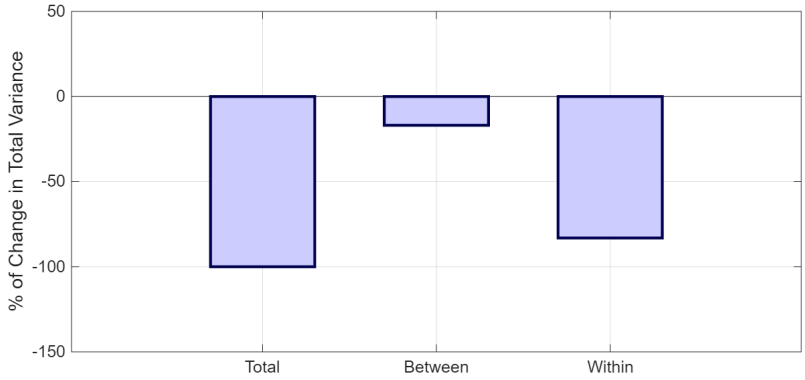


Figure 10 Wage-Bill: Small Firm Share and HHI

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.



Panel A. Baseline Pix Adoption



Panel B. Uniform Pix Adoption

Figure 11 Decomposition of Change in Variance of Wages

This figure decomposes the decline in the total variance of log wages into contributions from changes within cities and between cities. Panel A reports results under observed Pix adoption. Panel B reports results under counterfactual uniform adoption, in which mobile penetration gaps are fully closed. In each panel, the left bar corresponds to the total decline in variance (100%), the middle bar corresponds to the between-city component change divided by the change in total variance, and the right bar corresponds to the within-city component change divided by the total variance change.

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 wage inequality and wages across the wage distribution following the introduction of Pix in November 2020. The dependent variable in Column (1) is the Gini coefficient computed from the distribution of individual worker wages within each municipality-year, multiplied by 100. Columns (2) and (3) use the log of average wages for workers in the bottom and top 50% of that within-municipality-year wage distribution. Panel A presents baseline estimates. Panel B interacts the treatment with an indicator for tight low-skill labor markets, defined as municipalities where the ratio of low-skill workers to total workers is below the population-weighted median. Mobile Penetration × Post measures the average effect, and Mobile Penetration × Post × Tight measures the differential effect in tight 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-year fixed effects. Standard errors clustered at the municipality level are reported in parentheses. Mobile penetration is standardized to 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 Wages in 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 10 Effect of Mobile Penetration on Average Wages in Small Establishments by Municipal Homicide Rate

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, separately for municipalities with above-median and below-median homicide rates. 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 restricts the sample to municipalities with above-median homicide rates and Panel B to municipalities with below-median homicide rates. Both panels examine robustness across alternative fixed effects specifications. 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: Above-Median Homicide Rate

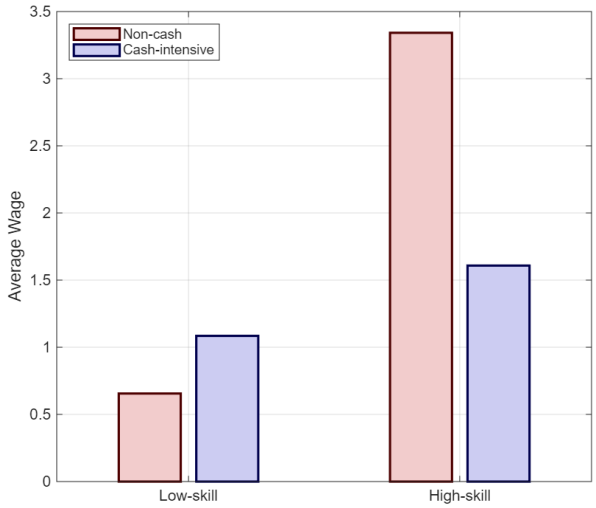
	(1)	(2)	(3)
Mobile Penetration × Small × Post	0.005***	0.005***	0.006***
	(0.002)	(0.002)	(0.002)
Observations	880,123	880,123	880,123
Municipality × Size × Industry	✓	✓	✓
Municipality × Size × Year	✗	✓	✓
Size × Year	✓	✓	✗
Industry × Year	✓	✗	✗
Municipality × Year	✓	✗	✗
Size × Industry × Year	✗	✗	✓

Panel B: Below-Median Homicide Rate

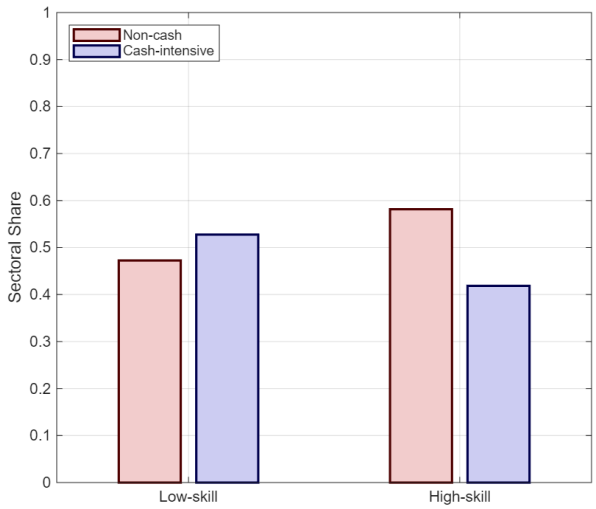
	(1)	(2)	(3)
Mobile Penetration × Small × Post	−0.002	−0.002	0.001
	(0.002)	(0.002)	(0.002)
Observations	495,065	495,065	495,065
Municipality × Size × Industry	✓	✓	✓
Municipality × Size × Year	✗	✓	✓
Size × Year	✓	✓	✗
Industry × Year	✓	✗	✗
Municipality × Year	✓	✗	✗
Size × Industry × Year	✗	✗	✓

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.

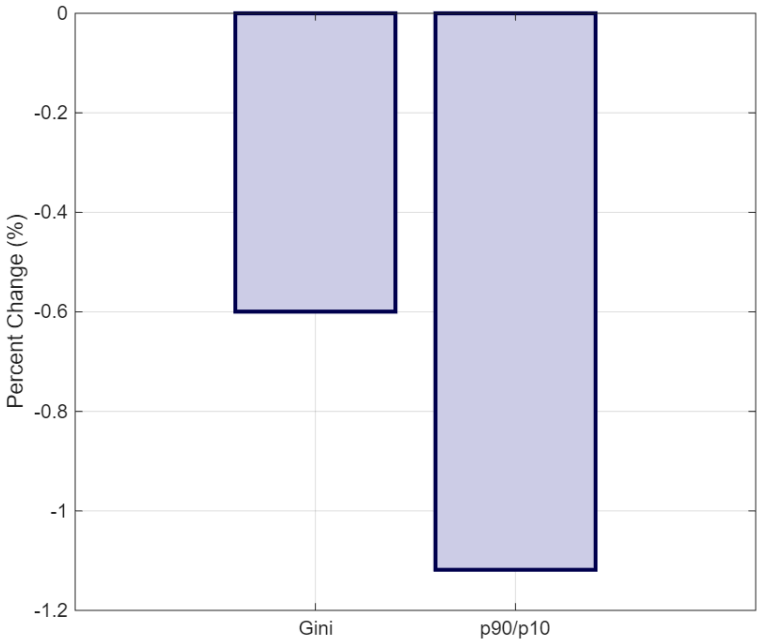
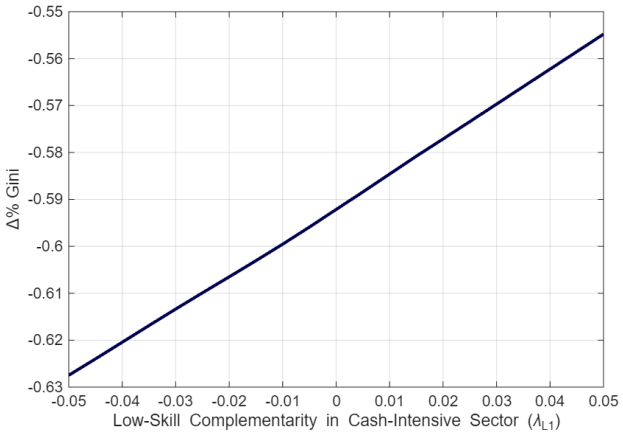
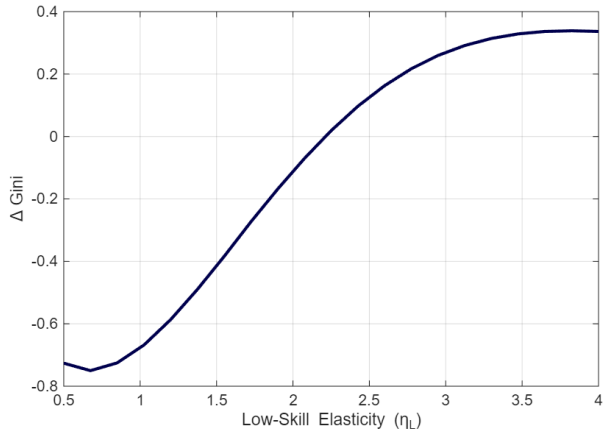


Figure A2 Effect of Lowering Transaction Cost on Wage Inequality

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.

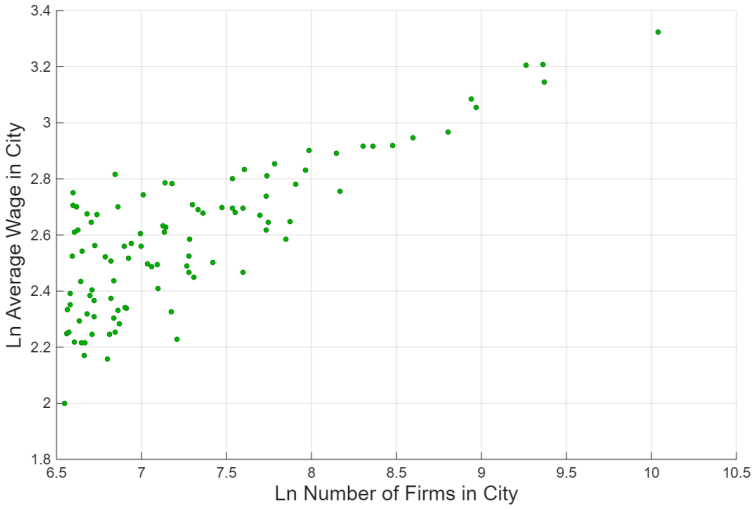


Figure A4 Average Wage and Number of Firms across Cities

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.

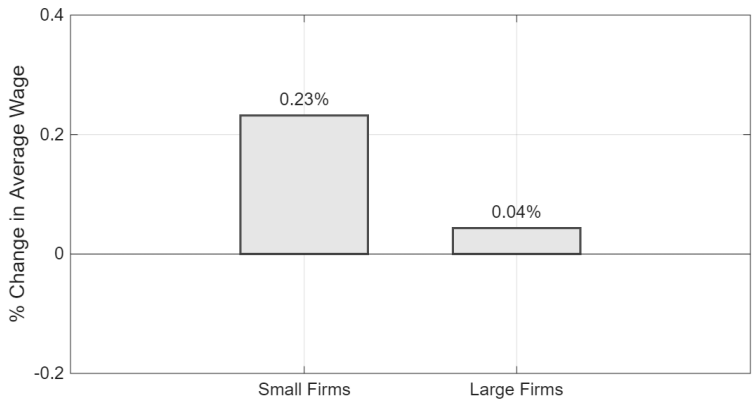


Figure A5 Change in Average Wage by Firm Size after Pix Implementation

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 relative to the baseline equilibrium with transaction costs.

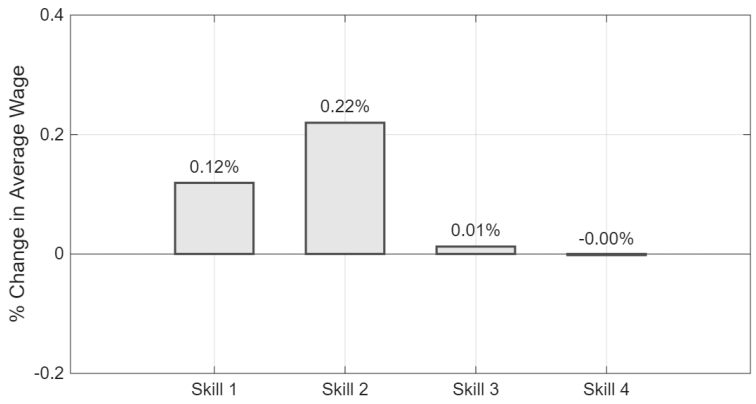


Figure A6 Change in Average Wage by Skill Group after Pix Implementation

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 with respect to the baseline equilibrium with transaction costs.

Table A1 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%

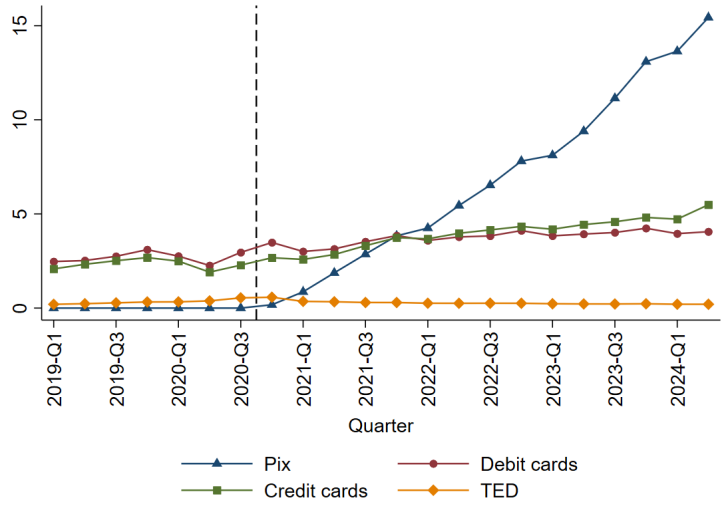
Table A2 Calibrated Parameters

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

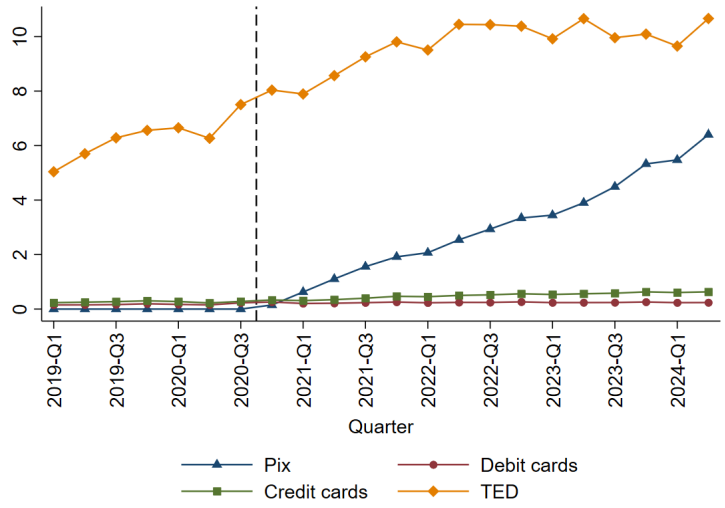
Table A3 Model Fit of the Brazilian Labor Market

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

A2 Additional Figures and Tables



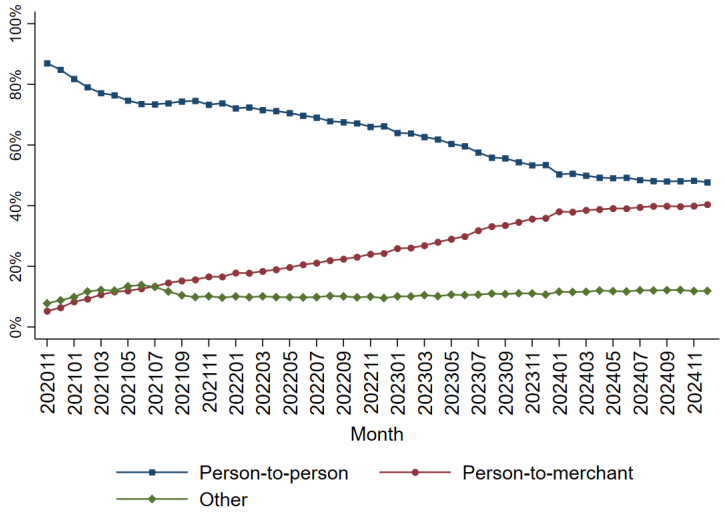
Panel A. Quantity of Transactions



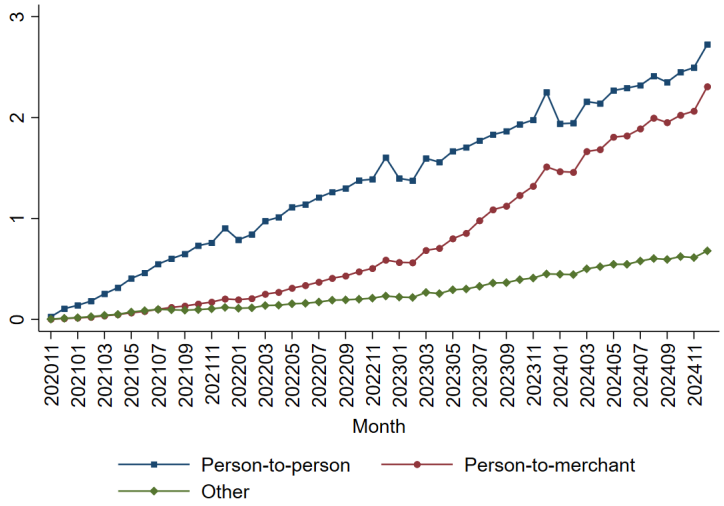
Panel B. Value of Transactions

Figure B.1 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 B.2 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.

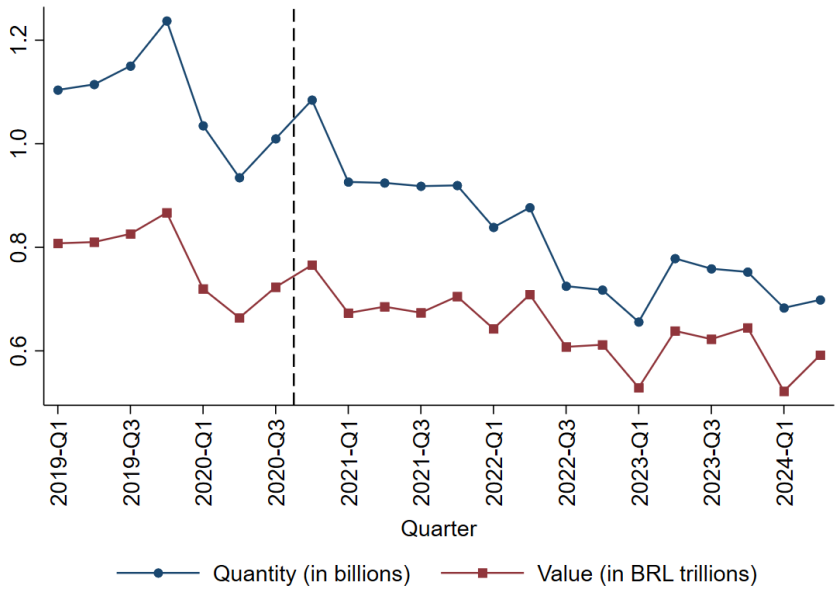


Figure B.3 Evolution of Cash Withdrawals

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.

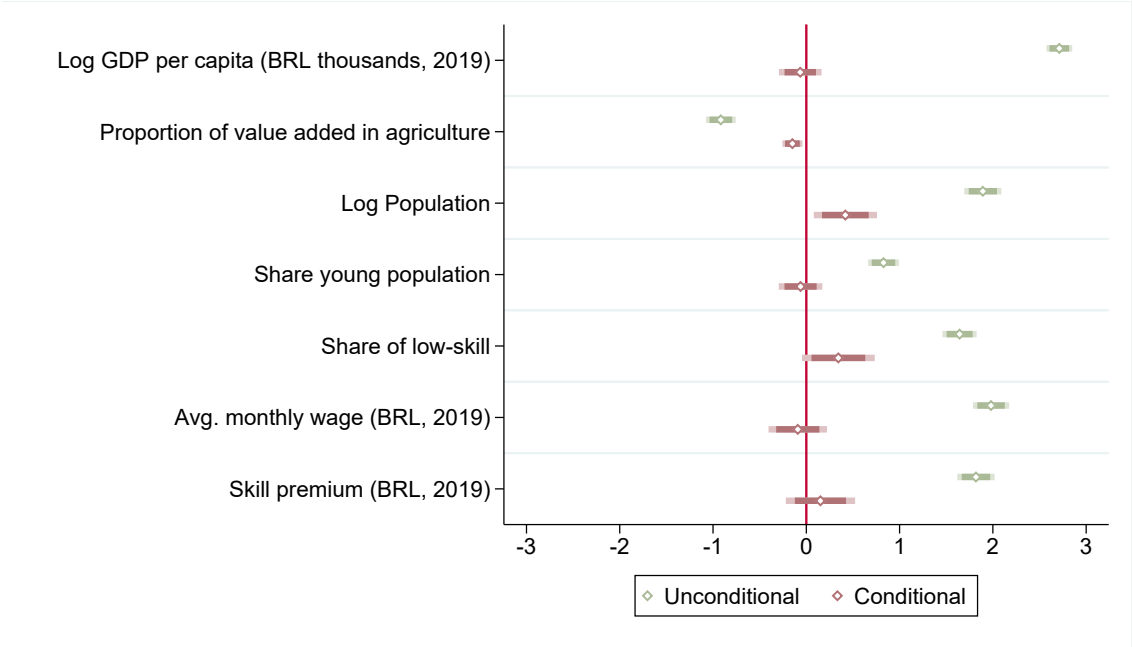


Figure B.4 Balance of Covariates

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.

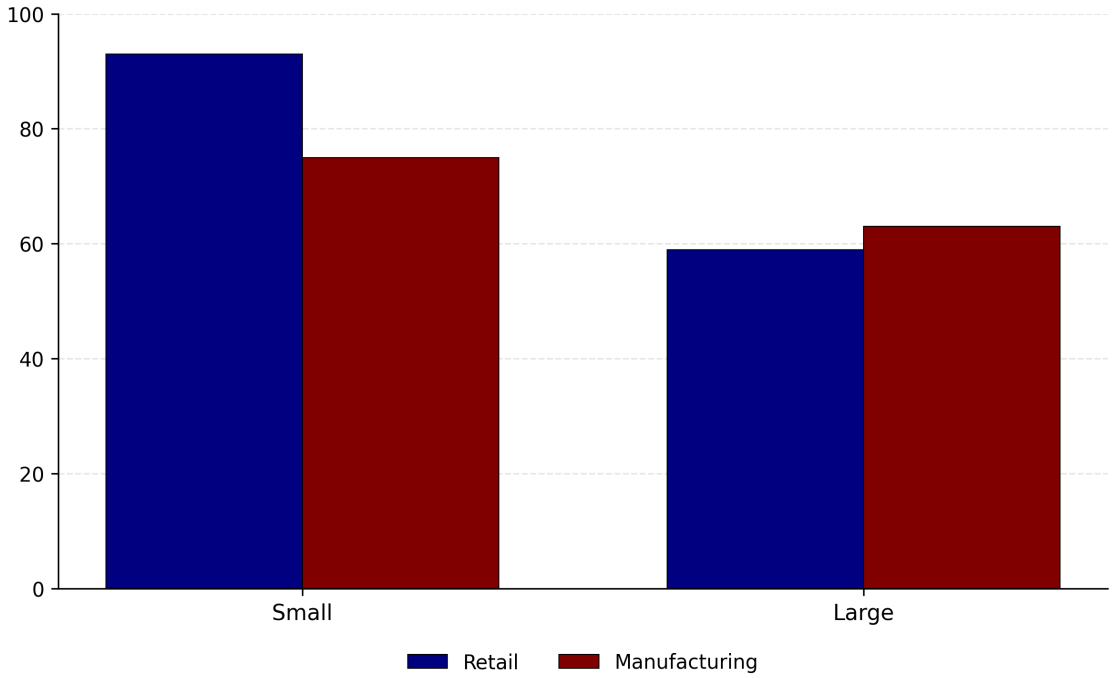
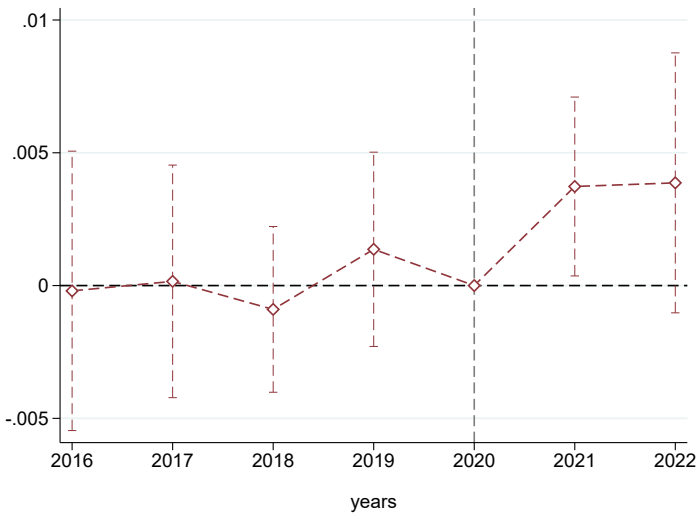
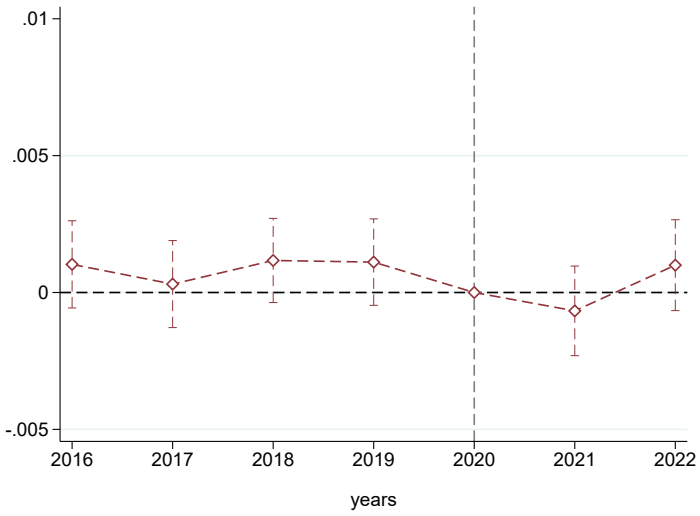


Figure B.5 Skill Composition by Industry and Firm Size

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.



Panel A. Small Retail



Panel B. Small Manufacturing

Figure B.6 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.

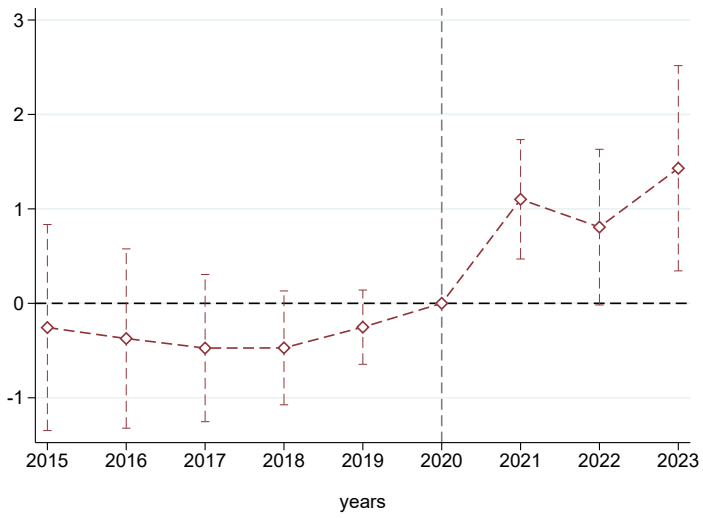


Figure B.7 Effect of Mobile Penetration on Micro-entrepreneur Entry

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 annual 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 B.8 Effect of Mobile Penetration on Informality

This figure presents the estimated yearly coefficients from state-level difference-in-differences regressions examining the effect of standardized mobile penetration on the share of informal workers around the introduction of Pix in November 2020. The dependent variable is the share of informal workers among those earning above BRL 12,000 annually, constructed from the Brazilian National Household Sample Survey (PNAD Contínua). The regression specification includes state fixed effects, and state characteristics interacted with time fixed effects. Dashed lines represent 95% confidence intervals from standard errors clustered at the state 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 population, standardized to have unit variance and winsorized at the 1% level.

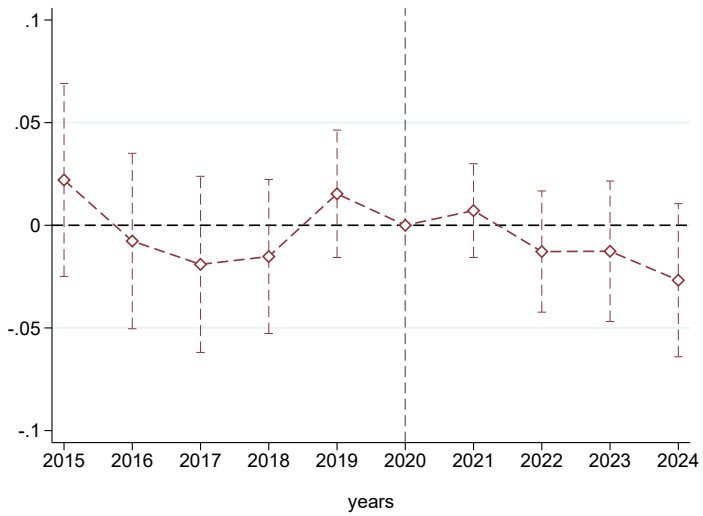


Figure B.9 The Effect of Mobile Penetration on Log of Business Loans

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 B.1 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 B.2 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.

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

Table B.3 Effect of Mobile Penetration on Wages in Physical Services and Delivery-Capable Services

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, estimated separately for physical services and delivery-capable services. The dependent variable is the logarithm of average monthly wages. Small establishments are defined as those with fewer than 20 employees. Delivery-capable services include restaurants. Physical services include repair of vehicles, sport activities, repair of computers, and personal services. Column 1 restricts the sample to physical services, and Column 2 to delivery-capable services. All specifications include municipality-by-size-by-industry, municipality-by-industry-by-year, 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)
	Physical Services	Delivery Capable
Mobile Penetration × Small × Post	0.019***	0.002
	(0.005)	(0.004)
Observations	133,506	64,406
Municipality × Size × Industry	✓	✓
Municipality × Industry × Year	✓	✓
Size × Industry × Year	✓	✓

Table B.4 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 annual 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 B.5 Effect of Mobile Penetration on Average Wages 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 × Small × Post	0.007***	0.007**
	(0.002)	(0.003)
Observations	436,015	412,851
Municipality × Size × Industry	✓	✓
Municipality × Industry × Year	✓	✓
Size × Industry × Year	✓	✓

Table B.6 Effect of Mobile Penetration on Average Wages in Small Establishments by Municipal Informal Taxpayer Rate

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, separately for municipalities with above-median and below-median informal taxpayer rates. The dependent variable is the logarithm of average monthly wages. Small establishments are defined as those with fewer than 20 employees. Column 1 restricts the sample to municipalities with above-median informal taxpayer rates, and Column 2 to municipalities with below-median informal taxpayer rates. All specifications include municipality-by-size-by-industry, municipality-by-size-by-year, 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)
	Above-Median informality	Below-Median informality
Mobile Penetration × Small × Post	0.005**	0.005**
	(0.002)	(0.002)
Observations	626,518	747,103
Municipality × Size × Industry	✓	✓
Municipality × Size × Year	✓	✓
Size × Industry × Year	✓	✓

Table B.7 Effect of Mobile Penetration on Workforce Composition in Small Establishments

This table presents triple difference-in-differences estimates examining the differential effect of standardized mobile penetration on workforce composition in small establishments relative to large establishments following the introduction of Pix in November 2020. Each column reports the coefficient on Mobile Penetration × Small × Post for a different dependent variable. Female, High Skill, and Age ≥ 40 are indicators equal to one if the worker is female, has at least a college degree, or is 40 years or older, respectively. Log of Tenure is the logarithm of months employed at the current establishment. Age is measured in years. Small establishments are defined as those with fewer than 20 employees. All specifications include municipality-by-size-by-industry, municipality-by-industry-by-year, 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)	(5)
	Female	High Skill	Log Tenure	Age	Age ≥ 40
Mobile Penetration × Small × Post	0.001	0.001	−0.001	0.022	−0.000
	(0.001)	(0.001)	(0.005)	(0.021)	(0.001)
Observations	1,299,277	1,299,277	1,299,250	1,299,277	1,299,277
Municipality × Size × Industry	✓	✓	✓	✓	✓
Municipality × Industry × Year	✓	✓	✓	✓	✓
Size × Industry × Year	✓	✓	✓	✓	✓

Table B.8 Differences Between Formal and Informal Workers

This table examines differences in observable characteristics between formal and informal workers using individual-level microdata from the 2010 Brazilian Census. The dependent variable is an indicator equal to one if the worker is informally employed. Each column reports the coefficient from a separate regression of informal employment status on a single worker characteristic. Female is an indicator for female workers. High Skill is an indicator for workers with at least a college degree. Age is measured in years. The sample includes all individuals who report being actively employed at the time of the census. All specifications include municipality fixed effects. Standard errors are reported in parentheses. ***p<0.01, **p<0.05, *p<0.1.

	(1)	(2)	(3)
	Informal Worker Indicator		
Female	0.018***		
	(0.0004)		
High Skill		−0.208***	
		(0.0004)	
Age (years)			0.001***
			(0.00002)
Observations	8,382,159	8,382,159	8,382,094
Municipality	✓	✓	✓