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 the timing of Pix's rollout. Our results indicate that a one standard deviation increase in mobile penetration leads to a 1.5 percent 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 by 1 percentage point. Further evidence suggests that increased small-business labor demand, amplified by local labor market frictions, drives these findings. Our results highlight that a technology's impact on wage inequality depends critically on the specific frictions it addresses and the skill composition of affected sectors.

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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)—which significantly reduce transaction costs, alleviate cash-management burdens, enable immediate settlements, and generate digital transaction records to enhance financial access. These features alleviate frictions particularly burdensome for small, cash-intensive businesses, potentially reshaping wage structures differently from production technologies.[1] We analyze Brazil's Pix system, launched by the Central Bank in 2020, which achieved unprecedented adoption and lowered transaction costs dramatically to one-tenth of credit card fees.[2] Contrary to conventional skill-biased technical change patterns, we find digital payments reduce wage inequality by substantially increasing wages for low-skilled workers in cash-intensive sectors, with effects amplified where low-skill labor is scarce.

[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 percent, compared to 2.2 percent 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.

Using comprehensive administrative data on formal workers and firms from 2015 to 2022, our primary identification strategy is a triple difference-in-differences (DiD) design exploiting variation in Pix's nationwide introduction timing, pre-existing mobile penetration across municipalities—which strongly predicts Pix adoption—and industry cash intensity. Our baseline approach compares wage changes in cash-intensive versus non-cash-intensive establishments within the same municipality before and after Pix adoption, isolating Pix's impact while controlling for local economic conditions and industry-specific trends. As a robustness check, we complement this with a triple DiD specification contrasting small versus large establishments.

Our baseline triple DiD design assumes that, without Pix, wage trends in cash-intensive versus non-cash-intensive establishments would have evolved similarly across municipalities with different levels of pre-treatment mobile penetration. 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-year fixed effects to control for time-varying local economic conditions, municipality-by-industry-by-establishment-group fixed effects to absorb time-invariant differences across establishment types within municipalities, and size-by-industry-by-year fixed effects to flexibly capture differential industry-specific trends across establishment sizes over time. Additionally, we confirm there are no differential pre-trends in wages between cash-intensive and non-cash-intensive establishments prior to Pix's introduction, providing support for the parallel trends assumption.

We find that following Pix's introduction, cash-intensive establishments in municipalities with higher mobile penetration experienced significant wage increases compared to non-cash-intensive establishments in the same municipalities. Specifically, our triple DiD estimates indicate that a one standard deviation increase in mobile penetration leads to a 1.5 percent wage increase in cash-intensive establishments relative to non-cash-intensive ones. Importantly, we find no evidence of pre-trends. Our results remain robust when using our alternative triple DiD specification comparing small versus large establishments, which shows that a one standard deviation increase in mobile penetration is associated with approximately 1.4

percent higher wages in small establishments relative to large establishments within the same municipality.

Given that our results show larger wage effects in sectors and establishments typically employing a high proportion of low-skill workers, we next examine the impact of Pix adoption on wage inequality. Small and medium-sized establishments in retail and services are especially reliant on low-skill labor compared to larger establishments. 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 one percentage point reduction in the wage gap. This decline in inequality notably contrasts with 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, municipalities with higher mobile penetration experienced significant employment growth in cash-intensive establishments—a 4 percent increase in active jobs—after Pix's introduction. Second, higher mobile penetration led to increased small-business entry in retail sectors (an additional 0.007 small retail firms per 1,000 population), with no similar effect observed in manufacturing or large establishments, suggesting that Pix adoption reduced entry barriers particularly for small firms in cash-intensive sectors. Third, the decline in the college wage premium is notably stronger—approximately one percentage point—in areas characterized by tighter low-skill labor markets, with no significant effect in regions where low-skill workers are abundant. This differential effect aligns with the mechanism that rising demand for low-skilled workers generates upward wage pressure when the local labor supply is constrained, thereby 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 heterogeneity we identify through our triple DiD design provides compelling evidence that effects operate primarily through direct mechanisms. By comparing cash-intensive versus non-cash-intensive establishments within the same municipality and controlling for local economic shocks, we find wage effects are concentrated in cash-intensive sectors. Additionally, our complementary triple DiD specification shows that small establishments that rely more on cash transactions experience significant wage increases. This systematic pattern of heterogeneity across sectors and establishment sizes strongly suggests that reduced payment frictions drive 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.[3]

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.

[3]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.[4]

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 $p_y = p \times (1 - \tau)$.[5] 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:

$$\max_{\{L_j, H_j\}} p_j Q_j - wL_j - sH_j \tag{1}$$

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-

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

[5] 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: 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.[6] Second, the regulation exempts individuals from transaction fees to foster financial inclusion.[7] Since many small firms use the owner's personal bank account for transactions, they have seen a

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

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

significant reduction in fees compared to traditional methods such as credit and debit cards or TED transfers (the electronic wire transfer available before Pix). Even when firms pay fees, they are substantially smaller than those of other methods. According to Duarte et al. (2022), merchants pay an average fee of 0.22 percent per Pix transaction, compared to 2.2 percent for credit card payments.

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 percent drop in the number of cash withdrawals (Figure A3 in the Online Appendix), indicating a smaller reliance on cash. Surveys from the Central Bank of Brazil confirm a decline in cash usage. While 60.2 percent of respondents identified cash as the most common payment method in 2018, this figure dropped to 41.7 percent in 2021 and further decreased to 22 percent in 2024.[8]

As a potential replacement for cash, Pix likely played a more prominent role in cash-intensive sectors that engage in a large number of small-value transactions with final consumers. Indeed, as shown in Appendix Table A1, between 2021 and 2023, the retail sector accounted for 32.8 percent of the total number of Pix transactions, followed by the services sector with 31.6 percent . Despite representing 64.4 percent of Pix transactions, these sectors contributed 19.5 percent of GDP in 2019. In contrast, the manufacturing sector, which contributed 27.4 percent of GDP in 2019, accounted for only 3.1 percent of Pix transactions.

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

[8] The figures come from the survey *O brasileiro e sua relação com o dinheiro*

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.[9] Second, we use matched employer-employee data from the Brazilian Ministry of Labor (*Relação Anual de Informações Sociais*, RAIS).[10] 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 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 percent (median 48 percent). The share of the population with access to 3G+ is 54 percent (median 53 percent).

4.2 Research Design

This paper investigates the labor market and distributional effects of instant payment systems, a major financial technology innovation that has rapidly diffused yet remains understud-

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

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

ied. We explore whether financial technologies reshape labor markets and wage structures similarly to production technologies or follow a distinct pattern. By reducing transaction costs in cash-intensive sectors, we hypothesize that instant payment systems could increase demand for workers, particularly low-skilled workers. Specifically, lower fees, improved cash flow management, and enhanced credit access may enable firms in these sectors to expand hiring, thereby increasing wages.

Our empirical approach uses a triple difference-in-differences design that exploits three distinct sources of variation. First, we leverage the timing of Pix's nationwide introduction in late 2020. Second, we exploit geographic variation in pre-existing mobile penetration across Brazilian municipalities, which strongly predicts the intensity of Pix adoption. Municipalities with a higher proportion of mobile devices with 3G or higher capability in 2019 were technologically better positioned to adopt the instant payment system, providing a plausibly exogenous variation in Pix adoption potential. Finally, our group dimension contrasts cash-intensive versus non-cash-intensive establishments (or small versus large firms), under the hypothesis that cash-intensive businesses would disproportionately benefit from reduced transaction costs and improved cash flow management enabled by Pix. Together, these three dimensions allow us to credibly isolate the impact of instant payment technology adoption on labor market outcomes.

We measure each municipality's exposure to instant payment technology using pre-Pix (2019) mobile penetration rates, calculated as follows:

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

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 prior to Pix's introduction, with darker shades indicating higher penetration rates. By using pre-Pix mobile penetration, our measure isolates variation in municipalities' capacity to adopt instant payments, avoiding endogenous changes in digital infrastructure that might have occurred in response to the technology's introduction.

To estimate Pix's causal impact on wages, we employ a triple-difference-in-differences (DiD) design that combines variation in the timing of Pix's introduction, municipalities' pre-existing mobile penetration, and establishment-level cash intensity. This strategy compares wage changes before and after Pix across municipalities with different mobile penetration levels and between cash-intensive and non-cash-intensive establishments within the same municipality. Specifically, we estimate:

$$Y_{kjct} = \beta \times (\text{Mobile Penetration}_c \times \text{Cash Intensive}_k \times \text{Post}_t) + \delta_{ct} + \delta_{kjc} + \delta_{kjt} + u_{kjct} \quad (7)$$

where Y_{kjct} is the average wage for establishment group k in industry j, municipality c, and year t. Mobile Penetration$_c$ measures the pre-Pix ratio of mobile devices with 3G or higher to population in municipality c. Cash Intensive$_k$ is an indicator equal to one for establishments in industries with above-median cash intensity, defined as the ratio of household purchases to total industry sales using the pre-Pix Brazilian input-output matrix. Post$_t$ is an indicator variable equal to one for periods after Pix's introduction (November 2020 onward).

The granular nature of our data allows us to include a rich set of fixed effects to address potential confounders: municipality-by-year fixed effects (δ_{ct}) control for local economic shocks varying by year; municipality-by-size-bin-by-industry fixed effects (δ_{kjc}) absorb time-invariant differences across establishment types within each municipality; and size-bin-by-industry-by-year fixed effects (δ_{kjt}) capture trends affecting specific industries and establishment sizes over time.[11] The coefficient of interest, β, captures the differential effect of mobile penetration on wages in cash-intensive establishments relative to non-cash-intensive establishments after the introduction of Pix, conditional on all the fixed effects. Standard errors are clustered at the municipality level to account for serial correlation.

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

Our identification strategy leverages heterogeneity in an industry's "cash intensity," defined as the ratio of household purchases to total industry sales using the pre-Pix Brazilian input-output matrix. This measure captures the degree to which industries rely on cash transactions and face payment frictions. According to Central Bank of Brazil data, around 77 percent of household retail transactions involved cash prior to Pix, compared to minimal usage for business-to-business or government payments. Table A1 further illustrates which industries rely heavily on small consumer payments. For instance, Retail accounts for 32.8 percent of all Pix transactions by quantity yet represents only 10.1 percent of GDP, indicating a high frequency of small-value consumer purchases. Accommodation and Food Services also appear disproportionately reliant on Pix transactions relative to their GDP share, aligning with the frequent, small-scale payments common in restaurants and hotels. By contrast, Manufacturing represents just 3.1 percent of Pix transactions but nearly 28 percent of GDP, consistent with predominantly larger, business-oriented transactions that historically rely less on cash. This variation supports our characterization that some industries—including retail, accommodation, and food services—are substantially more "cash-intensive" and thus likely to benefit the most from the reduced transaction costs and improved liquidity management that Pix offers.

The key identifying assumption underlying our triple difference-in-differences design is that in the absence of Pix, wage trends between cash-intensive and non-cash-intensive establishments would have evolved similarly in municipalities with high versus low mobile penetration, conditional on the fixed effects included in our specification. We test this assumption by examining pre-trends below.

One concern with our identification strategy is that mobile penetration might correlate with unobserved factors influencing wage trends.[12] For example, municipalities with higher

[12] We examine differences in pre-Pix characteristics across municipalities by mobile penetration level. Figure A4 shows unconditional differences (green estimates): higher-penetration municipalities are larger, more urban, and have higher wages and skill premia. However, these differences disappear when comparing municipalities within size and agricultural exposure deciles (red estimates). Nevertheless, our specification includes municipality-by-year fixed effects to control for local time-varying shocks, ensuring our estimates rely solely on within-municipality differences between cash-intensive and non-cash-intensive establishments.

mobile penetration might differ systematically in infrastructure, potentially biasing our estimates if these factors affect cash-intensive and non-cash-intensive establishments differently over time. To mitigate this issue, we include municipality-by-year fixed effects, absorbing local economic trends correlated with mobile penetration, and size-by-industry-by-year fixed effects to comprehensively control for sector-specific trends varying by establishment size over time. Our triple-difference estimator thus relies solely on differential wage changes between cash-intensive and non-cash-intensive establishments within the same municipality, compared across municipalities varying in pre-existing mobile penetration.

Another concern is the COVID-19 pandemic, which disrupted economic activity and may have affected municipalities differently. Our triple-difference design directly addresses this issue: municipality-by-year fixed effects control for local pandemic severity and related policy measures, while size-by-industry-by-year fixed effects fully capture national sector- and establishment-size-specific shocks. Any residual bias would thus require pandemic effects to systematically differ between cash-intensive and non-cash-intensive establishments and vary by municipal mobile penetration. Municipality-by-year fixed effects also control for other local economic policies varying during the sample period.

As a complementary strategy, we employ a triple difference-in-differences design exploiting variation in establishment size. We hypothesize that small establishments facing higher transaction costs and financial frictions benefit more from Pix than large ones. This approach isolates Pix's impact by comparing wage changes before and after its introduction across municipalities with varying mobile penetration and between small and large establishments within the same municipality, while controlling for local economic shocks. We estimate:

$$Y_{kjct} = \beta \times (\text{Mobile Penetration}_c \times \text{Small}_k \times \text{Post}_t) + \delta_{ct} + \delta_{kjc} + \delta_{kjt} + u_{kjct} \tag{8}$$

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 (defined by employment thresholds, e.g., fewer than 4 or fewer than 9 employees). This specification includes a comprehensive set of fixed effects: municipality-by-year fixed effects (δ_{ct}), municipality-by-size-bin-by-industry fixed effects (δ_{kjc}), and size-bin-by-industry-by-year fixed effects (δ_{kjt}). Again, standard errors are clustered at the municipality level. 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). Standard errors are clustered at the municipality level.

5 Main Results

In this section, we examine how Pix adoption affects local economies. First, we explore the relationship between pre-existing mobile penetration and Pix adoption. Next, we analyze the effects of Pix on wages across establishments, focusing on differences by cash intensity and establishment size. Finally, we investigate the implications for wage inequality, exploring whether Pix disproportionately benefits low-skilled workers.

5.1 Pix Adoption

We begin by examining the relationship between our treatment variable—pre-existing mobile penetration at the municipality level—and subsequent Pix adoption. Figure 2 reports coefficient estimates from regressions of Pix usage on mobile penetration, controlling for municipality fixed effects, region-by-year fixed effects, and key municipality characteristics (e.g., size, agricultural exposure) interacted with time. 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.

5.2 Wage Effects

5.2.1 Wage Effects by Cash Intensity

This section analyzes the impact of Pix adoption on wages in Brazil using a triple difference-in-differences framework. Our approach exploits variation across municipalities in mobile penetration and establishment-level cash intensity. Table 2 reports the primary estimates, with the dependent variable defined as the log of average wages. The triple interaction term (Mobile Penetration $\times$ Cash Intensive $\times$ Post) captures Pix's wage effect by comparing cash-intensive and less cash-intensive establishments across municipalities with differing mobile penetration before and after Pix's rollout. To address potential confounders, our specification includes municipality-by-year, municipality-by-size-bin-by-industry, and size-bin-by-industry-by-year fixed effects. These fixed effects control for time-varying local economic conditions, establishment-specific heterogeneity within municipalities, and differential industry-specific trends across establishment sizes over time.

In Column (1), the triple interaction coefficient is 0.015, indicating that a one standard deviation increase in mobile penetration leads to a 1.5 percent (around BRL 30.3, or USD 7.7) monthly wage increase for cash-intensive establishments relative to non-cash-intensive ones post-Pix. In Column (2), we introduce municipality-by-year fixed effects alongside municipality-by-size-bin-by-industry and size-bin-by-industry-by-year fixed effects; the estimate remains similar (1.2 percent) and highly significant, demonstrating robustness to a more rigorous set of controls for local economic conditions and differential trends.

Figure 3 plots dynamic effects from our triple difference specification using establishment cash intensity, with coefficients normalized to 2019 as the baseline. Pre-Pix coefficients (2015–2019) are small, statistically insignificant, and show no differential trends, supporting the parallel trends assumption. After Pix's introduction, a wage differential gradually emerges, reaching approximately 2 percent by 2022. These results indicate that Pix adoption significantly increased wages in cash-intensive establishments, particularly in municipalities with higher mobile penetration. The timing of this substantial increase in wage effects closely parallels the rise in Pix adoption shown in Figure 2, strengthening our causal interpretation that instant payment technology significantly increased wages in cash-intensive establishments.

5.2.2 Wage Effects by Establishment Size

To further validate our findings, we implement a complementary triple difference-in-differences strategy leveraging variation in establishment size within municipalities. This approach is motivated by the idea that small establishments typically face higher transaction fees and greater financial frictions and, therefore, could benefit disproportionately from instant payment technology. Table 3 presents the results using two definitions of small establishments. For establishments with up to 4 employees (Columns (1)-(2)), a one standard deviation increase in mobile penetration is associated with a 1.8 percent wage increase with standard controls, and the effect remains robust at 1.6 percent (around BRL 32.32, or USD 8.21) when adding municipality-by-year fixed effects. For establishments with up to 9 employees (Columns (3)-(4)), the effects are 1.4 percent and 1.2 percent, respectively. The monotonic pattern, with larger effects for smaller establishments, is consistent with our mechanism that Pix particularly benefits the smallest firms facing the highest transaction barriers.

Figure 4 plots the dynamic effects from our triple difference specification based on establishment size (up to 9 employees), with coefficients normalized to 2019 as the baseline year. Pre-Pix coefficients (2015–2019) are small, statistically insignificant, and exhibit no differential trends, further supporting the parallel trends assumption. Post-Pix, the wage differential emerges clearly and increases sharply in 2022, reaching more than 2 percent by the end of the sample period. For robustness, Figure A5 in the appendix shows similar dynamic effects using the more restrictive definition of small establishments (up to 4 employees). These findings align with our cash-intensity results, further demonstrating the robustness of our main findings on Pix's wage impacts.

5.3 Effects on Wage Inequality

Having shown that Pix adoption led to larger wage increases in cash-intensive sectors and small establishments, we now explore the implications for wage inequality. According to our model, instant payment technologies reduce wage inequality by decreasing the skill premium, provided that cash-intensive sectors disproportionately employ low-skill workers. To examine whether this condition holds in our setting, we begin by analyzing workforce composition across industries and establishment sizes.

Figure 5 Panel A provides compelling evidence that this condition is satisfied. Small retail establishments are particularly intensive in low-skill workers, allocating 91 percent of payroll to workers without college degrees, compared to only 58 percent in large retail establishments. Similarly, in services, the payroll share for low-skill workers is 61 percent in small establishments versus 37 percent in large ones. These sectors are particularly important for understanding the impact of Pix, as retail and services combined account for 52 percent of Pix transaction value and over 64 percent of total transactions (Table A1). Manufacturing, by contrast, exhibits a more uniform skill composition across establishment sizes and accounts for just 3.1 percent of Pix transactions, despite contributing 27.7 percent of GDP.[13]

Given this workforce composition, our model predicts that as Pix reduces transaction costs, wage gains should disproportionately benefit low-skill workers, thus compressing the college wage premium. We examine whether this mechanism translates into lower observed wage inequality at the municipality level.

To test this prediction, we measure inequality using the college wage premium, defined

[13]Figure 5 Panel B further illustrates substantial differences in the college wage premium across sectors and establishment sizes before Pix's introduction. For example, in retail, the college premium was approximately 83 percent in small firms, compared to 336 percent in large establishments.

as the difference in log average wages between college and non-college workers at the municipality level:

$$\text{College Premium}_c = \ln(\text{avg. wage}_{\text{college}}) - \ln(\text{avg. wage}_{\text{non-college}}) \tag{9}$$

Figure 6 confirms our model's prediction using a difference-in-differences (DiD) specification at the municipality level. Specifically, we regress the college premium on standardized mobile penetration, controlling for municipality fixed effects, region-by-year fixed effects, and municipality characteristics interacted with year fixed effects. This approach isolates the effect of Pix adoption on wage inequality while accounting for time-invariant municipality traits and region-specific trends. The estimates show no differential trends prior to Pix's introduction, supporting the 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. Table 4 Column (1) quantifies this effect, showing that a one standard deviation increase in mobile penetration is associated with a statistically significant 1 percentage point decline in the college premium following Pix adoption.

The decline in the college premium 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.

6 Mechanisms

In this section, we explore the mechanisms underlying our main findings. We first examine whether instant payment adoption stimulates labor demand among small businesses, particularly in cash-intensive sectors. Next, we analyze how local labor market frictions amplify these effects, emphasizing the role of low-skill labor scarcity. Finally, we discuss alternative explanations.

6.1 Labor Demand Effects

Our main results show that Pix adoption led to higher wages in small establishments and cash-intensive sectors, particularly benefiting low-skilled workers. These patterns suggest that Pix may operate through a labor demand channel. According to our model, when transaction costs decrease in cash-intensive sectors (through Pix adoption), the effective price received by firms increases, which should stimulate firm entry and expansion. This would increase demand for workers, particularly in sectors like retail and services that are both cash-intensive and heavily reliant on low-skilled labor. If local labor markets exhibit frictions that prevent immediate worker reallocation, this increased demand should translate into higher equilibrium wages. To evaluate this mechanism, we first examine whether Pix increases labor demand in cash-intensive sectors.

To test this hypothesis, we examine employment growth using a triple difference-in-differences approach comparing cash-intensive and non-cash-intensive industries. Figure 7 illustrates that cash-intensive sectors experienced significantly greater job growth after Pix. Table 5 shows that a one standard deviation increase in mobile penetration raises employment in cash-intensive industries by 4.0 percent (Column (1)). This effect remains robust at 3.3 percent when adding municipality-by-year, municipality-by-size-by-industry, and size-by-industry-by-year fixed effects, strongly supporting the hypothesis that Pix adoption stimulated employment in cash-intensive sectors.

Given that job growth in cash-intensive sectors could stem from either the expansion of existing firms or the entry of new ones, we next examine whether Pix adoption stimulated new business formation. Pix may lower entry barriers by reducing transaction costs and enhancing cash flow management, particularly benefiting small, cash-intensive firms. Figure 8 presents entry patterns by sector and firm size. After Pix's introduction, municipalities with higher mobile penetration saw significant increases in small retail firm entry (Panel A). In contrast, entry rates remained unchanged for small manufacturing firms (Panel B) and large firms across both sectors (Panels C and D). Table 6 quantifies these results, showing that a one standard deviation increase in mobile penetration increased small retail firm entry per 1,000 population by 0.007, with no significant effects elsewhere. These findings suggest that Pix adoption reduced barriers to entry by lowering transaction costs, particularly benefiting small firms in cash-intensive sectors. This increase in firm creation likely contributed to greater local labor demand, which is consistent with our findings.

The heterogeneity in employment and wage effects across industries with varying cash intensity helps rule out alternative explanations. If wage increases stemmed from general technological improvements or aggregate demand, we would expect similar effects across sectors, irrespective of cash intensity. Instead, our triple-difference estimates, which include municipality-by-year fixed effects to control for local time-varying factors and size-bin-by-industry-by-year fixed effects to control for sector- and establishment-size-specific trends, show that effects are concentrated exclusively in cash-intensive sectors, with no evidence of impact in less cash-dependent industries such as manufacturing. These results strongly suggest reduced payment frictions drive our findings.

These findings align closely with the predictions of our model. By reducing transaction costs, Pix effectively raises the net price received by firms in cash-intensive sectors. According to our model, this should stimulate greater demand for low-skilled labor, particularly in industries such as retail and services. Our empirical findings support this interpretation, showing increased employment and firm entry concentrated precisely in these sectors.

6.2 Local Labor Market Frictions

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

Figure 9 illustrates how the decline in the college premium varies systematically with local labor market tightness. Panel A shows that in areas where low-skill workers are relatively scarce (above-median labor market tightness), the college premium declines significantly by approximately one percentage point following Pix adoption. In contrast, Panel B reveals that areas with abundant low-skill workers experience a negligible and statistically insignificant effect. Table 4 quantifies how Pix adoption affects the college premium across labor market conditions. Column (2) shows a one standard deviation increase in mobile penetration reduces the premium by an additional 1.0 percentage points in tight labor markets but has no significant effect in abundant ones. The difference is statistically significant ($p < 0.01$). These results strongly indicate that the wage effects of Pix are amplified in areas where low-skill labor is scarce.

These 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, firms—particularly small establishments in cash-intensive sectors—must offer higher wages to attract workers, leading to larger declines in the college premium. 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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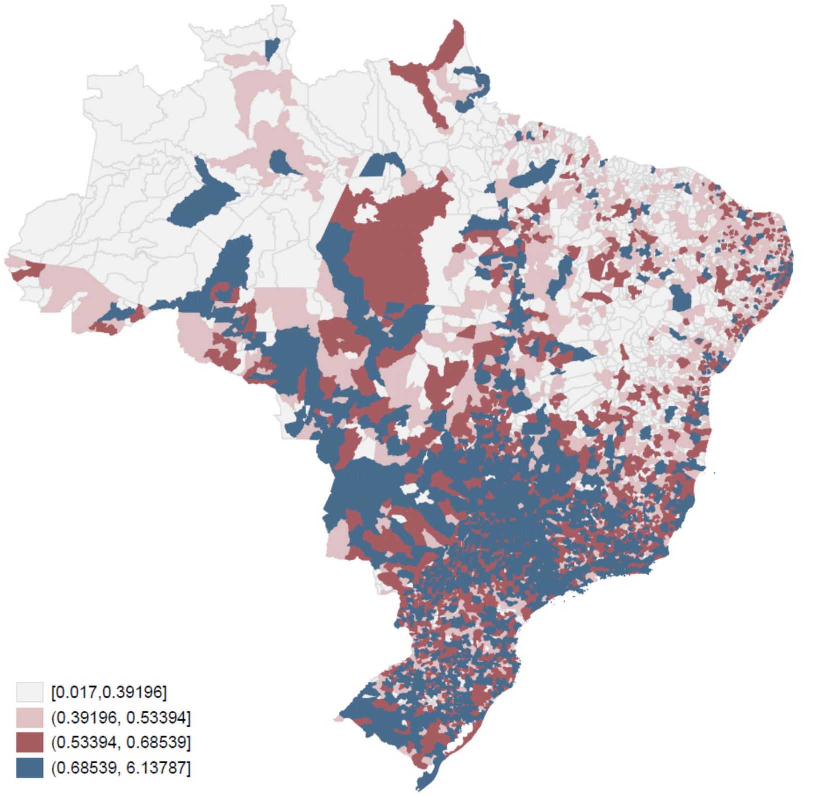
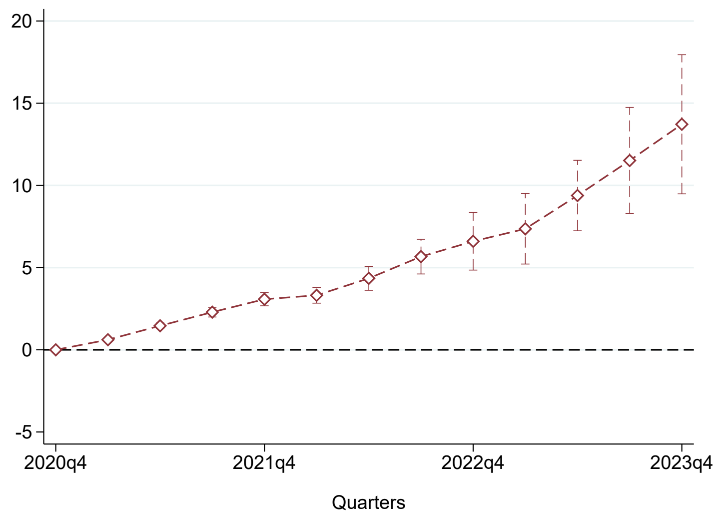
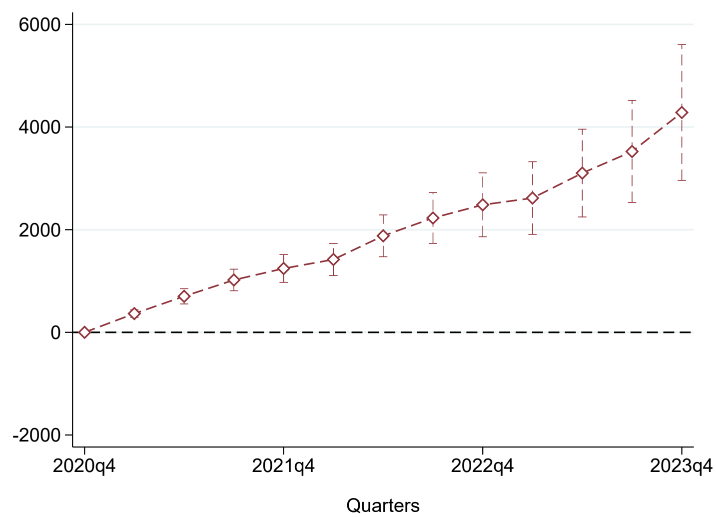


Figure 1 Geographic Distribution of Mobile Technology Penetration

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 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. Number of Transactions per Capita



Panel B. Value of Transactions per Capita

Figure 2 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 the 2019 population, while Panel B uses the value of Pix transactions divided by the 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.

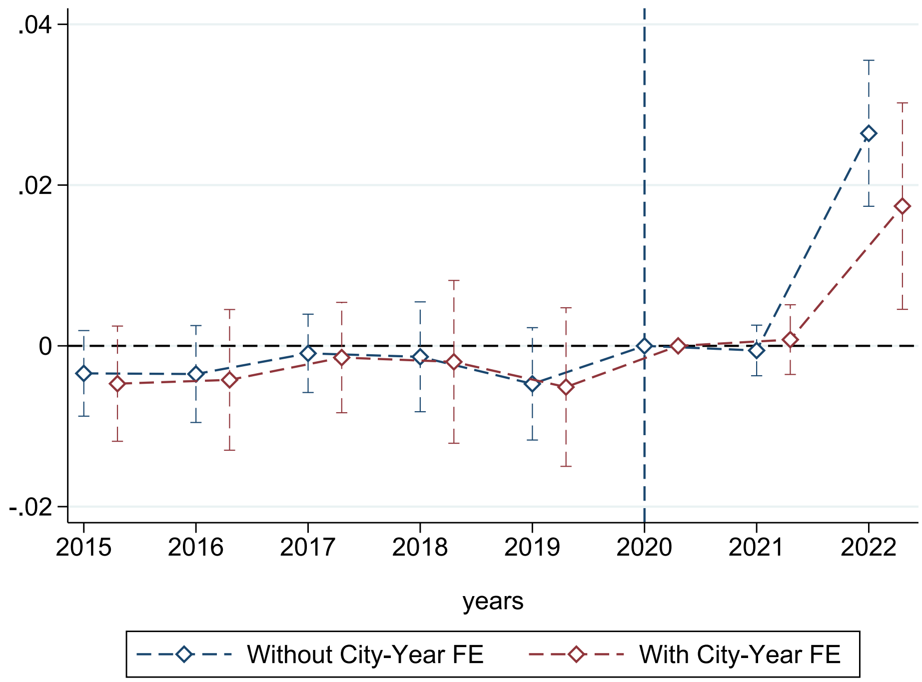


Figure 3 Triple Difference-in-Differences: The Effect of Mobile Penetration on Wages by Cash Intensity

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 in cash-intensive versus non-cash-intensive establishments around the introduction of Pix in late 2020. Cash intensity is defined using the Brazilian input–output matrix as the ratio of household purchases to industry total sales, with sectors above the median ratio classified as cash-intensive. The model interacts mobile penetration with an indicator for cash-intensive sectors and includes fixed effects for municipality-by-industry-by-size bin, size bin-by-industry-by-year, region-by-year, and municipality characteristics interacted with year. A version of the specification that additionally includes municipality-by-year fixed effects is depicted by the red dashed line. Regressions are weighted by municipality population, with standard errors clustered at the municipality level and 95% confidence intervals shown by dashed lines. Mobile penetration is standardized and winsorized at the 1% level. The sample period is 2015–2022.

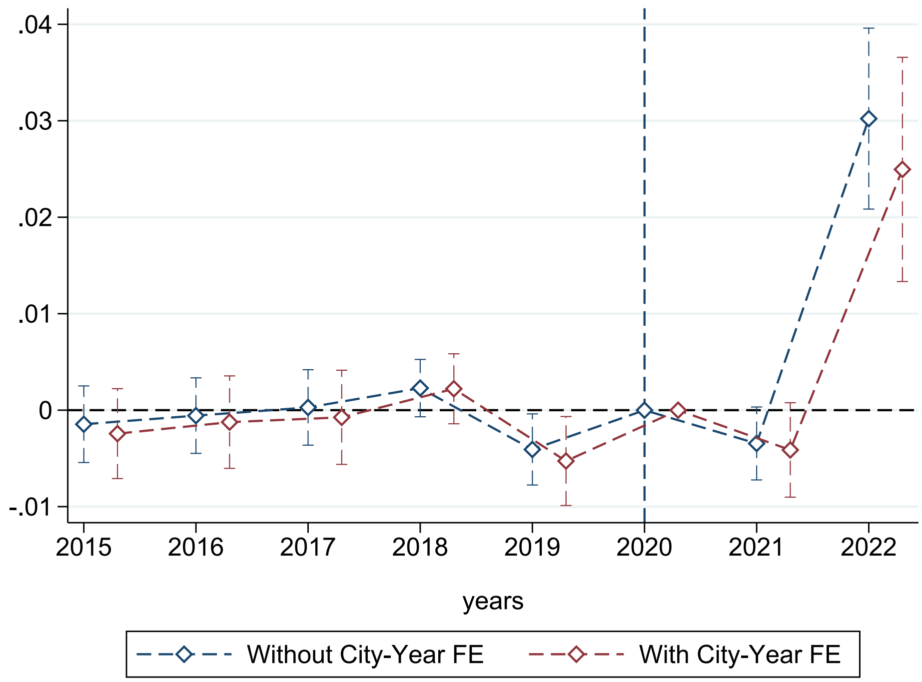


Figure 4 Triple Difference-in-Differences: The Effect of Mobile Penetration on Wages by Establishment Size

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 up to 9 employees. The model interacts standardized mobile penetration with an indicator for small establishments and includes fixed effects for municipality-by-year, size bin-by-industry-by-year, and municipality-by-size-bin-by-industry. The dependent variable is the logarithm of average monthly wages at the municipality-industry-size-bin-year level. Regressions are weighted by municipality population, with standard errors clustered at the municipality level and 95% confidence intervals shown by dashed lines. Mobile penetration is standardized and winsorized at the 1% level. The sample period is 2015–2022.

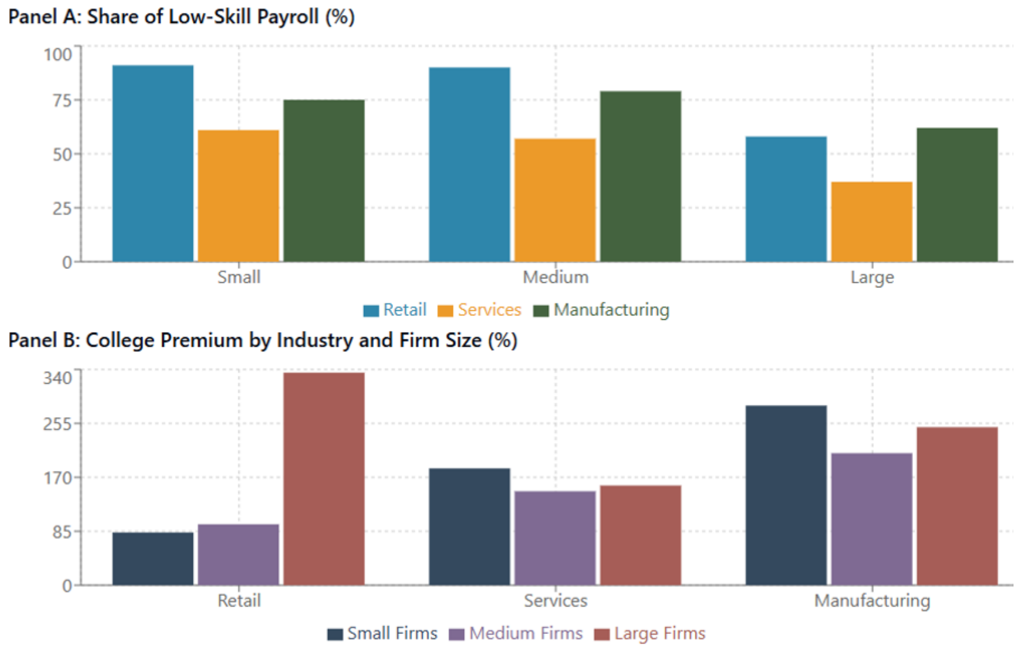


Figure 5 Skill Composition and Wage Patterns by Industry and Firm Size

This figure presents the relationship between skill composition, wages, and firm characteristics across various 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 are defined as having up to 9 employees, medium firms as having 10–249 employees, and large firms as having 250 or more employees. Panel B shows the college wage premium (calculated as the percentage increase in wages for college-educated workers over those of non-college-educated workers) by industry and firm size. Base monthly wages (in reais) for low-skill workers are: retail (1,387), services (1,622), and manufacturing (1,839). The data are from RAIS employer-employee matched data for 2019. The bars display results separately for the retail (blue), services (orange), and manufacturing (green) sectors across various firm size categories.

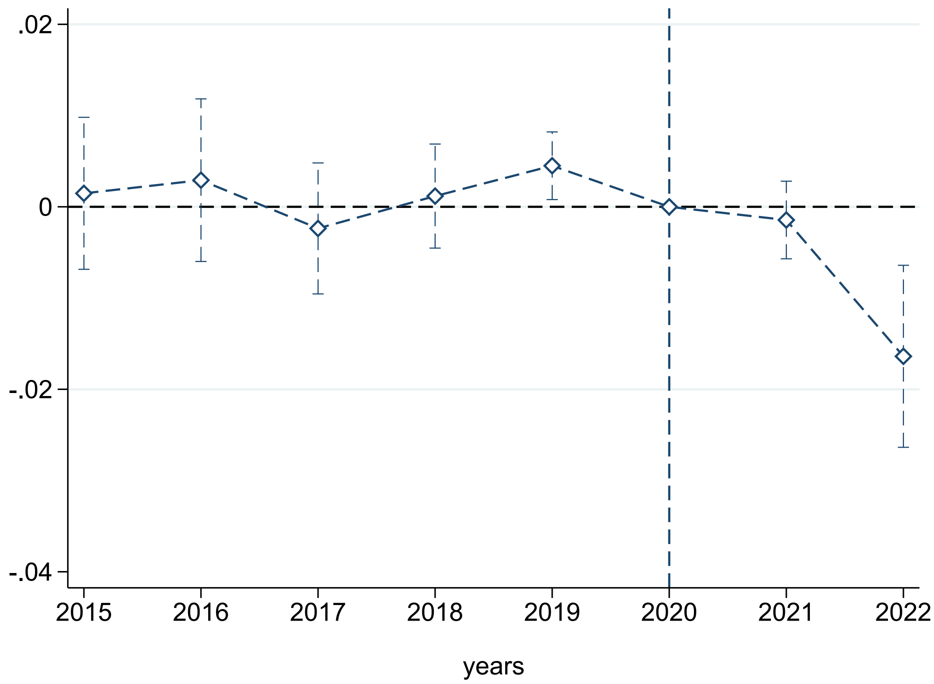


Figure 6 The Effect of Mobile Penetration on College Wage Premium

This figure plots the estimated yearly coefficients from a regression of the college wage premium on mobile penetration at the municipality level around the introduction of Pix in 2020. The college wage premium is defined as the difference in the logarithm of average monthly wages between college-educated and non-college-educated workers within each municipality-year. The regression specification includes municipality fixed effects, region-by-year fixed effects, and municipality characteristics interacted with year as controls. A vertical dashed line marks the introduction of Pix in 2020. Regressions are weighted by municipality population, with standard errors clustered at the municipality level and 95% confidence intervals shown by dashed lines around the point estimates. Mobile penetration is standardized and winsorized at the 1% level. The sample period is 2015–2022.

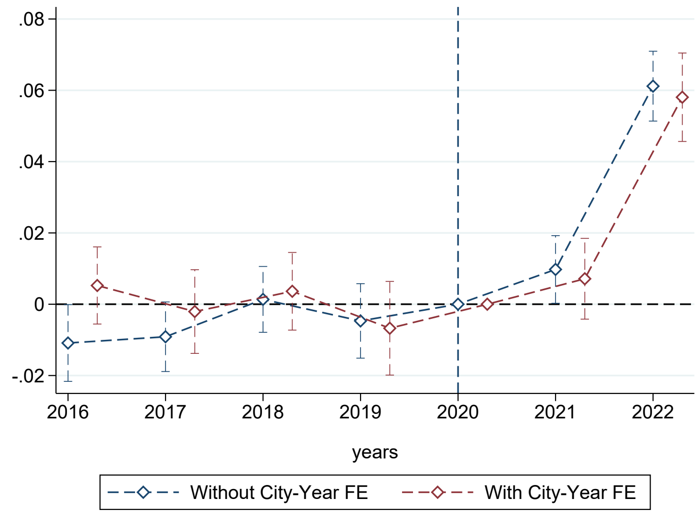
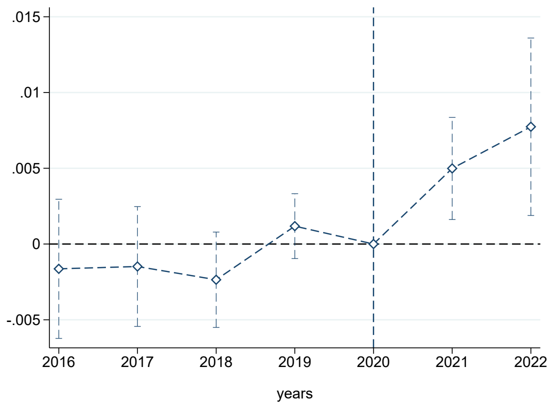
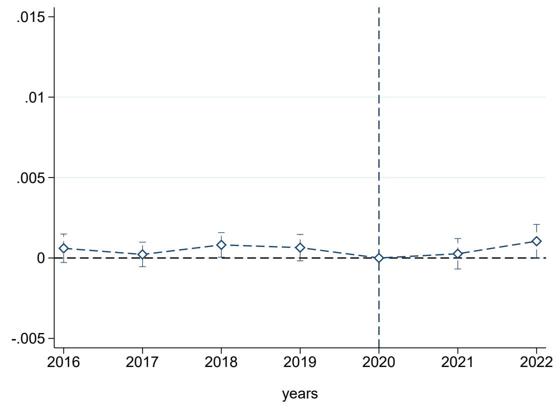


Figure 7 Triple Difference-in-Differences: The Effect of Mobile Penetration on the Number of Active Jobs by Cash Intensity

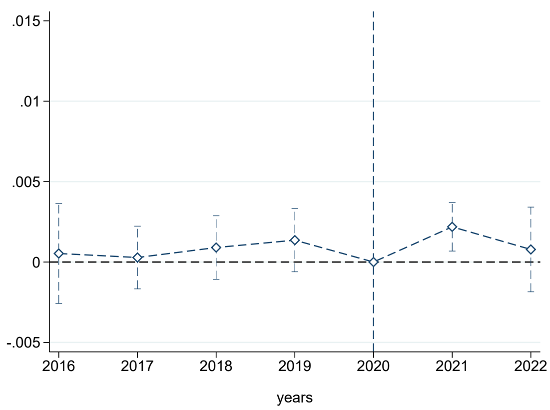
This figure plots the estimated yearly coefficients from a triple difference-in-differences specification that measures the differential effect of mobile penetration on the delta logarithm of the number of active jobs in highly cash-intensive versus less cash-intensive industries around the introduction of Pix in late 2020. Cash intensity is defined using the Brazilian input–output matrix as the ratio of household purchases to total industry sales, with industries above the median ratio classified as highly cash-intensive. The model interacts standardized mobile penetration with an indicator for highly cash-intensive industries and includes fixed effects for municipality-by-size-bin-by-industry, size bin-by-industry-by-year, region-by-year, and municipality characteristics interacted with year. A version of the specification that additionally includes municipality-by-year fixed effects is depicted by the red dashed line. Regressions are weighted by municipality population, with standard errors clustered at the municipality level and 95% confidence intervals shown by dashed lines. Mobile penetration is standardized and winsorized at the 1% level. The sample period is 2015–2022.



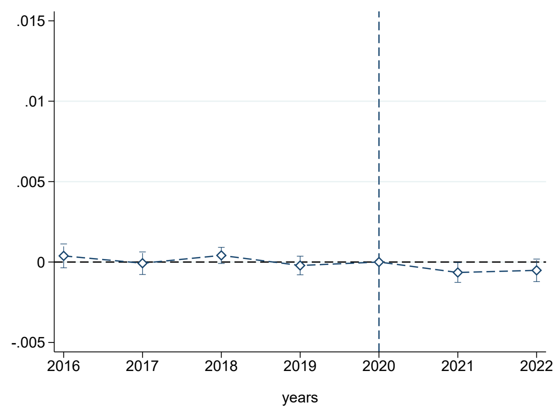
Panel A. Small Retail



Panel B. Small Manufacturing



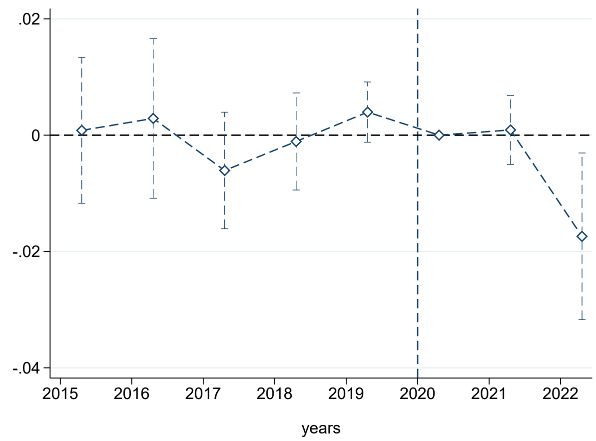
Panel C. Large Retail



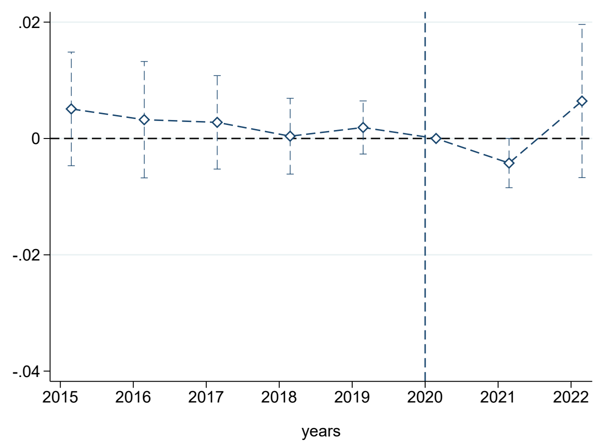
Panel D. Large Manufacturing

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

This figure plots the estimated yearly coefficients from a regression of the number of firm entrants per 1,000 population on mobile penetration at the municipality level around the introduction of Pix in 2020, estimated separately for retail and manufacturing industries and by firm size. Small firms (Panels A and B) are defined as those with annual sales between USD 70,000 and USD 970,000, and large firms (Panels C and D) as those with annual sales exceeding USD 970,000. The regression specification includes municipality fixed effects, region-by-year fixed effects, and municipality characteristics interacted with year as controls. A vertical dashed line marks the introduction of Pix in 2020. Dashed lines around the point estimates represent 95% confidence intervals based on municipality-level clustered standard errors. Regressions are weighted by municipality population. Mobile penetration is standardized and winsorized at the 1% level. The sample period is 2016–2022.



Panel A. Low-Skill Scarce



Panel B. Low-Skill Abundant

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

This figure plots the estimated yearly coefficients from a difference-in-differences regression of the college wage premium on mobile penetration at the municipality level around the introduction of Pix in 2020, separately estimated for areas with different levels of labor market tightness. The college wage premium is defined as the difference in the logarithm of average monthly wages between college-educated and non-college-educated workers within each municipality-year. Labor market tightness is measured as the ratio of job vacancies to low-skill workers in each municipality. Panel A shows the estimates for municipalities with above-median labor market tightness (lower availability of low-skill workers), while Panel B presents the estimates for municipalities with below-median labor market tightness (higher availability of low-skill workers). The regression specification includes municipality fixed effects, region-by-year fixed effects, and municipality characteristics interacted with year as controls. A vertical dashed line marks the introduction of Pix in 2020. Dashed lines around the point estimates represent 95% confidence intervals based on municipality-level clustered standard errors. Regressions are weighted by municipality population. Mobile penetration is standardized and winsorized at the 1% level. The sample period is 2015–2022.

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 a college degree. The average wage is the mean monthly wage across all workers in the municipality. The College premium is calculated as the difference in average monthly wages between high-skill and low-skill workers.

	(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
College premium	1,615	1,481	781	5,570

Table 2 Triple Difference-in-Differences: The Effect of Mobile Penetration on Average Wages by Cash Intensity

This table presents triple difference-in-differences estimates of the differential effect of mobile penetration on the average wages in cash-intensive versus non-cash-intensive establishments following the introduction of Pix in late 2020. The dependent variable is the logarithm of average monthly wages. Mobile penetration is defined as the ratio of mobile devices with 3G or higher capability to total municipal population. Cash intensity is defined using the Brazilian input-output matrix as the ratio of household purchases to total industry sales. The key coefficient of interest, Mobile penetration × Cash-intensive industry × Post, measures how the effect of mobile penetration on wages varies with cash intensity. The specification includes fixed effects for municipality-by-size-bin-by-industry and size-bin-by-industry-by-year in both columns, region-by-year and municipality characteristics interacted with year in Column (1), and municipality-by-year in Column (2), the latter to control for time-varying local shocks. Regressions are weighted by municipality population, with standard errors clustered at the municipality level reported in parentheses. Mobile penetration is standardized and winsorized at the 1% level. The sample period is 2015–2022. *p<0.01, p<0.05, *p<0.1.

	(1)	(2)
Mobile penetration × Cash intensive × Post	0.015***	0.012***
	(0.002)	(0.002)
Observations	1,772,864	1,772,857
Municipality × Size × Industry	✓	✓
Size × Industry × Year	✓	✓
Region × Year	✓	✗
Controls × Year	✓	✗
Municipality × Year	✗	✓

Table 3 Triple Difference-in-Differences: The Effect of Mobile Penetration on Average Wages by Establishment Size

This table presents triple difference-in-differences estimates of the differential effect of mobile penetration on average wages between small and large establishments following the introduction of Pix in late 2020. The dependent variable is the logarithm of average monthly wages. Mobile penetration is defined as the ratio of mobile devices with 3G or higher capability to total municipal population. In Columns (1) and (2), small establishments are defined as those with up to 4 employees, while in Columns (3) and (4), small establishments are defined as those with up to 9 employees. The key coefficient of interest, Mobile penetration × Small establishment × Post, measures how the effect of mobile penetration on wages varies with establishment size. The specification includes fixed effects for municipality-by-size-bin-by-industry and size-bin-by-industry-by-year in all columns, region-by-year and municipality characteristics interacted with year in Columns (1) and (3), and municipality-by-year in Columns (2) and (4), the latter to control for time-varying local shocks. Regressions are weighted by municipality population, with standard errors clustered at the municipality level reported in parentheses. Mobile penetration is standardized and winsorized at the 1% level. The sample period is 2015–2022. *p<0.01, p<0.05, *p<0.1.

	Up to 4		Up to 9	
	(1)	(2)	(3)	(4)
Mobile penetration × Small establishment × Post	0.018***	0.016***	0.014***	0.012***
	(0.003)	(0.004)	(0.002)	(0.003)
Observations	1,772,857	1,772,857	1,772,857	1,772,857
Municipality × Size × Industry	✓	✓	✓	✓
Size × Industry × Year	✓	✓	✓	✓
Region × Year	✗	✗	✓	✗
Controls × Year	✓	✗	✓	✗
Municipality × Year	✗	✓	✗	✓

Table 4 The Effect of Mobile Penetration on College Wage Premium

This table presents difference-in-differences estimates of the effect of mobile penetration on the college wage premium following the introduction of Pix in late 2020. The dependent variable is the college wage premium, defined as the difference in the logarithm of average monthly wages between college-educated and non-college-educated workers within each municipality-year. Mobile penetration is defined as the ratio of mobile devices with 3G or higher capability to total municipal population. Labor market tightness is measured as the ratio of job vacancies to low-skill workers in each municipality, with low-skill scarce defined as a dummy for municipalities with above-median tightness and low-skill abundant for below-median tightness. Column (1) estimates the overall effect, while Column (2) includes an interaction with labor market tightness to capture differential effects across labor market conditions. The specification includes fixed effects for municipality, region-by-year, and municipality characteristics interacted with year. Regressions are weighted by municipality population, with standard errors clustered at the municipality level reported in parentheses. Mobile penetration is standardized and winsorized at the 1% level. The sample period is 2015–2022. *p<0.01, p<0.05, *p<0.1.

	(1)	(2)
Mobile penetration × Post	-0.010***	
	(0.004)	
Mobile penetration × Low-skill scarce × Post		-0.010***
		(0.004)
Mobile penetration × Low-skills abundant × Post		0.001
		(0.004)
p-value (scarce = abundant)		[0.000]
Observations	44,501	44,501
Municipality	✓	✓
Region × Year	✓	✓
Controls × Year	✓	✓

Table 5 Triple Difference-in-Differences: The Effect of Mobile Penetration on Active Jobs by Cash Intensity

This table presents triple difference-in-differences estimates of the differential effect of mobile penetration on active jobs in cash-intensive versus non-cash-intensive establishments following the introduction of Pix in late 2020. The dependent variable is the delta logarithm of the number of active jobs. Mobile penetration is defined as the ratio of mobile devices with 3G or higher capability to total municipal population. Cash intensity is defined using the Brazilian input-output matrix as the ratio of household purchases to total industry sales, with sectors above the median ratio classified as cash-intensive. The key coefficient of interest, Mobile penetration × Cash-intensive industry × Post, measures how the effect of mobile penetration on active jobs varies with cash intensity. The specification includes fixed effects for municipality-by-size-bin-by-industry, size-bin-by-industry-by-year, and municipality characteristics interacted with year in both columns, region-by-year and municipality characteristics interacted with year in Column (1), and municipality-by-year in Column (2), the latter to control for time-varying local shocks. Regressions are weighted by municipality population, with standard errors clustered at the municipality level reported in parentheses. Mobile penetration is standardized and winsorized at the 1% level. The sample period is 2015–2022. *p<0.01, p<0.05, *p<0.1.

	(1)	(2)
Mobile penetration × Cash intensive × Post	0.040***	0.033***
	(0.003)	(0.003)
Observations	1,356,319	1,356,319
Municipality × Size × Industry	✓	✓
Size × Industry × Year	✓	✓
Region × Year	✓	✗
Controls × Year	✓	✗
Municipality × Year	✗	✓

Table 6 The Effect of Mobile Penetration on Firm Entry by Size and Industry

This table presents difference-in-differences estimates of the effect of mobile penetration on firm entry by size and industry following the introduction of Pix in late 2020. The dependent variable is the number of firm entrants per 1,000 population. Mobile penetration is defined as the ratio of mobile devices with 3G or higher capability to total municipal population. Columns (1) and (2) estimate the effect for small firms (with annual sales between USD 70,000 and USD 970,000) and large firms (with annual sales above USD 970,000) in the retail sector, respectively, while Column (3) estimates the effect for all firms in the manufacturing sector. The key coefficient of interest, Mobile penetration × Post, measures how mobile penetration affects firm entry. The specification includes fixed effects for municipality, region-by-year, and municipality characteristics interacted with year. Regressions are weighted by municipality population, with standard errors clustered at the municipality level reported in parentheses. Mobile penetration is standardized and winsorized at the 1% level. The sample period is 2015–2022. *p<0.01, p<0.05, *p<0.1.

	Num. Entrants per capita		
	Retail		Manuf.
	Small (1)	Large (2)	Small and Large (3)
Mobile penetration × Post	0.007** (0.001)	0.001 (0.003)	-0.000 (0.000)
Observations	38,948	38,948	38,948
Municipality	✓	✓	✓
Region × Year	✓	✓	✓
Controls × Year	✓	✓	✓

Online Appendix

A1 Theoretical Framework

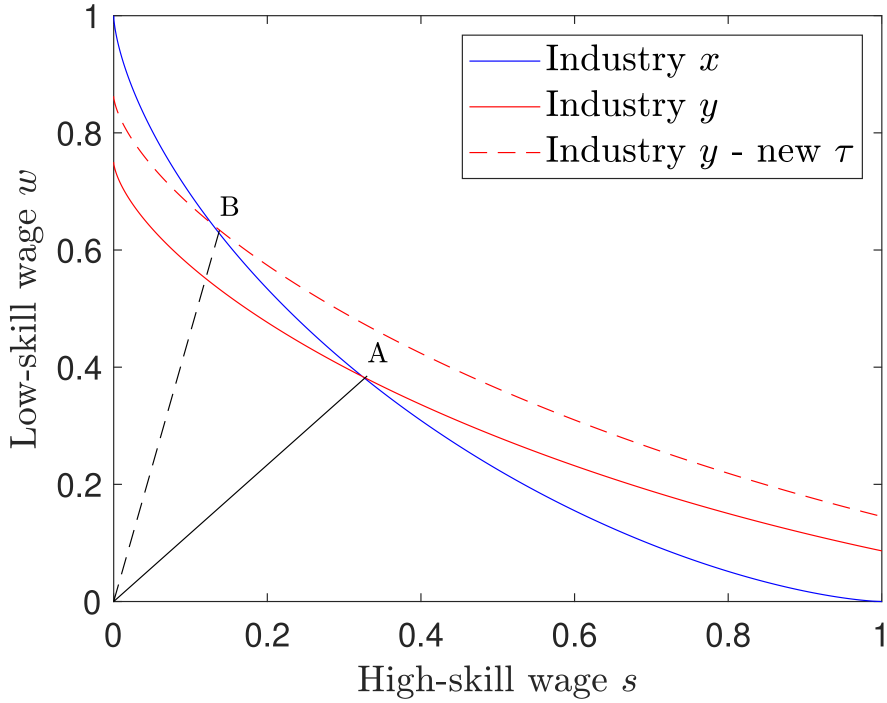
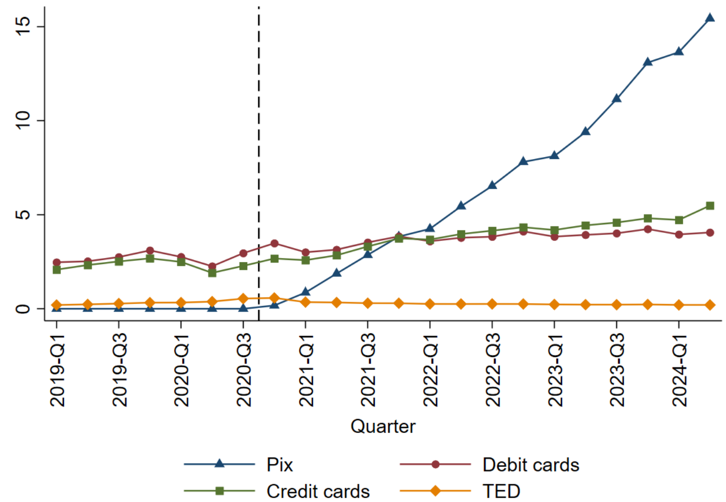


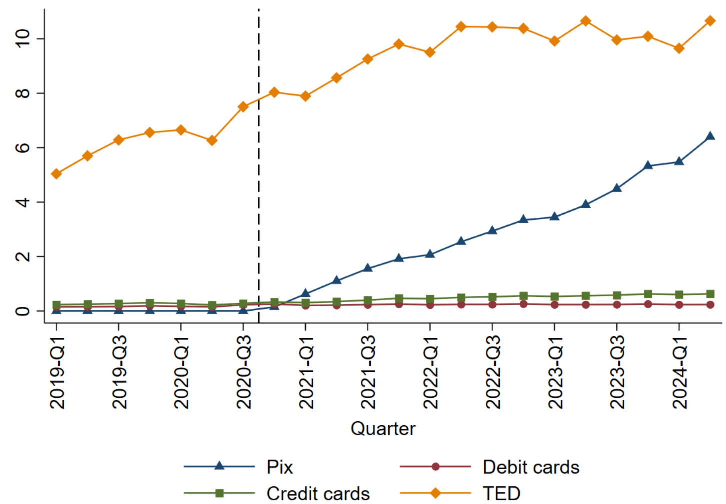
Figure A1 Impact of Reducing Transaction Costs τ on Skill Premium

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.

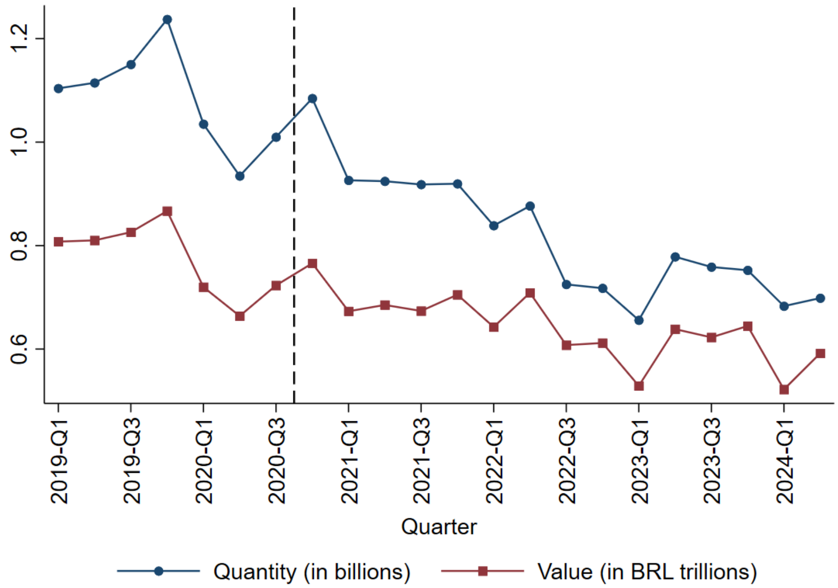


Figure A3 Evolution of Cash Withdrawals

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.

A3 Additional Figures and Tables

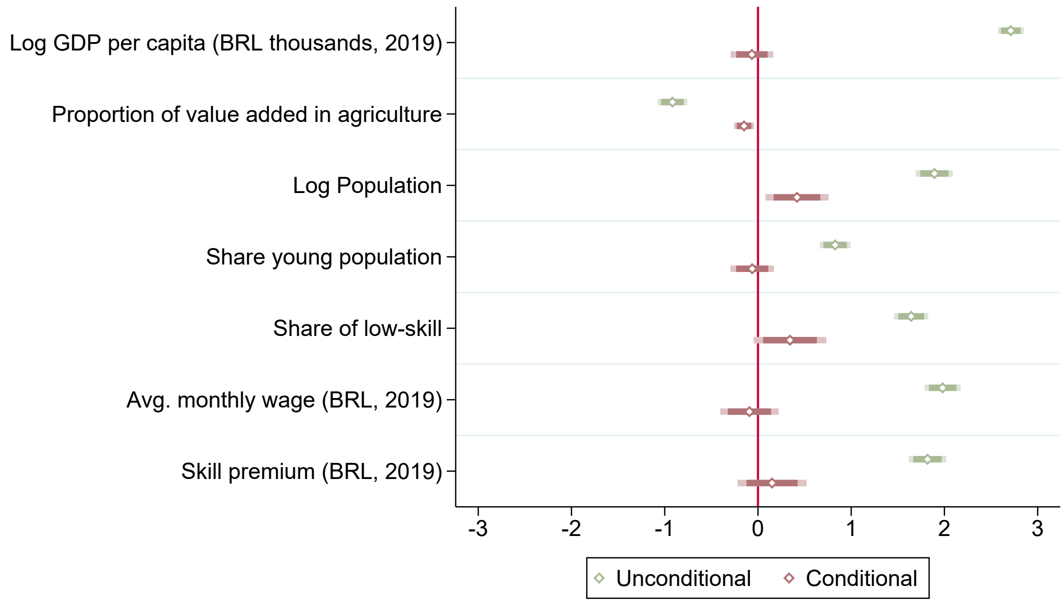


Figure A4 Balance of Covariates

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.

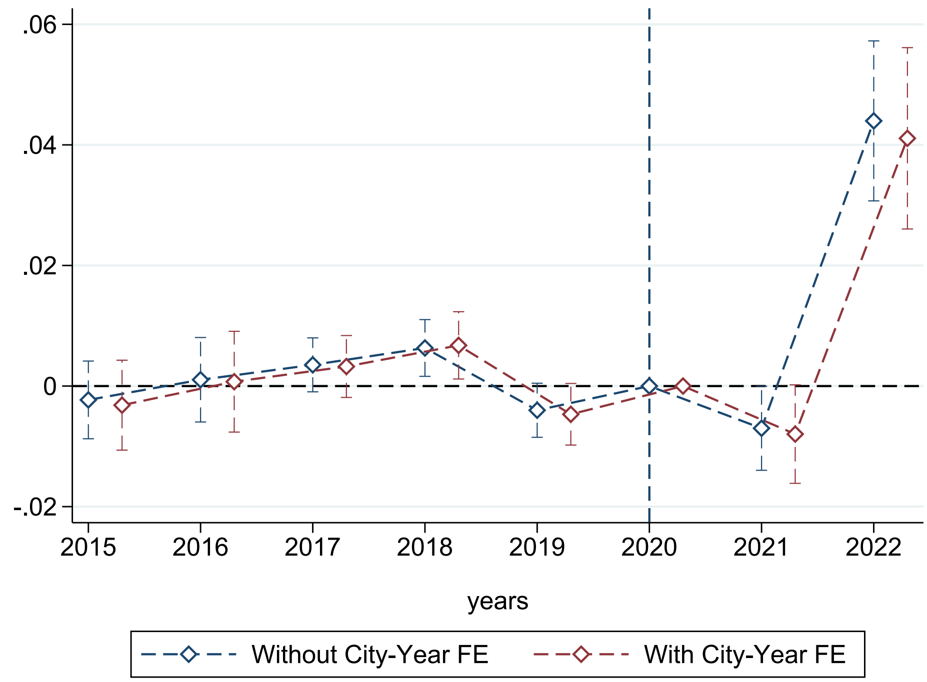


Figure A5 Triple Difference-in-Differences: The Effect of Mobile Penetration on Wages by Establishment Size

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 up to 4 employees. The model interacts standardized mobile penetration with an indicator for small establishments and includes fixed effects for municipality-by-year, size bin-by-industry-by-year, and municipality-by-size-bin-by-industry. The dependent variable is the logarithm of average wages at the municipality-industry-size-bin-year level. Regressions are weighted by municipality population, with standard errors clustered at the municipality level and 95% confidence intervals shown by dashed lines. Mobile penetration is standardized and winsorized at the 1% level. The sample period is 2015–2022.

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

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

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