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

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Abstract

A longstanding debate questions whether technological change widens wage gaps by benefiting skilled labor. We show that financial technologies—specifically, instant payment systems—can instead reduce wage inequality. Using comprehensive data on the universe of employees in Brazil, we study the nationwide rollout of Pix, an instant payment platform introduced in late 2020. Our empirical strategy leverages a triple difference design that exploits variation in pre-existing mobile penetration across municipalities, the differential benefits of Pix for cash-intensive versus non-cash-intensive sectors, and changes in outcomes before and after its adoption. Our results indicate that a one standard deviation increase in mobile penetration leads to a 1.1% wage increase in cash-intensive sectors relative to non-cash-intensive sectors following Pix's introduction. These wage gains concentrate among workers with lower levels of education, thereby reducing the college wage premium. Further evidence suggests that increased small-business labor demand, coupled with local market frictions, drives these findings. By highlighting how digital payment technologies can stimulate demand for low-skilled labor in small, cash-intensive firms, our results suggest that the distributional effects of technology depend crucially on which market frictions it alleviates.

*We thank Thorsten Beck, Andrés Gonzalez, Jeanne Lafortune, Filippo Mezzanotti, Andy Winton, and the participants of seminars at PUC-Chile, the IDB Discussion Seminars on Digital Finance and Financial Inclusion, and the WEFIDEV Workshop for their valuable feedback and suggestions. This study was financed by the Research Network of the Inter-American Development Bank (RG-K1198).

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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, supported by evidence from computerization and automation, suggests that new technologies increase inequality by complementing skilled labor and substituting for routine tasks typically performed by less-educated workers (Autor et al., 2003; Acemoglu and Autor, 2011). However, the labor market and distributional effects of financial technologies remain largely unexplored despite their rapid adoption across both developed and developing economies. This raises a fundamental question: do financial technologies affect labor markets and wage structures similarly to production technologies, or do they follow a different pattern? Answering this question is crucial for policymakers seeking to design inclusive growth strategies in an era of rapid digital transformation.

In this paper, we contribute to this debate by examining the labor market impacts of instant payment systems—a major financial innovation adopted by over 60 countries as of 2023 (BIS, 2023). By reducing transaction costs, improving cash flow management, and facilitating financial access (particularly for small businesses in cash-intensive sectors), these systems could alter wage structures in ways distinct from production technologies.[1] We analyze Brazil's Pix system, launched in November 2020, which achieved unprecedented adoption and dramatically lowered transaction costs to one-tenth of credit card fees.[2] Contrary to conventional skill-biased technical change patterns, we find digital payments reduce wage inequality through substantial wage gains for low-skilled workers in cash-intensive sectors, with effects amplified where low-skill labor is scarce.

Using comprehensive administrative data on formal workers and firms from 2015 to

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

[2] Pix is a 24/7 instant payment system launched by Brazil's Central Bank in November 2020. The system enables real-time transfers through banks' mobile applications using simplified identifiers (email, phone numbers, or tax IDs). Two key features drove adoption: mandatory participation by large banks and zero fees for individuals. Even when firms use business accounts, transaction fees average 0.22%, compared to 2.2% for credit cards. By early 2024, over 152 million individuals and 15 million firms had registered, with transaction volumes surpassing both credit cards and traditional transfers within its first year.

2022, we implement two complementary identification strategies. Our baseline approach exploits variation in pre-existing mobile penetration across municipalities—which strongly predicts Pix adoption—in a difference-in-differences (DiD) design comparing high- versus low-penetration areas. To address potential local confounders, we implement a triple DiD design comparing cash-intensive versus non-cash-intensive establishments within municipalities, supplemented by an alternative specification contrasting small versus large establishments.

The identifying assumption of our baseline DiD design is that trends in the outcomes would have been similar in municipalities with higher pre-treatment mobile penetration versus municipalities with lower mobile penetration had Pix not been introduced. A critical concern is that pre-treatment mobile penetration might be correlated with other factors that differentially affect outcomes over time (i.e., differential time-varying confounders). To address this, we conduct several tests. First, we show that conditional on the controls and fixed effects used in the specification, there are no significant differences across municipalities in observable characteristics during the pre-Pix period. This suggests that any post-Pix differences are unlikely to be driven by pre-existing disparities. Second, we find no evidence of pre-trends in outcomes, providing support for the identifying assumption of this approach.

To further address the concern of differential time-varying confounders, our second identification strategy is a triple DiD design that compares cash-intensive versus non-cash-intensive firms within the same municipality. The specification includes municipality-by-year fixed effects to absorb local economic shocks, municipality-by-industry fixed effects to control for time-invariant industry-location characteristics and industry-by-year fixed effects to account for sector-specific trends. As mentioned, our findings are robust to a complementary triple DiD specification that compares small versus large establishments within municipalities.

We find that areas with higher mobile penetration experienced significant wage increases following Pix's introduction. Specifically, small firms saw a 3% increase in average wages, while medium-sized establishments experienced a 1% increase. These effects are concentrated in small and medium firms within the retail and service sectors. For example, small

and medium retail establishments saw wage increases of 3%, and service establishments experienced wage increases of 1%. We do not find any significant effects on small and medium manufacturing firms. Importantly, we find no evidence of pre-trends, and the effects are immediately realized following the introduction of Pix. These results and the robustness of our findings in both approaches support our causal interpretation of our estimates.

Given that our results show larger wage effects in sectors and establishments that typically employ low-skill workers, we next examine the impact of Pix adoption on wage inequality.[3] Using the college wage premium—the difference in average wages between college and non-college workers—as our measure of inequality, we find that a one standard deviation increase in mobile penetration leads to a two percentage point reduction in the wage gap. This decline in inequality stands in sharp contrast to the typical effects of technological change documented in the literature.

Our evidence points to increased labor demand from small businesses, combined with local labor market frictions, as the key mechanism behind these inequality-reducing effects. This is consistent with our model, which suggests that reducing transaction costs in cash-intensive sectors increases the effective price received by firms, leading to higher demand for low-skilled labor in sectors where low-skill labor is used intensively.

We find three key pieces of evidence supporting this mechanism. First, we find that municipalities with higher mobile penetration experienced significant job growth in small retail firms after Pix's introduction, while manufacturing employment remained unchanged. These results are consistent with the hypothesis that Pix adoption stimulated employment in cash-intensive sectors. Second, we find that higher mobile penetration led to a 3% percent increase in small business entry in retail sectors, with no comparable effect in manufacturing or large establishments. This suggests that the adoption of Pix lowers barriers to entry

[3]Small and medium-sized establishments in retail and services are particularly intensive in low-skill labor. In retail, low-skill workers account for 91% and 90% of the wage bill in small and medium-sized establishments, respectively, compared to 58% in large establishments. The pattern is similar but less pronounced in services, where low-skill workers represent 61% and 57% of the wage bill in small and medium-sized establishments, versus 37% in large establishments.

for small firms in cash-intensive sectors, potentially due to reduced transaction costs and improved cash flow management. Third, we find that the decline in the college premium is more pronounced in areas with tighter low-skill labor markets.[4] This result is consistent with the mechanism that increased demand for low-skilled workers leads to upward wage pressure in markets with limited labor supply, ultimately reducing wage inequality.

While our findings point to increased labor demand and local market frictions as the main drivers, several alternative explanations merit consideration. First, a rent-sharing mechanism—where firms share higher profits stemming, for example, from lower transaction costs—seems unlikely given the low unionization and limited firm-specific human capital in small retail and service establishments. Second, the formalization of previously informal businesses may raise wages via minimum wage compliance. Although formalization likely plays some role (and is policy-relevant for developing economies), it alone cannot explain why wage gains are strongest in low-skill-scarce markets, a pattern more indicative of a localized labor-demand channel. Overall, our findings suggest that labor demand from small, cash-intensive businesses, amplified by local frictions, drives the wage increases for low-skilled workers and the reduction in wage inequality.

Finally, an important question is whether the impact of Pix operates through reduced payment frictions—direct effects such as lower transaction costs, improved cash flow management, and enhanced access to credit—or through broader financial channels such as effects on deposit competition (Sarkisyan, 2023) or greater aggregate demand from this technology. The sectoral pattern of our results is consistent with the effects operating primarily through direct mechanisms. We find that wage effects are concentrated in traditionally cash-intensive sectors like retail and services, while there are no significant effects in manufacturing. Additionally, large establishments, which typically rely less on cash transactions and have pre-existing access to sophisticated payment systems, show no positive wage effects. This heterogeneity across sectors and establishment sizes suggests that reduced payment frictions

[4]We define a labor market as tight for low-skill workers if the share of non-college workers in that market is below the median.

play an important role in the observed wage effects.

Our paper contributes to several strands of literature. We first add to the emerging literature on financial technology and digital payments. While recent work has documented the effects of digital payments on risk-sharing and poverty reduction (Jack and Suri, 2014; Suri and Jack, 2016), financial inclusion (Ouyang, 2021), and economic growth (Dubey and Purnanandam, 2023), the labor market impacts of these innovations remain largely unexplored. Our work complements papers analyzing the economic effects of payment system adoption (Chodorow-Reich et al., 2020; Crouzet et al., 2023), research on how instant payment systems affect deposit competition (Sarkisyan, 2023) and the role of payment technology complementarities (Sampaio and Ornelas, 2024), and work examining how physical bank infrastructure influences digital payment adoption (Mariani et al., 2023). Additionally, we contribute to the literature on how digital financial infrastructure, such as Open Banking, affects credit access, particularly for underserved populations (Alok et al., 2024). More broadly, we contribute to the emerging literature on fintech's role in fostering inclusive growth (Beck et al., 2022; Brunnermeier et al., 2023), its effects on labor markets (Jiang et al., 2021), and its impact on small business operations (Agarwal et al., 2019, 2022; Klapper, 2023; Dalton et al., 2024; Ghosh et al., 2024; Higgins, 2024). While prior research on instant payments has concentrated on their adoption, financial outcomes, and banking sector implications, our study is the first to document how these systems affect wage-setting and inequality. We find that instant payment systems can reduce wage inequality by increasing labor demand for low-skilled workers in cash-intensive sectors. Areas with higher mobile penetration experience increased small business entry and employment growth in retail sectors and higher wages for low-skilled workers, with effects amplified in tight labor markets. Our findings reveal a novel channel through which payment technologies can reduce wage inequality: by complementing low-skilled labor through increased labor demand, leading to higher equilibrium wages.

Second, we contribute to the literature on payment frictions and small business dynamics. Prior research has shown that payment frictions can constrain the growth of small firms

(Klapper, 2023) and that small businesses face significant barriers in accessing financial services (Beck and Demirguc-Kunt, 2006). We extend this literature by showing that areas with higher adoption of instant payment systems experience increased small business entry in retail sectors alongside higher wages—a connection previously unexplored. Our findings suggest that payment frictions are a significant barrier for small businesses and entrepreneurs in cash-intensive sectors and that alleviating these frictions can have meaningful effects on both firm creation and worker compensation.

Third, we contribute to the extensive literature on technological change and wage inequality. The conventional view, supported by evidence from computerization and automation, posits that new technologies generally raise inequality by complementing skilled labor and substituting for routine tasks (Autor et al., 2003; Acemoglu and Autor, 2011). This includes both skill-biased technological change, which directly complements higher-skilled labor (Goldin and Katz, 1998; Bound and Johnson, 1992; Krusell et al., 2000), and routine-biased technological change, which displaces routine-task workers (Goos et al., 2014; Autor and Dorn, 2013; Michaels et al., 2014). In contrast, we show that financial technologies can have markedly different distributional effects. Our finding that instant payment systems reduce wage gaps by benefiting low-skilled workers provides novel evidence that technological progress need not exacerbate wage inequality. This underscores how the frictions being alleviated shape a technology's labor market impact.[5]

The remainder of the paper is organized as follows: Section 2 develops a model to analyze the impact of instant payment systems on wages. Section 3 provides institutional details about Brazil's instant payment system. Section 4 describes the data and our empirical strategy. Section 5 presents our main findings. We discuss the mechanisms underlying our wage results in Section 6, before concluding in Section 7.

[5]We also contribute to the recent literature on the impact of financial shocks on labor market outcomes (Bai et al., 2018; Benmelech et al., 2019; Caggese et al., 2019; Barrot and Nanda, 2020; Fonseca and Van Doornik, 2022; Fonseca and Matray, 2024). We add to this literature by estimating the impact of recent financial technologies related to payment methods. Moreover, we estimate the effects of these technologies on labor market outcomes such as employment and wage inequality, and explore different channels through which these effects occur.

2 Conceptual Framework

We present a simple theoretical framework to discuss the potential implications of instant payment systems on wages and the skill premium.[6]

We consider two types of labor, low-skill and high-skill, with inelastic supplies L and H, respectively. Our model includes two industries $j \in \{x, y\}$ with a representative firm operating a constant returns to scale technology $Q^j(L_j, H_j)$. Industries differ in factor intensity. We assume that sector x is the numeraire, $p_x = 1$, and sector y is intensive in the use of cash to complete transactions, which is captured by a wedge τ between the price p paid by consumers and the price p_y received by the representative firm such that $p_y = p \times (1 - \tau)$.[7] Finally, we assume identical, homothetic preferences for the two goods, and perfect competition in all markets.

The representative firm in industry j takes prices as given and chooses the amount of low and high-skill labor to solve:

$$\max_{\{L_j, H_j\}} p_j Q_j - w L_j - s H_j \tag{1}$$

Where w denotes the salary of low-skill workers, and s represents the salary of high-skill workers. First order conditions lead to the following equations:

$$\begin{aligned} w &= p_j Q_L^j \\ s &= p_j Q_H^j \end{aligned} \tag{2}$$

Finally, market clearing conditions for low and high-skill labor lead to the following equa-

[6] For similar frameworks, see Katz and Murphy (1992), Goldin and Katz (2007), and Autor et al. (2008), among others.

[7] The parameter τ can be interpreted either as cash handling costs (including trips to branches and ATMs, theft prevention measures, and cash flow management time) or as fees charged for debit or credit card usage (such as the merchant discount rate).

tions:

$$\begin{aligned} L_x(w,s) + L_y(w,s) &= L \\ H_x(w,s) + H_y(w,s) &= H \end{aligned} \tag{3}$$

Thus, equations (2) and (3) determine the equilibrium $\{L_x, L_y, H_x, H_y, w, s\}$ as functions of $\{p_y, L, H\}$. Our first result is given by Proposition 1.

Proposition 1 *An increase in the relative price of the good produced in the cash-intensive sector reduces the skill premium if and only if low-skill workers are used intensively in producing that good.*

Since financial innovations related to instant payments will reduce τ in our model, they are equivalent to a higher price p_y received by the firm operating in the cash-intensive industry. Thus, instant payment systems will reduce skill-premium if and only if cash-intensive industries are also low-skill intensive. Otherwise, instant payment systems would actually increase skill-premium. Figure A1 in the Online Appendix provides a graphic proof of this result. For this figure, we consider the following CES technology with parameter $\rho \leq 1$ in sector j:

$$Q^j = \left[A_j L_j^{\rho} + H_j^{\rho}\right]^{\frac{1}{\rho}} \tag{4}$$

By combining first order and zero profits conditions, we obtain the following equilibrium equations provided by industry x and y, respectively, that together determine the values w and s:

$$\begin{aligned} w &= A_x^{\frac{1}{\rho}} \left[1 - s^{\frac{\rho}{\rho-1}}\right]^{\frac{\rho-1}{\rho}} \\ w &= A_y^{\frac{1}{\rho}} \left[p_y^{\frac{\rho}{\rho-1}} - s^{\frac{\rho}{\rho-1}}\right]^{\frac{\rho-1}{\rho}} \end{aligned} \tag{5}$$

Figure A1 in the Online Appendix plots two equilibrium points, A and B, associated with different transaction costs $\tau^A > \tau^B$. The solid blue line represents the equilibrium condition given by industry x, while the solid (dashed) red line represents the condition provided by

industry y in the initial (final) equilibrium. Notice that the slope of the two lines that connect the origin and each of the equilibrium points is inversely related to the skill premium. Thus, a decline in τ leads to a reduction in skill-premium. This result requires industry y to use low-skill labor more intensively, as such intensity leads to a flatter red line. Thus, our theoretical model highlights the role of industry-specific skill intensity in shaping the impact of instant payment systems on the skill premium.

3 Institutional Background

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

As of early 2024, over 152 million individuals and 15 million firms have registered for Pix, with a substantial percentage using it regularly for transactions. Beyond better user experience and convenience, two other factors likely contributed to Pix's success. First, the regulation mandates the participation of large banks (defined as those with more than 500,000 accounts). Since the Brazilian market is concentrated and dominated by a small number of large banks, this measure ensured widespread availability and interoperability.[8] Second, the regulation exempts individuals from transaction fees to foster financial inclusion.[9] Since many small firms use the owner's personal bank account for transactions, they have seen a significant reduction in fees compared to traditional methods such as credit and debit cards or TED transfers (the electronic wire transfer available before Pix). Even when firms pay

[8]Banks with more than 500,000 customers accounted for more than 99% of the bank accounts in 2020. Source: Central Bank of Brazil (access).

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

fees, they are substantially smaller than other methods. According to Duarte et al. (2022), merchants pay an average fee of 0.22% per Pix transaction, compared to 2.2% for credit card payments.

Given its advantages, Pix quickly gained prominence as a payment method. About a year after its launch, the number of Pix transactions surpassed those of credit and debit cards and TED transfers. Regarding the transaction value, Pix exceeded credit and debit cards just two quarters after its introduction (Figure A2 in the Online Appendix). The rise in Pix coincides with a 35% drop in the number of cash withdrawals (Figure A3 in the Online Appendix), indicating a smaller reliance on cash. The rapid adoption of Pix in Brazil provides an ideal setting to study the labor market impacts of financial technology innovation. By reducing transaction costs and improving liquidity management, Pix has the potential to significantly affect business operations, particularly for small firms in cash-intensive sectors like retail and services.

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.[10] Second, we use matched employer-employee data from the Brazilian Ministry of Labor (*Relação Anual de Informações Sociais*, RAIS).[11] This dataset includes information on wages and job contracts for all Brazilian employment records between 2015 and 2022 at the municipality-industry-firm-size level. 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 data allows us to compute the monthly creation of micro-firms, small businesses, and large enterprises at

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

[11] We use the publicly available version of the data, which excludes firm and worker identifiers.

the municipality-industry level from January 2017 to July 2023. 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).

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 skill premium of 61% (median 48%). The share of the population with access to 3G+ is 54% (median 53%).

4.2 Research Design

We estimate the relative impact of instant payment technology adoption using two empirical approaches: a DiD design and a triple DiD. The DiD compares outcomes in municipalities with higher mobile penetration (the "treated" municipalities) to municipalities with lower penetration (the "control" municipalities). Our DiD design explicitly controls for any pre-existing differences between municipalities with higher and lower mobile penetration, such as baseline differences in economic development or digital infrastructure. We also explicitly control for any common time effects, such as aggregate economic shocks or seasonal patterns.

The key identifying assumption for our DiD approach is that, in the absence of Pix, outcomes in municipalities with higher and lower mobile penetration would have evolved in parallel. This "parallel trends" assumption allows us to interpret the difference between municipalities with higher and lower mobile penetration after Pix introduction as the causal effect of instant payment technology adoption.

We measure the exposure to instant payment technology in each municipality using pre-Pix mobile penetration rates. Specifically, we calculate:

$$\text{Mobile Penetration}_c = \frac{\text{Number of cellphones with 3G or above}_c}{\text{Population}_c} \tag{6}$$

Figure 1 shows the spatial distribution of mobile penetration across municipalities, measured as the ratio of mobile devices with 3G or higher capability to total population. The map reveals substantial differences in mobile infrastructure across municipalities prior to Pix's introduction, with darker shades indicating higher penetration rates. By using pre-Pix mobile penetration, our measure removes any endogenous changes in digital infrastructure made in response to Pix adoption. This mobile penetration measure, therefore, isolates the variation in municipalities' capacity to adopt instant payments, purged of any changes due to the technology's introduction.

For a given outcome Y, our DiD regression specification takes the form:

$$Y_{ct} = \beta_t \times \text{Mobile Penetration}_c + \delta_c + \delta_{rt} + \delta_{x(c)t} + u_{ct} \tag{7}$$

where δ_c are municipality fixed effects, δ_{rt} are region-by-year fixed effects, and $\delta_{x(c)t}$ are time-varying fixed effects for municipality clusters $x(c)$ based on pre-period characteristics. The estimated effects of Mobile Penetration$_c$ are allowed to be time-varying, with β_t denoting the year-by-year impact of mobile infrastructure. All specifications are weighted by municipality population, and standard errors are clustered at the municipality level to account for serial correlation.

In this specification, the β_t coefficients can be interpreted as the relative impact of mobile penetration in each year. We omit 2019, so that other β_t's can be interpreted relative to this pre-Pix baseline period. Our estimates of β_t from 2021 onwards will, therefore, capture the relative impact of mobile penetration during the Pix period.

To examine the design's identifying assumption, we conduct several tests. First, we investigate whether municipalities with different levels of mobile penetration exhibited systematic differences in key economic and demographic characteristics. Figure 2 plots standardized differences in pre-Pix characteristics between municipalities with high and low mobile penetration. The unconditional correlations (green estimates) show that municipalities with higher mobile penetration tend to be larger, more urban, and have higher wages and skill

premia. However, these differences largely disappear in our preferred specification, which compares municipalities within the same size decile and agricultural exposure decile (red estimates). After conditioning on these characteristics, we find no significant differences in GDP per capita, demographic composition, skill shares, average wages, or college premium. Second, we assess the assumption of parallel trends by testing for pre-trends in all our outcome variables.

To identify the causal effect of Pix adoption on wages while addressing concerns about time-varying local confounders, in our second empirical approach, we employ a triple DiD strategy that exploits the interaction of three distinct sources of variation. First, we use the timing of Pix's introduction in late 2020, which provides time variation in access to instant payment technology. Second, we leverage cross-sectional variation in municipalities' exposure to Pix based on pre-existing mobile penetration rates, as areas with higher mobile penetration were better positioned to adopt the technology. Third, we exploit within-municipality variation between establishments with high versus low cash intensity in their operations, as the benefits of instant payments should be more pronounced for businesses that frequently handle cash transactions. This triple DiD approach allows us to compare wage changes before and after Pix's introduction across municipalities with different levels of mobile penetration and between high and low cash-intensive establishments within the same municipality.

This apporach allows us to strip out any location-specific economic trends through high-dimensional fixed effects. Specifically, we estimate:

$$Y_{kjct} = \beta_t \times \text{Mobile Penetration}_c \times \text{Cash intensive}_k + \delta_{ct} + \delta_{jc} + \delta_{jt} + u_{jct} \tag{8}$$

where Y_{kjct} represents average wages for establishment group k in industry j, municipality c, and year t. Mobile Penetration$_c$ is the pre-Pix ratio of 3G+ cellphones to population, and Cash intensive$_k$ is an indicator for establishments that rely more on cash. Specifically, we define an industry-specific measure of cash intensity, assuming that households exhibit higher cash needs to complete transactions than government and firms. Thus, using the pre-Pix

Brazilian input-output matrix, we define cash intensity as the ratio of household purchases to industry total sales. The granular nature of our data allows us to include a rich set of fixed effects: Municipality-by-year fixed effects (δ_{ct}) control for any time-varying local economic conditions, municipality-by-industry-by-establishment-group fixed effects (δ_{kjc}) absorb time-invariant heterogeneity across establishment types within locations, establishment-group-by-year fixed effects (δ_{kt}) control for aggregate changes affecting establishments of different sizes and industry-by-year fixed effects (δ_{jt}) account for sector-specific shocks.[12]

As a complementary identification strategy, we employ a triple DiD design that exploits establishment size variation within municipalities. This approach compares wage changes before and after Pix's introduction, across municipalities with different levels of mobile penetration, and between small and large establishments within the same municipality. The intuition is that small establishments, which typically face higher transaction costs and other financial frictions, should benefit more from Pix adoption than large establishments. Like our previous design, by examining differential effects across establishment sizes within the same local market, this strategy helps address concerns about confounding local economic shocks. We estimate:

$$Y_{kjct} = \beta_t \times \text{Mobile Penetration}_c \times \text{Small}_k + \delta_{ct} + \delta_{kjc} + \delta_{kt} + \delta_{jt} + u_{kjct} \tag{9}$$

where Y_{kjct} represents average wages in size bin k, industry j, municipality c, and year t. Mobile Penetration$_c$ is the pre-Pix ratio of 3G+ cellphones to population, and Small$_k$ is an indicator for small establishments. This specification includes a comprehensive set of fixed effects: municipality-by-year fixed effects (δ_{ct}) control for any time-varying local economic conditions, municipality-industry-size bin fixed effects (δ_{kjc}) absorb time-invariant heterogeneity across establishment types within locations, size bin by year fixed effects (δ_{kt}) account for aggregate trends specific to different establishment sizes, and industry by year fixed effects (δ_{jt}) control for sector-specific shocks. Size bins are constructed based on the

[12]Industries are defined at the 2-digit CNAE level (Brazilian ISIC).

number of employees (0, up to 4, 9, 19, 49, 99, 249, 499, 999, and 1000 or more workers).

We also address other potential threats to identification. A key concern is that the COVID-19 pandemic coincided with Pix's introduction and may have had differential impacts across municipalities. We address this by controlling for local COVID-19 infection rates and policy responses, examining pre-trends in outcomes during the early pandemic period (pre-Pix), and conducting robustness checks excluding the peak pandemic period.

We also investigate whether other economic policies or reforms were implemented differentially across municipalities during our sample period. Our region-by-time fixed effects help account for any regional policy changes, and we explicitly control for other major municipal policy changes. Additionally, we examine whether changes in population composition across municipalities could affect our estimates by analyzing population flows during our sample period.

5 Main Results

In this section, we examine the effects of instant payment technology adoption across municipalities using our baseline DiD approach. We first analyze the effects on wages across different establishment sizes, before examining heterogeneous impacts across industries. We then study the effects on wage inequality.

We begin by examining the relationship between our treatment variable—pre-existing mobile penetration at the municipality level—and subsequent Pix adoption. Figure 3 presents coefficients from regressions of Pix usage on mobile penetration. Panel A shows estimates for the number of transactions per capita, while Panel B depicts estimates for transaction values per capita. Both panels reveal that municipalities with higher mobile penetration experienced substantially greater Pix adoption, with the relationship strengthening over time as the payment system diffused through the economy. The growing magnitude of the coefficients suggests that pre-existing differences in mobile infrastructure significantly influenced the intensity of Pix adoption across municipalities. This pattern validates our use of mobile

penetration as a source of variation for differential exposure to the introduction of Pix.

5.1 Wage Effects

Panel A of Table 2 presents estimates of mobile penetration's impact on average wages from our DiD specification. We report results for all establishments (Column 1) and separately by size: small, medium, and large establishments (Columns 2-4). All specifications are weighted by municipality population and include municipality fixed effects, region-by-year fixed effects, and interactions between predetermined municipal characteristics and year indicators. Standard errors are clustered at the municipality level.

Our results reveal that after Pix's introduction, municipalities with higher mobile penetration experienced significantly larger increases in average wages, with effects concentrated in small and medium-sized establishments. In our preferred specification with full controls, a one standard deviation increase in mobile penetration is associated with a 3 percent increase in average wages at small establishments and a 1 percent increase at medium-sized establishments. In contrast, we find a modest negative effect of -1 percent on wages at large establishments.

Figure 4 plots the dynamic effects of mobile penetration on log average wages. The estimates show no systematic relationship between mobile penetration and wage growth prior to Pix's introduction, supporting our parallel trends assumption. The wage effects emerge immediately following Pix's adoption and persist through 2022.

One challenge to our baseline DiD strategy is that municipalities with different levels of mobile penetration might experience differential trends in local economic conditions or policy changes over time. For example, municipalities with higher mobile penetration might simultaneously implement other policies, which could confound our estimates. We address this concern through a triple DiD approach that exploits within-municipality variation in establishment cash intensity. This approach effectively controls for any municipality-level changes that affect all establishments similarly by comparing outcomes between cash-intensive and

non-cash-intensive establishments within the same local market. As a complementary analysis, we also implement an alternative triple DiD strategy that leverages variation in establishment size, comparing small versus large establishments within municipalities.

Table 3 presents results from our primary triple DiD specification exploiting variation in establishment cash intensity. The estimates show that cash-intensive establishments in municipalities with higher mobile penetration experienced larger wage increases following Pix's introduction. Specifically, the coefficient of interest indicates that a one standard deviation increase in mobile penetration is associated with approximately 1.1 percent higher wages in cash-intensive establishments relative to non-cash-intensive establishments within the same municipality. This effect remains stable and highly significant after including municipality-by-year fixed effects to control for time-varying local economic conditions (Column 2). The robustness of our estimates to these stringent fixed effects supports the interpretation that the wage increases are driven by Pix adoption rather than concurrent municipality-level changes that might affect all establishments similarly.

Figure 5 plots the dynamic effects from our triple difference specification using establishment cash intensity. The results reveal no differential pre-trends between cash-intensive and non-cash-intensive establishments prior to Pix's introduction. The wage differential emerges sharply following Pix adoption in late 2020 and grows steadily throughout our sample period, reaching approximately 2 percentage points by 2022. These results are particularly compelling as they account for any time-varying municipality-level confounders that might affect wages uniformly across establishments with different cash intensities. The timing and pattern of the effects, combined with the lack of pre-trends, suggest that our findings reflect the causal impact of Pix adoption rather than unobserved local economic conditions or contemporaneous policy changes at the municipality level

To further validate our findings and provide additional insight into the distributional effects of Pix adoption, we implement a complementary triple DiD strategy that exploits variation in establishment size within municipalities. This approach is motivated by the

observation that small establishments typically face higher transaction costs and greater barriers to accessing traditional payment systems, suggesting they might benefit more from instant payment technology. Table 4 presents results from this alternative specification. We report estimates using different thresholds to define small establishments, ranging from establishments with up to 4 employees to those with up to 19 employees. Consistent with our primary analysis using cash intensity, we find robust evidence that small establishments in municipalities with higher mobile penetration experienced larger wage increases following Pix's introduction. The estimates indicate that a one standard deviation increase in mobile penetration is associated with approximately 1.1 to 1.6 percent higher wages in small establishments relative to large establishments within the same municipality, magnitudes that align closely with our cash intensity results.

Figure 6 plots the dynamic effects from our triple difference specification, revealing no differential pre-trends between small and large establishments prior to Pix's introduction. The wage differential emerges immediately after Pix adoption and persists throughout our sample period. These results are particularly compelling as they account for any time-varying municipality-level confounders that might affect wages uniformly across establishment sizes. The findings suggest that our baseline results are not driven by unobserved local economic conditions or policies that vary over time at the municipality level.

5.2 Heterogeneous Effects Across Industries

Having established that Pix adoption led to larger wage increases in small establishments, we next examine whether these effects vary systematically across industries. This analysis is particularly informative for three reasons. First, sectors differ in their reliance on cash transactions, with retail and services traditionally being more cash-intensive than manufacturing. Second, understanding which industries drive our results provides insights into the distributional implications of financial technology adoption, as sectors vary substantially in their skill composition and wage structure. Third, and importantly, the pattern of hetero-

geneity helps us distinguish the effects of Pix from other concurrent changes in local financial markets. While Pix adoption might correlate, for example, with changes in deposits that should affect all sectors similarly, the benefits of digital payments should be concentrated in traditionally cash-intensive sectors.

Figure 7 highlights these important cross-industry differences. Panel A shows that small retail establishments are particularly intensive in low-skill workers, with 91 percent of their payroll going to workers without college degrees, compared to only 58 percent in large retail establishments. Similar patterns exist in services, where small establishments' low-skill payroll share is 61 percent versus 37 percent for large establishments. Manufacturing shows a more uniform skill composition across establishment sizes. Panel B reveals substantial variation in the college premium across industries and establishment sizes. In retail, for instance, the college premium in small firms is around 83 percent, while large establishments exhibit a much larger premium of 336 percent. Similar patterns emerge in services and manufacturing, with consistently larger skill premiums in larger establishments.

Additionally, Figure 8 shows that after Pix's introduction in 2020, municipalities with higher mobile penetration experienced significant wage increases in retail and services, while manufacturing wages remained unchanged. This pattern suggests that Pix adoption particularly benefited cash-intensive industries.

Motivated by these stark differences in workforce composition across industries and establishment sizes, Table 5 examines heterogeneity in wage effects across industries. We find that the impact of Pix adoption is concentrated in the retail and services sectors, with no significant effects in manufacturing. For small and medium establishments in retail, a one standard deviation increase in mobile penetration raises wages by 3 percent, while the effect in services is 1 percent. These sectoral patterns align with the hypothesis that Pix adoption generates larger benefits in cash-intensive industries.

The concentration of wage effects in retail and services, combined with these sectors' workforce composition, suggests that Pix adoption particularly benefited the most financially

vulnerable workers—those in small, low-skill-intensive establishments in cash-dependent sectors. This pattern provides important insights into how financial technology adoption can affect wage inequality through its differential impact across industries and establishment sizes.

5.3 Effects on Wage Inequality

A key debate in the literature on technological change centers on its distributional consequences. The canonical skill-biased technical change hypothesis 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). However, recent work suggests that some technologies might have different distributional effects depending on which tasks or workers they complement (Autor et al., 2003). Given that our results show larger wage effects among low-skill workers in small establishments, we next examine whether Pix adoption affected overall wage inequality.

We measure inequality using the college wage premium, defined as the difference in log average wages between college and non-college workers at the municipality level:

$$\text{College Premium}_c = \ln(\text{avg. wage}_{\text{college}}) - \ln(\text{avg. wage}_{\text{non-college}}) \tag{10}$$

The red line in Figure 9 corresponds to the estimates of the effect of mobile penetration on the college premium from our DiD specification. The estimates show no differential trends prior to Pix's introduction, supporting our identification assumption. Following Pix adoption, we observe a significant decline in the college premium of approximately 2 percentage points in municipalities with higher mobile penetration. This reduction in wage inequality emerges gradually and persists through the end of our sample period.

The decline in the college premium is particularly notable given that most technological innovations have been found to increase skill premiums. Our results suggest that by reducing frictions in cash-intensive sectors that disproportionately employ low-skill workers, digital

payment technologies can generate more inclusive patterns of wage growth.

6 Mechanisms

In this section, we explore the mechanisms through which instant payment technology adoption affects local labor markets. Our results suggest that increased labor demand from small businesses, combined with local labor market frictions, is the main mechanism driving the observed wage effects. This section presents evidence supporting this interpretation and helps rule out alternative explanations.

6.1 Labor Demand Channel

To test whether this technology leads to greater demand for workers, we first examine job creation patterns across sectors to test whether Pix adoption increased labor demand. Figure 10 compares employment effects between retail and manufacturing, showing that municipalities with higher mobile penetration experienced significant job growth in small retail firms after Pix's introduction in 2020 while manufacturing employment remained unchanged. Tables 6 and 7 show that a one standard deviation increase in mobile penetration led to 0.382 additional jobs per capita in retail, with the strongest effects among small firms (0.250). In contrast, manufacturing showed no job growth, with effects near zero across all firm size categories (-0.071 overall). These results support the hypothesis that Pix adoption stimulated employment in cash-intensive sectors.

We next examine whether increased labor demand stems from new business formation. Figure 11 shows municipalities with higher mobile penetration experienced significant growth in small retail firm entry after Pix adoption, while manufacturing entry remained flat. Table 8 shows a one standard deviation increase in mobile penetration is associated with a 0.07 increase in the number of retail firms per 10,000 inhabitants, with no comparable effect in manufacturing. These effects are concentrated among firms with annual sales between 70,000

and 970,000 USD. Figure 12 and Table 9 confirm these effects are unique to small businesses, showing no significant changes in large firm entry across sectors. This pattern suggests that by reducing transaction costs and improving cash flow management, Pix lowered entry barriers in cash-intensive sectors, ultimately increasing labor demand.

The sectoral heterogeneity in both employment and wage effects also helps rule out alternative explanations. If the wage increases were driven by general technological change, productivity improvements, or broader financial development (such as increased access to credit), we would expect to see effects across all sectors, including manufacturing. Instead, the concentration of effects in retail and services suggests that reduced payment frictions are the key driver.

These findings are consistent with the predictions of our theoretical model. By reducing transaction costs, Pix effectively increases the price received by firms in cash-intensive sectors. According to the model, this price increase should lead to higher demand for low-skilled labor, particularly in sectors where such labor is used intensively, like retail and services. Our evidence of employment growth and increased small firm entry in these sectors strongly supports the model.

6.2 Role of Labor Market Frictions

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

Figure 9 illustrates that the decline in the college premium varies systematically with local labor market tightness. In areas where low-skill workers are relatively scarce (below-median share of non-college workers), the college premium declines by approximately 1 percentage point. In contrast, areas with abundant low-skill workers show a smaller and imprecise

decline. This pattern is consistent with upward wage pressure when increased labor demand meets limited local supply.

The heterogeneous effects based on labor market tightness help explain both the magnitude and distribution of wage gains. In areas where low-skill workers are scarce, small establishments must offer higher wages to attract workers, leading to larger declines in wage inequality. This finding aligns with search and matching models where wage effects are amplified in tight labor markets (Pissarides, 2000).

6.3 Discussion of Alternative Mechanisms

While our evidence supports increased labor demand and local market frictions as the dominant channels through which Pix adoption influences wage outcomes, several alternative channels merit further discussion.

One candidate explanation is rent-sharing, where firms share productivity gains from Pix adoption with workers. The classic rent-sharing channel suggests that when firms become more profitable, they share these gains with workers due to bargaining power or efficiency wage considerations (Card et al., 2018). However, several patterns in our data are difficult to reconcile with rent-sharing as the primary mechanism. First, small retail and service establishments typically have low unionization rates and limited firm-specific human capital—factors the literature considers as crucial for rent-sharing (Manning, 2011). Second, if rent-sharing were the primary channel, we would expect larger effects in establishments where workers have more bargaining power, typically larger firms with higher union density. Instead, we find the opposite pattern. Third, the concentration of wage effects in municipalities with scarce low-skill labor suggests that market-level forces, rather than within-firm sharing, drive our results.

Another potential explanation is that Pix facilitated the formalization of previously informal businesses, potentially boosting wages through two main channels. First, formalization can enforce compliance with minimum wage laws, raising average pay. Second, newly formal

businesses often gain greater access to credit and other financial services, spurring expansion and higher wages. While formalization likely plays some role—and is an important goal for developing economies—it alone cannot explain why wage effects are strongest where low-skill labor is scarce. Instead, this pattern aligns more closely with a localized labor-demand mechanism. Nevertheless, formalization itself may represent an additional societal benefit of Pix, particularly in contexts where drawing businesses into the formal sector can improve working conditions and tax revenues.

Overall, our findings suggest that Pix adoption increases labor demand from small businesses, particularly in retail and services. Combined with local labor market frictions, this leads to higher equilibrium wages for low-skill workers. This mechanism provides a unified explanation for our key findings: the cross-sectional pattern of effects across sectors and establishment sizes, the concentration of gains among low-skill workers, and the geographic variation in wage impacts based on local labor market conditions.

7 Conclusion

Our findings provide novel evidence on how financial technology adoption shapes labor markets and wage inequality. While the canonical skill-biased technical change hypothesis suggests that technological innovation increases inequality by favoring skilled workers, we show that digital payment technologies can generate more inclusive patterns of wage growth. Studying Brazil's nationwide instant payment system, we find that Pix adoption led to larger wage increases for low-skilled workers, particularly in small retail and service establishments, resulting in a significant reduction in the college wage premium.

The distributional effects we document stem from the technology's impact on traditionally cash-intensive sectors that disproportionately employ low-skill workers. Our evidence suggests that Pix increased labor demand from small businesses. Combined with local labor market frictions, this led to higher equilibrium wages, with effects amplified in areas where low-skill labor is scarce.

These results have important implications for both economic theory and policy. First, they demonstrate that financial innovation can complement low-skilled labor by mitigating frictions in sectors where these workers are predominantly employed, thereby not exacerbating inequality. Second, they suggest that investments in digital payment infrastructure could serve as a valuable complement to traditional policies aimed at inclusive growth. The substantial wage effects we document underscore the potential for improvements in the financial environment of small businesses to generate broad-based economic benefits.

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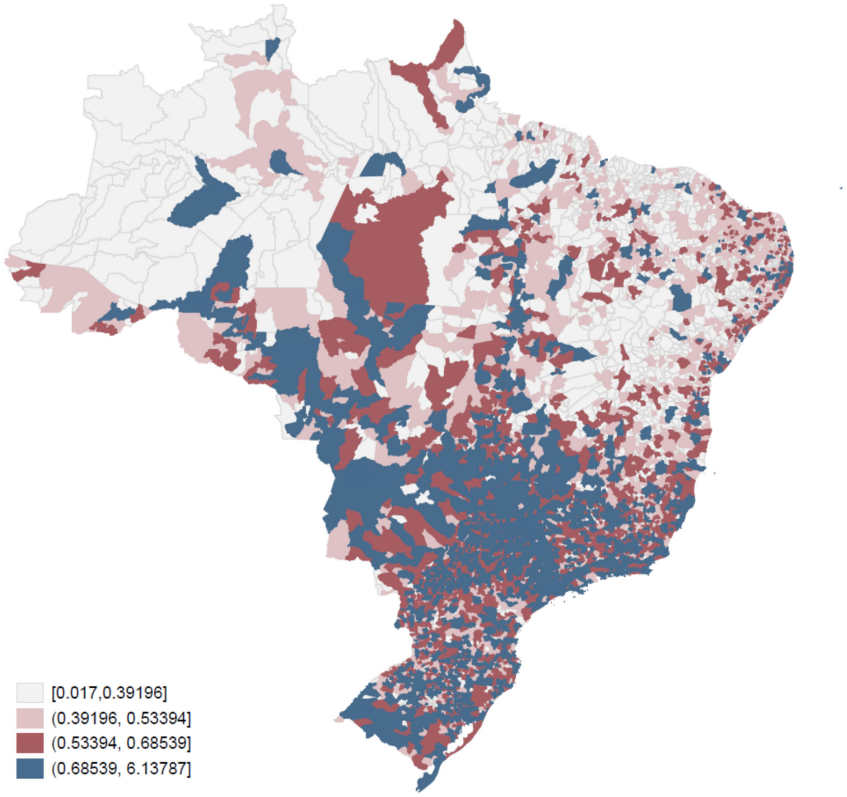


Figure 1 Geographic Distribution of Mobile Technology Penetration

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 total population in each municipality. The map uses four color categories to represent different levels of penetration. These ranges represent quartiles of the mobile penetration distribution across municipalities. The data combines telecommunications infrastructure information from ANATEL (Agência Nacional de Telecomunicações) with population estimates from IBGE (Instituto Brasileiro de Geografia e Estatística).

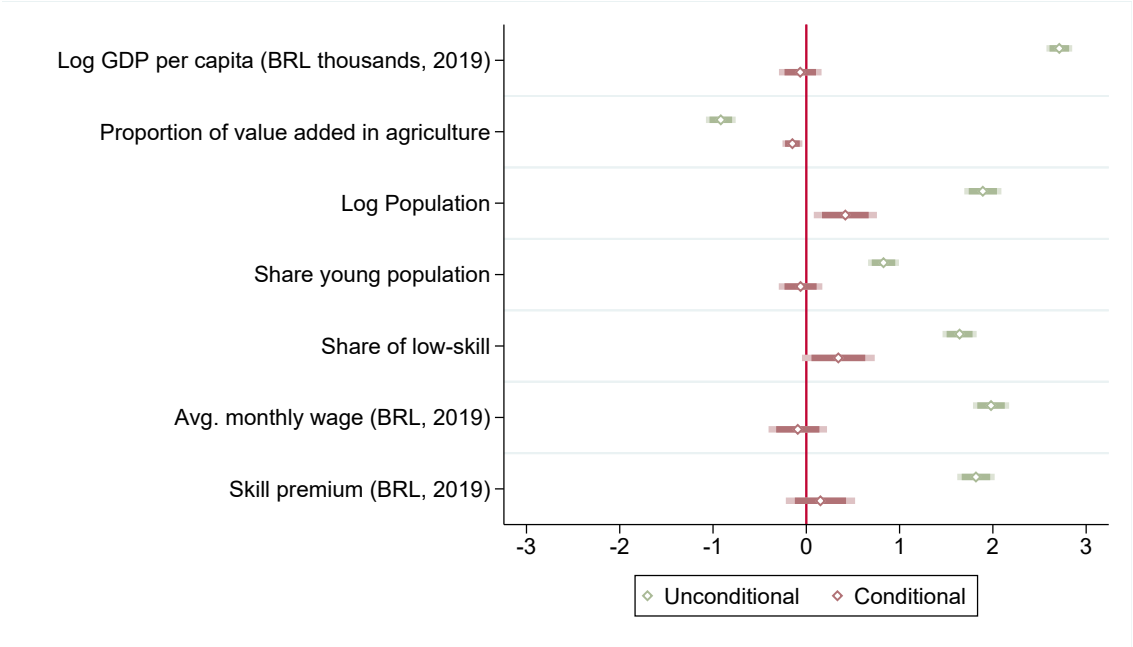
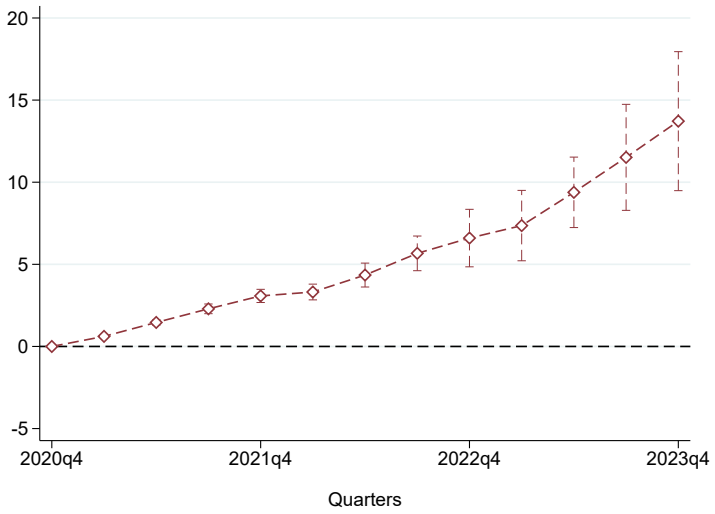
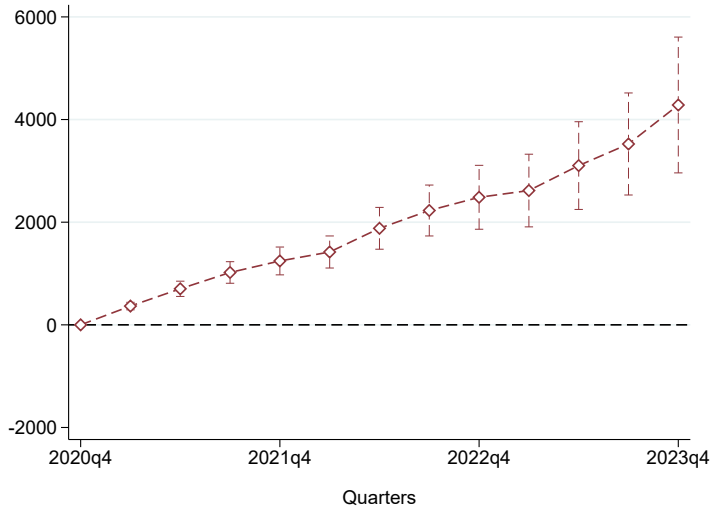


Figure 2 Balance of Covariates

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.



Panel A. Number of Transactions per Capita



Panel B. Value of Transactions per Capita

Figure 3 Effect of Mobile Penetration on Pix Transactions

This figure shows the estimated quarterly coefficients from regressing per-capita Pix transactions on standardized mobile penetration at the municipality level. The dependent variable in Panel A is the number of Pix transactions divided by 2019 population, while Panel B uses the value of Pix transactions divided by 2019 population. Both panels plot coefficient estimates from municipality-level regressions that include municipality fixed effects, time fixed effects, and municipality characteristics interacted with time fixed effects. The dashed lines represent 95% confidence intervals constructed using robust standard errors. The sample period is 2020:Q4-2023:Q4.

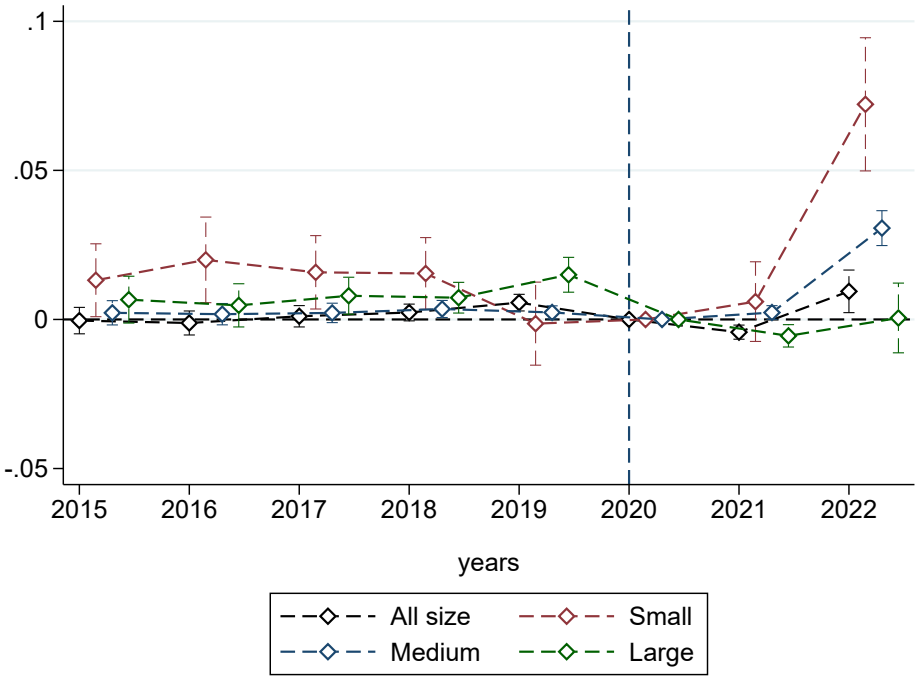


Figure 4 Effect of Mobile Penetration on Average Wages by Firm Size

This figure shows the estimated yearly coefficients from regressing log average wages on standardized mobile penetration at the municipality level, separately for different firm size categories around Pix introduction in 2020. The regression specification controls for municipality fixed effects, region-by-year fixed effects, and municipality characteristics interacted with year fixed effects. Small firms are defined as those with up to 49 employees, medium firms have 50-249 employees, and large firms have 250 or more employees. The dashed vertical line indicates the introduction of Pix in 2020. Dashed lines around point estimates represent 95% confidence intervals constructed using municipality-level clustered standard errors. The sample period is 2015-2022.

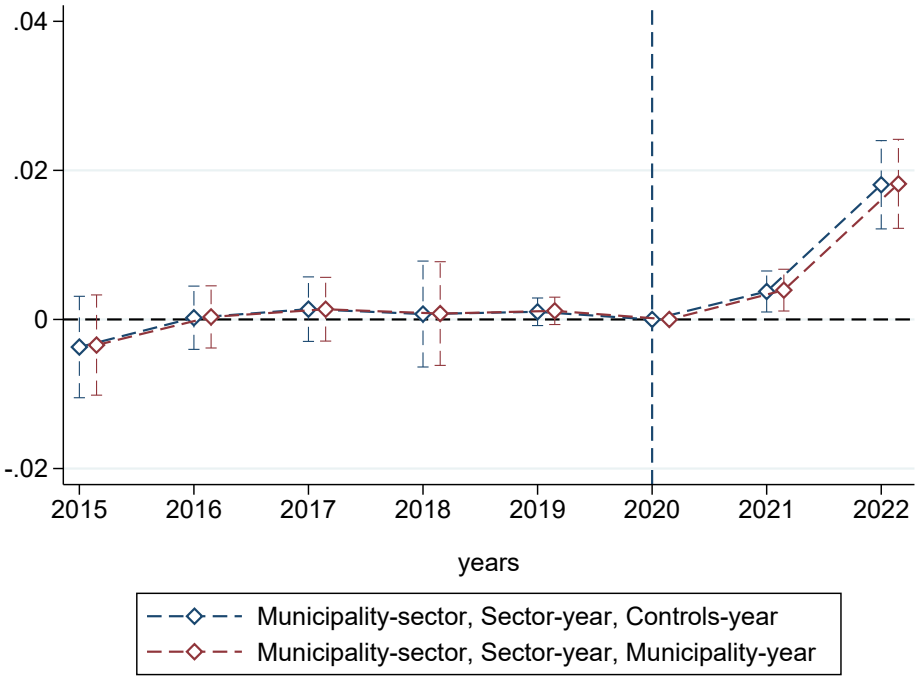


Figure 5 Triple Difference-in-Differences: Differential Cash Intensity Effects of Mobile Penetration on Wages

This figure shows the estimated yearly coefficients from a triple difference-in-differences specification that captures the differential effect of mobile penetration on wages between cash-intensive and non-cash-intensive establishments around Pix introduction in late 2020. Using the Brazilian input-output matrix, we define cash intensity as the ratio of household purchases to industry total sales. The specification interacts mobile penetration with an indicator for cash-intensive establishments and includes municipality-by-year, industry-by-year, and municipality-by-industry fixed effects. The dependent variable is the logarithm of average wages. The regression is weighted by municipality population, and standard errors are clustered at the municipality level. Dashed lines represent 95% confidence intervals. The sample period is 2015-2022.

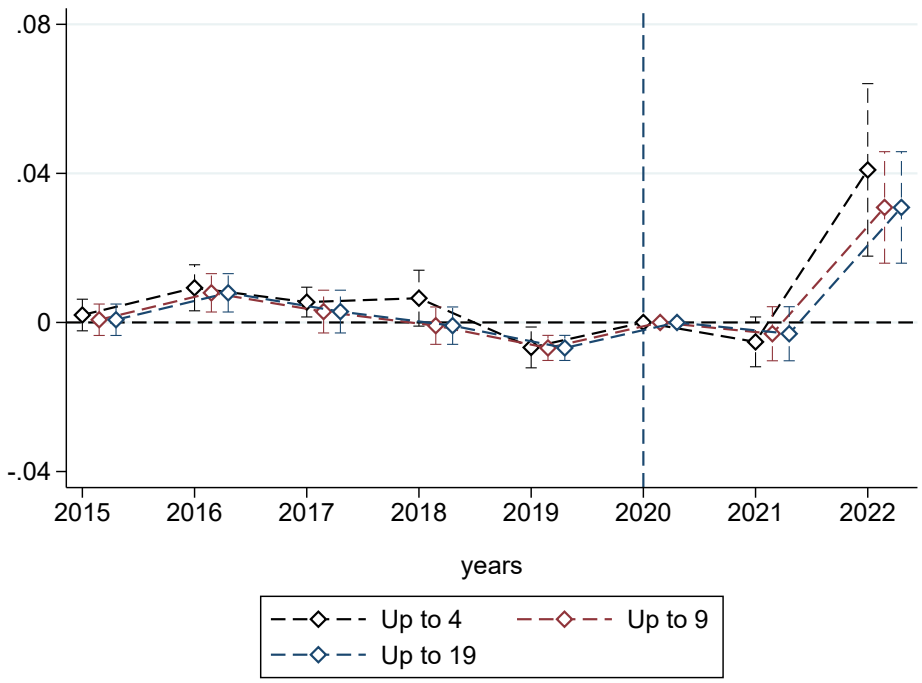


Figure 6 Triple Difference-in-Differences: Differential Size Effects of Mobile Penetration on Wages

This figure shows the estimated yearly coefficients from a triple difference-in-differences specification that captures the differential effect of mobile penetration on wages between small and large establishments around Pix introduction in late 2020. The specification interacts mobile penetration with an indicator for small establishments and includes municipality-by-year, size bin-by-year, industry-by-year, and municipality-industry-size bin fixed effects. Small establishments are defined as those with up to 9 employees. The dependent variable is the logarithm of average wages at the municipality-industry-size bin-year level. The regression is weighted by municipality population and standard errors are clustered at the municipality level, with dashed lines representing 95% confidence intervals. The sample period is 2015-2022.

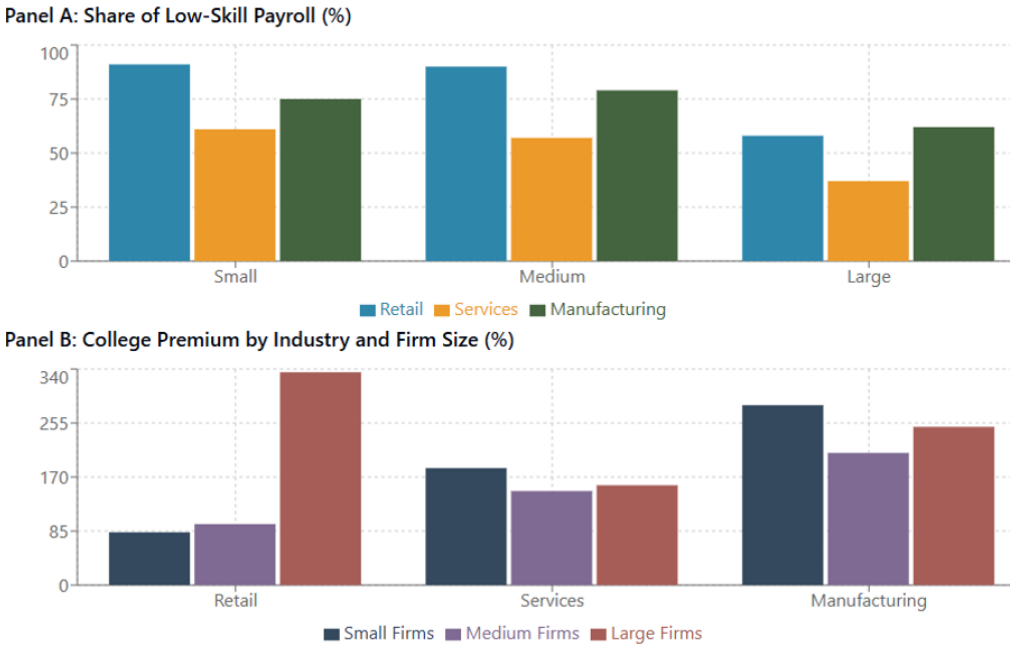


Figure 7 Skill Composition and Wage Patterns Across Industries and Firm Sizes

This figure presents the relationship between skill composition, wages, and firm characteristics across different industries and firm sizes. Panel A displays the share of low-skill payroll (as a percentage of total payroll) across different firm size categories and industries. Small firms have up to 49 employees, medium firms have 50-249 employees, and large firms have 250 or more employees. Panel B shows the college wage premium (calculated as the percentage increase of college-educated over non-college-educated workers' wages) by industry and firm size. Base monthly wages (in Reals) for low-skill workers are: Retail (1,387), Services (1,622), and Manufacturing (1,839). Data is from RAIS employer-employee matched data for 2019. The bars display results separately for retail (blue), services (orange), and manufacturing (green) sectors across different firm size categories.

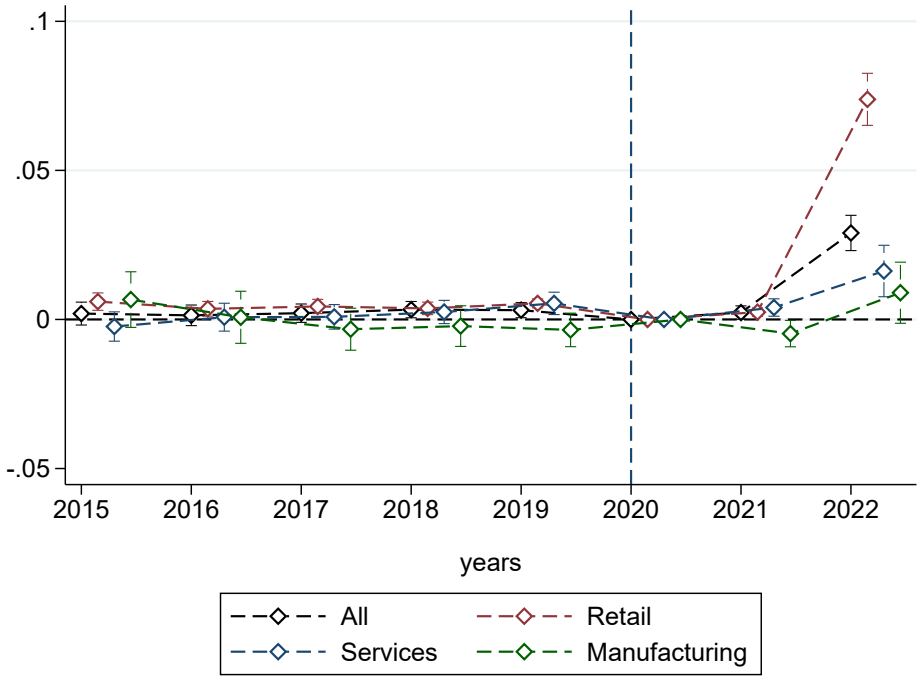


Figure 8 Effect of Mobile Penetration on Average Wages by Industry - Small and Medium Size Establishments

This figure shows the estimated yearly coefficients from regressing log average wages on standardized mobile penetration at the municipality level, separately for different industries in small and medium-sized establishments around Pix introduction in 2020. The regression specification controls for municipality fixed effects, region-by-year fixed effects, and municipality characteristics interacted with year fixed effects. The analysis is conducted separately for all industries combined, retail sector, services sector, and manufacturing sector. Small and medium-sized establishments are defined as those with fewer than 100 employees. The dashed vertical line indicates the introduction of Pix in 2020. Dashed lines around point estimates represent 95% confidence intervals constructed using municipality-level clustered standard errors. The regression is weighted by municipality population. The sample period is 2015-2022.

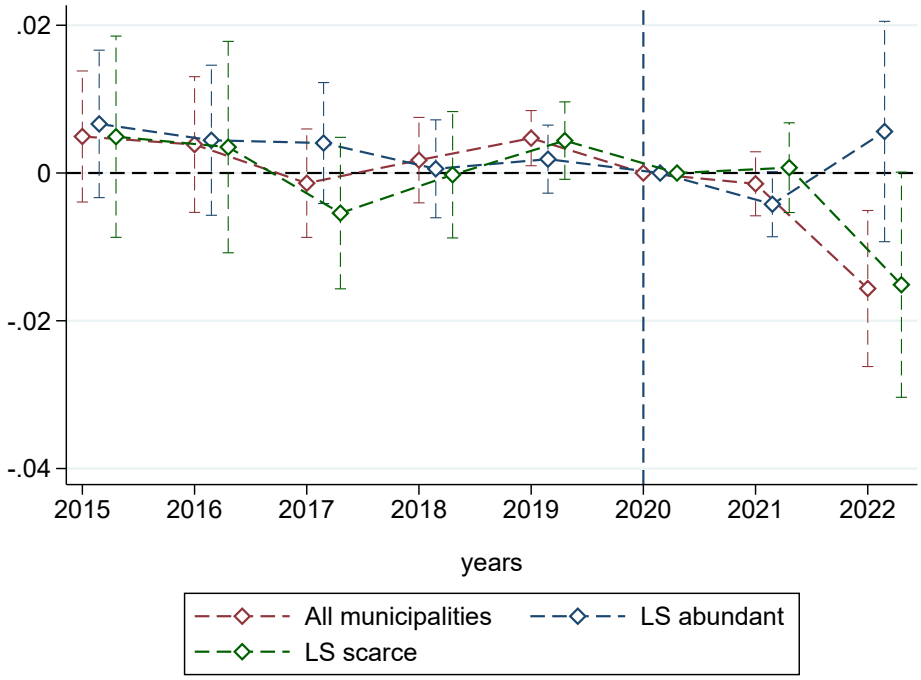
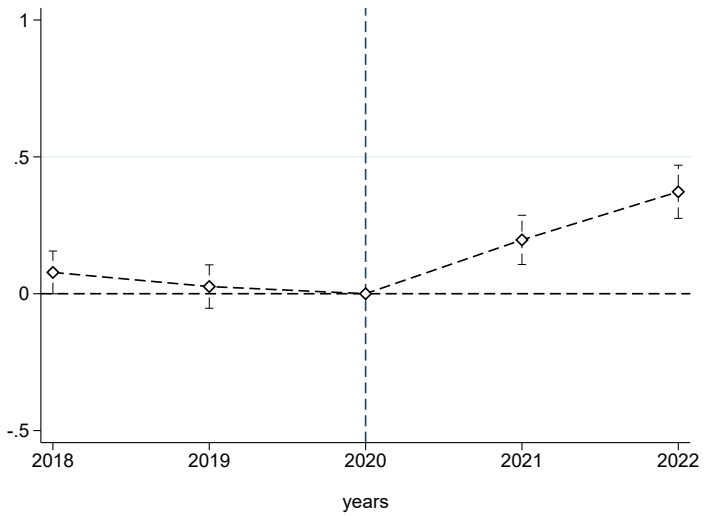
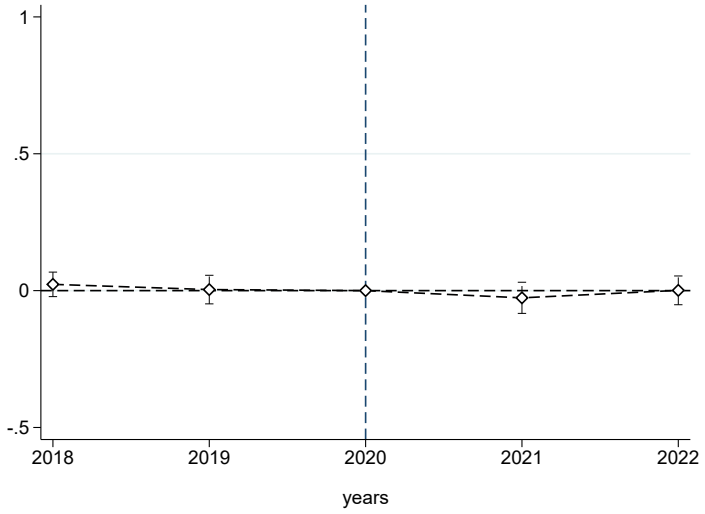


Figure 9 Effect of Mobile Penetration on College Premium by Labor Market Tightness

This figure shows the estimated yearly coefficients from regressing the college premium on standardized mobile penetration at the municipality level around Pix introduction in 2020, separately for areas with different levels of labor market tightness. The college premium is defined as the difference in log average monthly wages between college-educated and non-college-educated workers within each municipality-year. The red line depicts the effect for all the municipalities. The blue line corresponds to the estimates for municipalities with below-median labor market tightness (higher availability of low-skill workers), while the green line corresponds to the municipalities with above-median labor market tightness (lower availability of low-skill workers). Labor market tightness is measured using the ratio of job vacancies to low-skill workers in each municipality. The regression specification controls for municipality fixed effects, region-by-year fixed effects, and municipality characteristics interacted with year fixed effects. The dashed vertical line indicates the introduction of Pix in 2020. Dashed lines around point estimates represent 95% confidence intervals constructed using municipality-level clustered standard errors. The regression is weighted by municipality population. The sample period is 2015-2022.



Panel A. Small Firms in Retail



Panel B. Small Firms in Manufacturing

Figure 10 Effect of Mobile Penetration on Net Job Created

This figure plots the estimated yearly coefficients from regressing the change in the number of job contracts in retail (Panel A) and in manufacturing (Panel B) per capita on standardized mobile penetration at the municipality level. Mobile penetration is measured as the pre-Pix ratio of 3G+ cellphones to population in each municipality. The sample is restricted to small firms, defined as those with annual sales between USD 70,000 and USD 970,000. The specification includes municipality fixed effects, region-by-year fixed effects, and municipality controls interacted with year fixed effects. The regression is weighted by municipality population and standard errors are clustered at the municipality level, with dashed lines representing 95% confidence intervals. The vertical line indicates the introduction of Pix in late 2020. The sample period is 2015-2022.

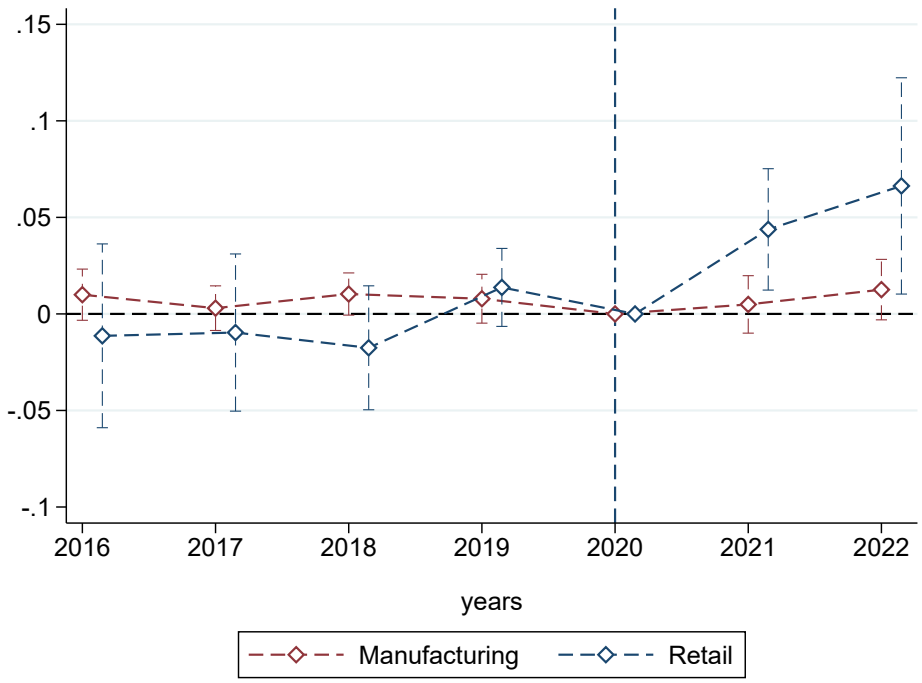


Figure 11 Effect of Mobile Penetration on Small Firm Entry by Industry

This figure shows the estimated yearly coefficients from regressing the number of small firm entrants per capita on standardized mobile penetration at the municipality level, separately for retail and manufacturing sectors around Pix introduction in 2020. Small firms are defined as those with annual sales between USD 70,000 and USD 970,000. The regression specification controls for municipality fixed effects, region-by-year fixed effects, and municipality characteristics interacted with year fixed effects. The dashed vertical line indicates the introduction of Pix in 2020. Dashed lines around point estimates represent 95% confidence intervals constructed using municipality-level clustered standard errors. The regression is weighted by municipality population. The sample period is 2016-2022.

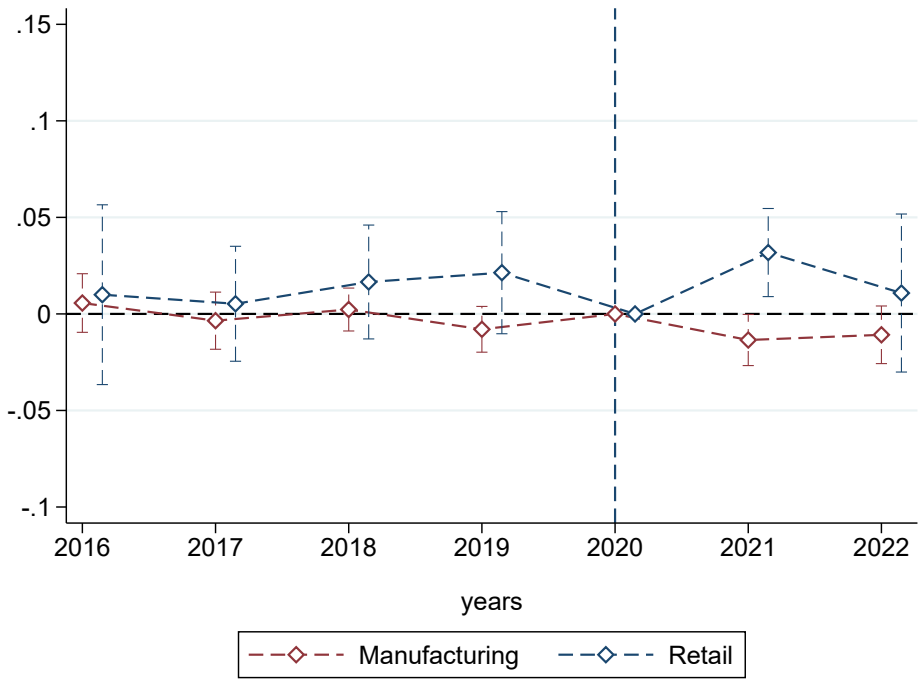


Figure 12 Effect of Mobile Penetration on Large Firm Entry by Industry

This figure shows the estimated yearly coefficients from regressing the number of large firm entrants per capita on standardized mobile penetration at the municipality level around Pix introduction in 2020. The analysis is conducted separately for all industries combined, manufacturing, and retail sectors. Large firms are defined as those with annual sales above USD 970,000. The regression specification controls for municipality fixed effects, region-by-year fixed effects, and municipality characteristics interacted with year fixed effects. The dashed vertical line indicates the introduction of Pix in 2020. Dashed lines around point estimates represent 95% confidence intervals constructed using municipality-level clustered standard errors. The regression is weighted by municipality population. The sample period is 2016-2022.

Table 1 Summary Statistics

This table reports summary statistics of average city-level characteristics. Wage values are in BRL. Number of bank branches are from the ESTBAN database. Wages are from the RAIS database. Local GDP per capita, population, and the share of agriculture and services in local value added are from the Brazilian Institute of Geography and Statistics.

	Mean	Median	SD	N
	(1)	(2)	(3)	(4)
GDP per capita	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. 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
Skill premium	1,615	1,481	781	5,570

Table 2 Effect of Mobile Penetration on Average Wages by Firm Size

This table presents estimates from regressing log average wages on standardized mobile penetration interacted with a post-2020 indicator at the municipality level, separately for different firm size categories. Mobile penetration is defined as the ratio of mobile devices with 3G or higher capability to total population in 2019, standardized to have unit variance. The regression specification controls for municipality fixed effects, region-by-year fixed effects, and municipality characteristics interacted with year fixed effects. Small firms are defined as those with fewer than 50 employees, medium firms have 50-249 employees, and large firms have 250 or more employees. The regression is weighted by municipality population and standard errors (in parentheses) are clustered at the municipality level. The sample period is 2015-2022. ***p<0.01, **p<0.05, *p<0.1.

	ln(Avg. wage)			
	All	Small	Medium	Large
	(1)	(2)	(3)	(4)
Mobile penetration × Post	0.00	0.03***	0.01***	-0.01**
	(0.00)	(0.01)	(0.00)	(0.00)
Observations	44,552	43,022	44,551	32,768
Municipality	✓	✓	✓	✓
Region × Year	✓	✓	✓	✓
Controls × Year	✓	✓	✓	✓

Table 3 Differential Cash-Intensiveness Effect of Mobile Penetration on Wages

This table presents estimates from triple difference-in-differences regressions examining how mobile penetration differentially affects wages in cash-intensive versus non-cash-intensive establishments after Pix adoption. Using the Brazilian input-output matrix, we define cash intensity as the ratio of household purchases to industry total sales. The key coefficient of interest, Mobile penetration × Cash intensive industry × Post, captures how the effect of mobile penetration on wages varies with establishment cash intensity following Pix's introduction in late 2020. The dependent variable is the logarithm of average wages. Column (2) adds municipality-by-year fixed effects to control for time-varying local shocks. The specification includes municipality-by-industry fixed effects and industry-by-year fixed effects. The regression is weighted by municipality population and standard errors clustered at the municipality level are reported in parentheses. The sample period is 2015-2022. ***p<0.01, **p<0.05, *p<0.1.

	(1)	(2)
Mobile penetration × Cash intensive × Post	0.011***	0.011***
	(0.002)	(0.002)
Observations	611,162	611,150
Municipality × Industry	✓	✓
Industry × Year	✓	✓
Municipality × Year		✓

Table 4 Differential Establishment Size Effect of Mobile Penetration on Wages

This table presents estimates from triple difference-in-differences regressions examining how mobile penetration differentially affects wages between small and large establishments after Pix adoption. The key coefficient of interest, Mobile penetration × Small × Post, captures how the effect of mobile penetration on wages varies with establishment size following Pix's introduction in late 2020. The dependent variable is the logarithm of average wages at the municipality-industry-size bin-year level. Each column uses a different threshold to define small establishments, ranging from up to 4 employees to up to 19 employees. The specification includes municipality-by-year fixed effects, as well as size bin-by-year, industry-by-year, and municipality-industry-size bin fixed effects. The regression is weighted by municipality population and standard errors clustered at the municipality level are reported in parentheses. The sample period is 2015-2022. ***p<0.01, **p<0.05, *p<0.1.

	ln(Avg. wage)		
Small =	Up to 4	Up to 9	Up to 19
	(1)	(2)	(3)
Mobile penetration × Small × Post	0.016**	0.014***	0.011***
	(0.007)	(0.004)	(0.002)
Observations	3,101,643	3,101,643	3,101,643
Municipality × Industry × Size	✓	✓	✓
Municipality × Year	✓	✓	✓
Industry × Year	✓	✓	✓
Size × Year	✓	✓	✓

Table 5 Effect of Mobile Penetration on Wages Across Industries

This table presents estimates from regressing log average wages on standardized mobile penetration interacted with a post-2020 indicator at the municipality level, separately for different industries. The dependent variable is the logarithm of average wages at the municipality-year level, restricted to small and medium-sized establishments (up to 99 employees). Column (1) reports results for all industries combined, while columns (2)-(4) show separate estimates for retail, services, and manufacturing sectors. Mobile penetration is measured as the pre-Pix ratio of 3G+ cellphones to population in each municipality. The specification includes municipality fixed effects, region-by-year fixed effects, and municipality controls interacted with year fixed effects. The regression is weighted by municipality population and standard errors clustered at the municipality level are reported in parentheses. The sample period is 2015-2022. ***p<0.01, **p<0.05, *p<0.1.

	ln(Avg. wage) for Small & Medium Estab.			
	All	Retail	Services	Manuf.
	(1)	(2)	(3)	(4)
Mobile penetration × Post	0.01***	0.03***	0.01***	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Observations	44,552	44,468	44,540	38,949
Municipality	✓	✓	✓	✓
Region × Year	✓	✓	✓	✓
Controls × Year	✓	✓	✓	✓

Table 6 Jobs Created in the Retail Sector

This table presents estimates from regressing the change in the number of job contracts in retail per capita on standardized mobile penetration interacted with a post-2020 indicator at the municipality level, separately for the retail sector. Small firms are defined as those with annual sales between USD 70,000 and USD 970,000. Mobile penetration is measured as the pre-Pix ratio of 3G+ cellphones to population in each municipality. The specification includes municipality fixed effects, region-by-year fixed effects, and municipality controls interacted with year fixed effects. The regression is weighted by municipality population and standard errors clustered at the municipality level are reported in parentheses. The sample period is 2018-2022. ***p<0.01, **p<0.05, *p<0.1.

	Num. Jobs Created by size firm			
	All	Small	Medium	Large
	(1)	(2)	(3)	(4)
Mobile penetration × Post	0.382***	0.250***	0.126***	0.006
	(0.069)	(0.030)	(0.037)	(0.053)
Observations	27,845	27,845	27,845	27,845
Municipality	✓	✓	✓	✓
Region × Year	✓	✓	✓	✓
Controls × Year	✓	✓	✓	✓

Table 7 Jobs Created in the Manufacturing Sector

This table presents estimates from regressing the change in the number of job contracts in manufacturing per capita on standardized mobile penetration interacted with a post-2020 indicator at the municipality level for the manufacturing sector. Small firms are defined as those with annual sales between USD 70,000 and USD 970,000. Mobile penetration is measured as the pre-Pix ratio of 3G+ cellphones to population in each municipality. The specification includes municipality fixed effects, region-by-year fixed effects, and municipality controls interacted with year fixed effects. The regression is weighted by municipality population and standard errors clustered at the municipality level are reported in parentheses. The sample period is 2018-2022. ***p<0.01, **p<0.05, *p<0.1.

	Num. Jobs Created by size firm			
	All	Small	Medium	Large
	(1)	(2)	(3)	(4)
Mobile penetration × Post	-0.071	-0.022	-0.005	-0.045
	(0.120)	(0.017)	(0.035)	(0.119)
Observations	27,845	27,845	27,845	27,845
Municipality	✓	✓	✓	✓
Region × Year	✓	✓	✓	✓
Controls × Year	✓	✓	✓	✓

Table 8 Effect of Mobile Penetration on Small Firm Entry

This table presents estimates from regressing the number of small firm entrants per capita on standardized mobile penetration interacted with a post-2020 indicator at the municipality level, separately for manufacturing and retail sectors. Small firms are defined as those with annual sales between USD 70,000 and USD 970,000. Mobile penetration is measured as the pre-Pix ratio of 3G+ cellphones to population in each municipality. The specification includes municipality fixed effects, region-by-year fixed effects, and municipality controls interacted with year fixed effects. The regression is weighted by municipality population and standard errors clustered at the municipality level are reported in parentheses. The sample period is 2015-2022. ***p<0.01, **p<0.05, *p<0.1.

	Num. Entrants per capita	
	Manuf.	Retail
	(1)	(2)
Mobile penetration × Post	0.00	0.06**
	(0.01)	(0.03)
Observations	38,983	38,983
Municipality	✓	✓
Region × Year	✓	✓
Controls × Year	✓	✓

Table 9 Effect of Mobile Penetration on Large Firm Entry

This table presents estimates from regressing the number of large firm entrants per capita on standardized mobile penetration interacted with a post-2020 indicator at the municipality level, separately for different sectors. Columns (1) and (2) show separate estimates for manufacturing and retail sectors. Mobile penetration is measured as the pre-Pix ratio of 3G+ cellphones to population in each municipality. The specification includes municipality fixed effects, region-by-year fixed effects, and municipality controls interacted with year fixed effects. The regression is weighted by municipality population and standard errors clustered at the municipality level are reported in parentheses. The sample period is 2015-2022. ***p<0.01, **p<0.05, *p<0.1.

	Num. Entrants per capita	
	Manuf.	Retail
	(2)	(3)
Mobile penetration × Post	-0.01**	0.01
	(0.00)	(0.01)
Observations	38,983	38,983
Municipality	✓	✓
Region × Year	✓	✓
Controls × Year	✓	✓

Online Appendix

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A1 Theoretical Framework

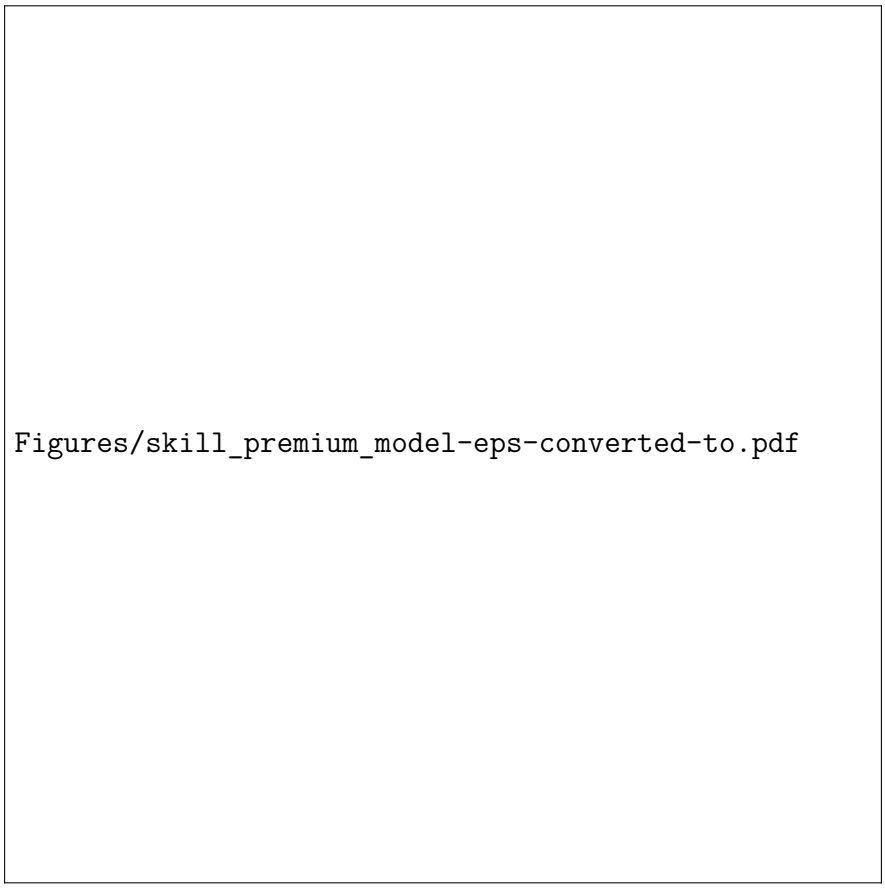
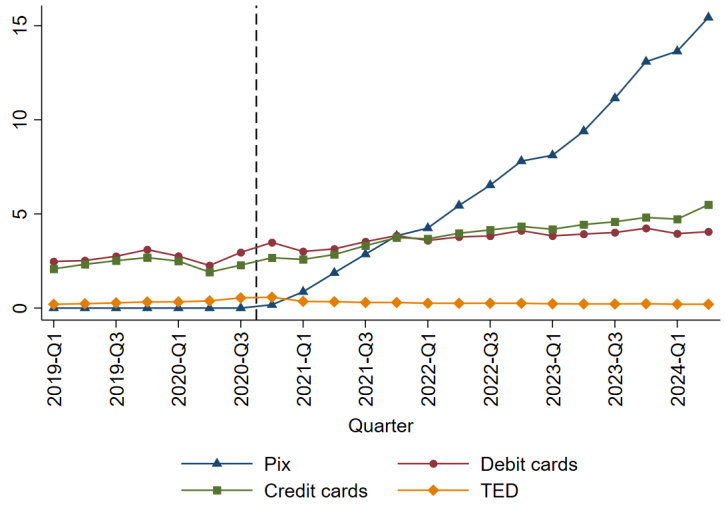


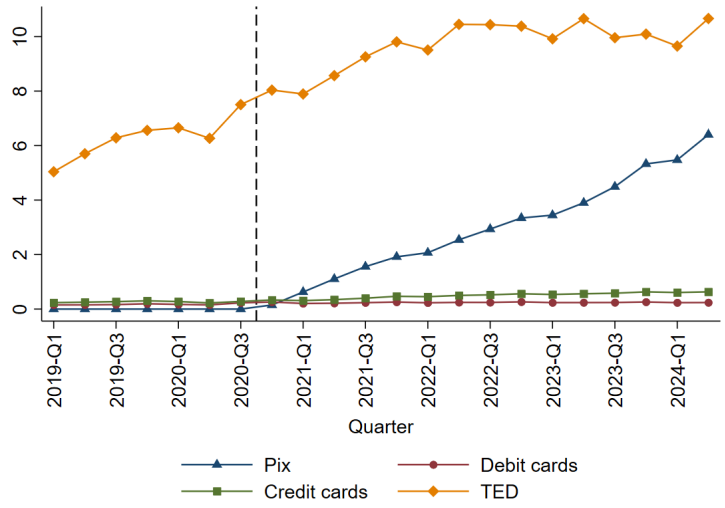
Figure A1 Impact of Reducing Transaction Costs τ on Skill Premium

This figure illustrates how reducing transaction costs (τ) affects the skill premium in a two-sector model with CES production technology. The figure plots equilibrium conditions for wages of low-skilled workers (w) and high-skilled workers (s) from two industries: a non-cash-intensive industry (x, blue line) and a cash-intensive industry (y, red lines). The solid blue line represents the equilibrium condition from industry x, which is unaffected by transaction costs. The red lines show the equilibrium condition from industry y under different transaction costs: the solid red line corresponds to high transaction costs (τ^A), while the dashed red line represents low transaction costs (τ^B). Points A and B denote the respective equilibrium points. The slope of the line connecting the origin to each equilibrium point is inversely related to the skill premium.

A2 Institutional Setting: Additional Details



Panel A. Quantity of Transactions



Panel B. Value of Transactions

Figure A2 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.

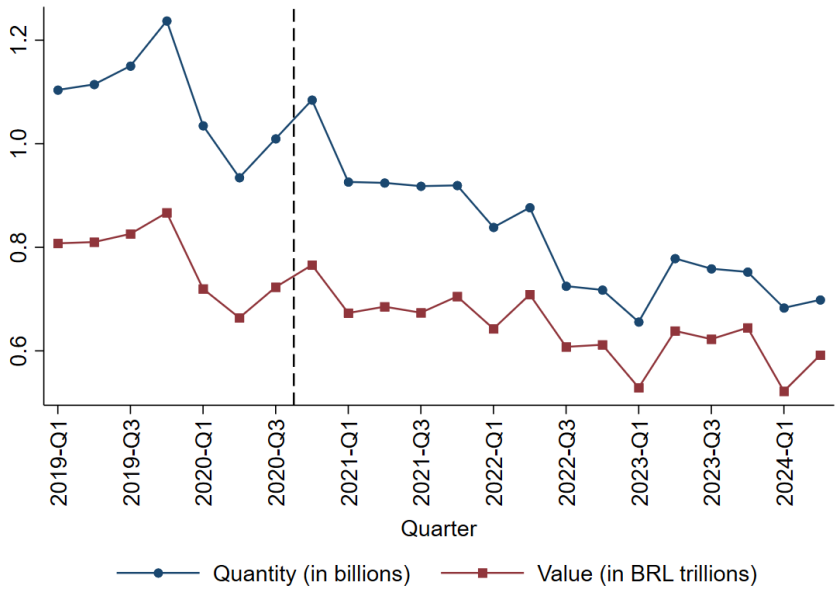


Figure A3 Evolution of Cash Withdrawals

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.