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Evidence from Instant Payment Systems

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Abstract[*]

A long-standing debate concerns 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 an administrative dataset covering all registered employees in Brazil, we study the nationwide rollout of Pix, an instant payment platform introduced in late 2020. Our empirical strategy is a triple difference-in-differences design that exploits variation in preexisting mobile penetration across municipalities, the differential benefits of Pix for cash-intensive versus non-cash-intensive sectors, and the timing of Pix's rollout. A one standard deviation increase in mobile penetration leads to a 1.2 percent wage increase in cash-intensive sectors relative to non-cash-intensive sectors following Pix's introduction. These wage gains are concentrated among workers with less education, 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 effects. Overall, instant payment systems disproportionately benefit small, cash-intensive businesses, enhancing labor demand in sectors reliant on low-skill workers and highlighting how financial technologies can shape distributional outcomes differently from skill-biased technologies.

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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, is that new technologies increase inequality by complementing skilled labor and substituting for routine tasks typically performed by less educated workers (Autor, Levy, and Murnane, 2003; Acemoglu and Autor, 2011). However, the distributional and labor market 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? Answering this question is crucial for policy makers seeking to design inclusive growth strategies in an era of rapid digital transformation.

We contribute to this debate by examining the labor market impacts of instant payment systems—a major financial innovation adopted in over 60 countries as of 2023 (Bank for International Settlements, 2023)—which significantly reduce transaction costs, alleviate cash-management burdens, enable immediate settlement, and generate digital transaction records to enhance financial access.[1] These features alleviate frictions that are particularly burdensome for small, cash-intensive businesses, which disproportionately employ low-skill workers. This creates a mechanism through which financial technology can reduce rather than increase wage inequality, unlike production technologies. 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] We find that contrary to conventional patterns of skill-biased technical change, digital payments reduce wage inequality by increasing wages for low-skill workers in cash-intensive sectors, with effects amplified where low-skill labor is scarce.

We begin by developing a simple model to examine how reducing the wedge faced by cash-intensive firms affects wage inequality. Shrinking this wedge, whether through lower transaction costs, expanded market access, or both, raises the effective price received by cash-intensive businesses, increasing their labor demand for low-skill workers. As a result, low-skill wages rise

[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 an instant payment system introduced by the Central Bank of Brazil in November 2020. It enables real-time transfers using simplified identifiers (for example, email addresses, phone numbers). Key features include mandatory participation by large banks, zero fees for individuals, and low transaction fees for firms (around 0.22 percent, compared to about 2.2 percent for credit cards). By early 2024, more than 152 million individuals and 15 million firms had registered for Pix.

relative to high-skill wages, implying that financial innovations can reduce inequality.

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, preexisting mobile penetration across municipalities—which strongly predicts Pix adoption—and industry cash intensity. We measure cash intensity as the share of household purchases in total industry sales using Brazil's pre-Pix input-output data.[3] 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 pretreatment 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 estimates indicate that a one standard deviation increase in mobile penetration leads to a 1.2 percent wage increase in cash-intensive establishments relative to non-cash-intensive ones. Importantly, we find no evidence of differential pre-trends. Our results remain robust when using our alternative triple DID specification comparing small versus large establishments, which shows that a one standard

[3] Industries with high cash intensity, such as retail and services, relied heavily on small-value household transactions and thus faced greater payment frictions before Pix's introduction.

deviation increase in mobile penetration is associated with approximately 1.6 percent higher wages in small establishments relative to larger establishments within the same municipality. These effects—worth BRL 291–388 annually, or 13–17 percent of the pre-Pix Bolsa Família transfer—contrast with the typically negative impact of technological change on low-skill workers.[4]

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 noncollege workers—as our measure of inequality, we find that a one standard deviation increase in mobile penetration leads to a 1 percentage point reduction in the wage gap. This decline in inequality notably contrasts with the typical effects of technological change documented in the literature.

A key identification challenge arises because Pix's rollout coincided with the COVID-19 pandemic. We address this through our triple-difference design with municipality-by-year fixed effects that absorb local pandemic shocks, industry-specific COVID-19 exposure controls, and direct measures of government transfers and mobility restrictions related to COVID-19. Across all specifications, our results remain robust, confirming that our estimates are driven by payment-technology adoption rather than pandemic-related factors. 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. These findings are consistent with our model, suggesting that reduced payment frictions and increased revenue opportunities jointly increase labor demand predominantly for low-skill workers in cash-intensive sectors, thus reducing wage inequality.

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—by

[4] Bolsa Família, Brazil's conditional-cash-transfer program, paid an average monthly benefit of BRL 190 (about BRL 2,280 annually) to low-income families in 2019.

approximately 1 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-skill 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—in which firms share with employees the higher profits stemming from causes such as lower transaction costs—seems unlikely given the low unionization and limited firm-specific human capital in small retail and service establishments. Second, although formalization can raise wages via minimum wage compliance, this channel alone cannot explain why wage effects are strongest in labor-scarce regions, which points instead to localized labor demand in small, cash-intensive businesses. Overall, our findings suggest that labor demand from small, cash-intensive businesses, amplified by labor market frictions, drives wage increases for low-skill workers and reduces wage inequality.

Finally, an important question is whether Pix's impact stems primarily from direct improvements in transaction processing (for example, lower payment fees, cash-handling cost reductions, and revenue gains) or whether broader financial channels—such as deposit competition (Sarkisyan, 2023) or local demand expansions—play a larger role. The heterogeneity we uncover through our triple DID design strongly indicates that the wage effects arise mainly from these direct transaction-related mechanisms. By comparing cash-intensive versus non-cash-intensive establishments within the same municipality, and contrasting small with large firms, we find that wage increases are concentrated precisely where reliance on cash transactions, and their associated frictions, is greatest. Moreover, while improved credit access through digital transaction histories may be a longer-term benefit, our evidence does not support a credit-driven explanation for the observed wage gains within our sample horizon. Thus, the pattern of wage effects across sectors and establishment sizes suggests that Pix's alleviation of frictions tied to cash transactions—including cost savings and revenue enhancements—is the primary driver.

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, Gupta, and Mezzanotti, 2023), how instant payment systems affect deposit competition (Sarkisyan, 2023), the role of payment-technology complementarities (Sampaio and Ornelas, 2024), and how physical bank infrastructure influences digital payment adoption (Mariani, Ornelas, and Ricca, 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, Vallee, and Zeng, 2024; Higgins, 2024).

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

Second, we contribute to the literature on payment-related 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 infrastructure (Beck and Demirguc-Kunt, 2006). We show that following the introduction of instant payments, small and cash-intensive establishments experience the largest gains: Firm entry increases and low-skill wages grow faster than high-skill wages, thereby compressing the college wage premium—a previously unexplored distributional effect. Our findings suggest that transaction frictions, specifically high processing costs and restricted customer access, significantly hinder small businesses in cash-intensive sectors.

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, Manning, and Salomons, 2014; Autor and Dorn, 2013; Michaels, Natraj, and Van Reenen, 2014). In contrast, we show that financial technologies can exhibit markedly different distributional effects. Our results suggest that the impact of technology on wage inequality critically depends on the intersection of three factors: which market frictions it alleviates, the types of businesses it disproportionately affects, and the skill composition of their workforces.[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, address additional channels in Section 7, and conclude in Section 8.

2 Conceptual Framework

We present a simple theoretical framework to discuss the potential implications of instant payment systems for 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 $j \in \{x, y\}$, each with a representative firm operating a constant-returns-to-scale technology $Q^j(L_j, H_j)$. Industries differ in factor intensity. We assume sector x is the numeraire, $p_x = 1$, and sector y relies heavily on cash transactions, facing a wedge τ between the price p paid by consumers and the effective 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-

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

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

[7] The parameter τ captures two primary ways in which cash dependence reduces firms' effective returns: (i) transaction costs and risks, including operational expenses tied to physical cash handling (for example, security, transportation, reconciliation), merchant fees of 2–3 percent, and settlement delays that strain working capital; and (ii) market-access constraints, such as lost sales from digitally oriented consumers.

and high-skill labor to solve equation (1):

$$\max_{\{Lj,Hj\}} p_j Q_j - wL_j - sH_j \tag{1}$$

Here, w denotes the salary of low-skill workers and s represents the salary of high-skill workers. The first-order conditions lead to the following equation:

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

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

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

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 main theoretical result is summarized in the following proposition.

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 to produce that good.*

Financial innovations related to instant payments shrink the transaction-cost wedge τ not only by lowering payment fees, eliminating settlement delays, and reducing cash-handling risks, but by creating new sales opportunities among digital payment customers. Thus, instant payment systems reduce the skill premium if and only if cash-intensive industries are also intensive in low-skill labor. Otherwise, instant payment systems would increase the skill premium. Assume the following CES technology with parameter $\rho \leq 1$ in sector j:

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

We can combine the first-order and zero-profits conditions to obtain the following equilibrium equations provided by industries x and y, respectively, which together determine the values w and s:

$$w = A_x^{\frac{1}{\rho}} \left[1 - s^{\frac{\rho}{\rho-1}}\right]^{\frac{\rho-1}{\rho}} \tag{5}$$

$$w = A_y^{\frac{1}{\rho}}\left[p_y^{\frac{\rho}{\rho-1}} - s^{\frac{\rho}{\rho-1}}\right]^{\frac{\rho-1}{\rho}}$$

Thus, a decline in τ leads to a reduction in the skill premium. This result requires industry y to use low-skill labor more intensively. Thus, our theoretical model highlights the role of industry-specific skill intensity in shaping the impact of instant payment systems on the skill premium.

Our model predicts that reducing τ will increase labor demand in cash-intensive sectors regardless of whether benefits arise through cost savings, revenue expansion, or both. In the empirical analysis that follows, we exploit variations in the intensity with which different municipalities and sectors experience reductions in the cash-transaction wedge to test these predictions.

Beyond the benefits driven by digital payments, an alternative channel is improved access to credit. This is a critical consideration, as fintech lenders, which may be particularly responsive to a digital shock like Pix, expanded significantly around the time of its introduction. To model this potential channel, we make two adjustments to our framework. First, we assign firms to a location, city $c \in \{1, . . . C\}$. Second, we introduce capital as a third input in the production function. This capital is financed at a city-specific interest rate $r(c)$ and inelastically supplied. Thus, firm j operating in city c solves the following problem:

$$\max_{\{L_{jc}, H_{jc}, K_{jc}\}} p_{jc} K_{jc}^{\alpha}\left(\left[A_{jc} L_{jc}^{P} + H_{jc}^{P}\right]^{\frac{1}{\rho}}\right)^{1-\alpha} - wL_{jc} - sH_{jc} - r_c K_{jc}$$

Thus, firms operating in city c can experience an additional increase in profits if their exposure to Pix, proxied by mobile penetration in our empirical setting, also reduces local interest rates, r_c. This reduction could occur, among other reasons, if higher mobile penetration facilitated the expansion of fintech lenders, increasing competition and improving credit conditions. The resulting empirical equation for wages is given as follows:

$$\Delta w_{jc} = \delta_j + \beta \times \Delta\tau_c + \gamma \times \Delta r_c + u_{jc}$$

Here, Δw_{jc} denotes the change in log of wages for low-skill workers in industry j and city c. The term δ_j represents a vector of industry fixed effects, capturing time-invariant technological differences; and u_{jc} is the error term in the empirical counterpart of our model. A key identification concern arises from the potential omission of local credit conditions. If we fail to account for changes in the interest rate, Δr_c, the error term becomes $v_{jc} = \Delta r_c + u_{jc}$. This would bias our estimate of β, the parameter capturing the Pix effect operating through cash-use-related benefits, if changes in credit access were correlated with Pix exposure. To address this confounder and isolate the cash-based mechanism, we incorporate city-time fixed effects in the following triple DID design:

$$\Delta w_{jc} - \Delta w_{j'c} = \left(\delta_j - \delta_{j'}\right) + \beta \times \left(\Delta\tau_{jc} - \Delta\tau_{j'c}\right) + \left(u_{jc} - u_{j'c}\right)$$

Here, industry j is cash intensive and industry j' is not. Thus, our identifying assumption holds. A remaining concern is that the improvement in credit conditions is associated with the information generated by instant payment transactions. In this case, the variation of interest rates in our model is city-industry-specific. As we explain below, our micro-data allow us to construct a panel of city-industry-establishment-size bins. Thus, we can focus on cash-intensive industries and estimate the following equation:

$$\Delta w_{kjc} - \Delta w_{k'jc} = \beta \times \left(\Delta\tau_{kcj} - \Delta\tau_{k'jc}\right) + \left(u_{kjc} - u_{kjc}\right)$$

Here, establishment-size bins k are small, and k' are large. Thus, if the improvements in credit conditions in cities with high mobile penetration are industry-specific, we can obtain a consistent estimation of β.

3 Institutional Background

In November 2020, the Central Bank of Brazil launched Pix, an 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 had registered for Pix, with a substantial percentage using it regularly. Beyond improving the user's experience and convenience, two other factors likely contributed to Pix's success. First, the Central Bank mandates the participation of large banks (defined as those with more than 500,000 accounts). Since Brazilian banking is dominated by a few large banks, this regulation ensures widespread availability and interoperability.[8] Second, the Central Bank exempts individuals from transaction fees to foster financial inclusion.[9] Since many small firms use their owner's personal bank account for transactions, they have seen a significant reduction in fees compared to traditional methods such as credit and debit cards or TED transfers (the electronic wire transfer available before Pix). Even when firms pay fees, they are substantially smaller than those for 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.

Because of these advantages, Pix quickly gained prominence as a payment method. About a year after its launch, the number of Pix transactions surpassed those of credit and debit cards and TED transfers. Pix's transactions exceeded that of credit and debit cards just two quarters after its introduction (Appendix Figure A2). Pix started mainly as a payment method between accounts linked to individuals. Gradually, transactions from individual-linked accounts to business-linked accounts started to grow (Appendix Figure A3).[10]

The rise of Pix coincided with a 35 percent drop in the number of cash withdrawals (Appendix Figure A4), indicating less reliance on cash. Surveys by the central bank 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 22 percent in 2024.[11]

As a replacement for cash, Pix likely played a more prominent role in cash-intensive sectors that engage in many 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 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 could significantly affect business operations, particularly for small firms in cash-intensive sectors like retail and services.

[8] Banks with more than 500,000 customers accounted for more than 99 percent of the bank accounts in 2020.
[9] Financial inclusion was one of the Central Bank goals with Pix. See https://www.bcb.gov.br/en/financialstability/pix_en.
[10] Bank accounts are associated with either an individual tax ID or a business tax ID. Some accounts tied to individuals may also be used for business purposes, especially by small businesses and informal firms. As with other instant payment systems, adoption dynamics were gradual (see, for example, Alvarez et al., 2023).
[11] The figures are from a Central Bank of Brazil survey, namely O brasileiro e sua relação com o dinheiro.

4 Data and Research Design

4.1 Data

We use data from multiple sources. First, from the Central Bank of Brazil, we obtained information on the number and value of Pix transactions initiated or received by firms and individuals, broken down by municipality and month.[12] Second, we use matched employer-employee data from the Brazilian Ministry of Labor (Relação Anual de Informações Sociais, or RAIS).[13] This dataset includes information on wages and job contracts for all Brazilian formal 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. These data allow 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 GDP per capita of BRL 24,500 (median of 18,200), four branches (median of one), and 36,460 inhabitants (median of BRL 11,065). The average municipality has a skill premium of 61 percent (median of 48 percent). The average share of the population with access to 3G+ is 54 percent (median of 53 percent).

4.2 Research Design

We hypothesize that by reducing transaction costs in cash-intensive sectors, instant payment systems increase demand for low-skill 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 DID design that exploits three sources of variation. First, we leverage the timing of Pix's nationwide introduction in late 2020. Second, we exploit geographic variation in preexisting mobile penetration across Brazilian municipalities, which strongly predicts the intensity of Pix adoption. Municipalities with a higher proportion of mobile

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

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

devices with 3G or higher capability in 2019 were technologically better positioned to adopt Pix, providing 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 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:

$$Mobile\ penetration_c = \frac{Number\ of\ cellphones\ with\ 3G\ or\ above_c}{Population_c} \tag{6}$$

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 a pre-Pix measure, we isolate 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 DID design that combines variation in the timing of Pix's introduction, municipalities' preexisting mobile penetration, and establishment-level cash intensity. This strategy compares wage changes before and after Pix adoption across municipalities with different mobile penetration levels and between cash-intensive and non-cash-intensive establishments within the same municipality. Specifically, we estimate:

$$Y_{kjct} = \beta x\left(Mobile\ penetration_c\ x\ Cash\ Intensive_j\ x\ Post_t\right) + \delta_{ct} + \delta_{kjc} + \delta_{kjt} + u_{kjct} \tag{7}$$

Here, Y_{kjct} is the average wage for establishment-size 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. $Cash\ Intensive_j$ is an indicator equal to 1 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 1 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.[14] 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.

Our identification strategy exploits heterogeneity in an industry's *cash intensity*, defined as the ratio of household purchases to total industry sales using Brazil's pre-Pix input-output matrix. This measure serves as an intent-to-treat proxy, capturing industries' ex ante incentives to adopt digital payments based on their exposure to the frictions directly addressed by Pix. As shown in Appendix Figure A5, industries with higher household sales subsequently experienced greater Pix transaction volumes, supporting the predictive power of our cash-intensity measure. Moreover, prior to Pix, Brazilian households relied heavily on cash, conducting roughly 77 percent of retail transactions in physical currency (Banco Central do Brasil, 2019). This dependence created significant payment frictions, including security risks, cash-handling costs, branch visits, and liquidity delays. Other payment methods—such as interbank transfers, payment vouchers, and credit cards—were costly, slow, or impractical for frequent, small-value transactions. Consequently, business-to-consumer industries with high household-driven sales, such as retail, services, and accommodation, faced greater cash dependency and stood to benefit substantially from Pix's instant, low-cost payments. Central bank data confirm this pattern: Retail accounts for 32.8 percent of Pix transactions yet only 10.1 percent of GDP, while manufacturing—historically less reliant on cash because of its business-oriented payments—represents 28 percent of GDP but just 3.1 percent of Pix transactions (Appendix Table A1). This empirical pattern supports our measure as a predictor of which sectors experienced the greatest reduction in payment frictions, generating meaningful variation in treatment intensity across industries.

The key identifying assumption underlying our triple DID design is that in the absence of Pix, wage trends between cash-intensive and non-cash-intensive establishments would have

[14] Industries are defined at the two-digit CNAE level (Brazil's equivalent of ISIC).

evolved similarly in municipalities with high versus low mobile penetration, conditional on the fixed effects included in our specification. While the assumption cannot be directly tested, we provide suggestive evidence in its favor by examining pre-trends, as outlined below.

One concern with our identification strategy is that mobile penetration might correlate with unobserved factors influencing wage trends.[15] For example, municipalities with higher 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 preexisting mobile penetration.

Another concern is that the COVID-19 pandemic, which disrupted economic activity, 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 time-varying 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. We further address pandemic-related concerns in Section 5.4.

As a complementary strategy, we employ a triple DID 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 equation (8):

$$Y_{kjct} = \beta \ x \ (Mobile\ penetration_c \ x \ Small_k \ x \ Post_t) + \delta_{ct} + \delta_{kjc} + \delta_{kjt} + u_{kjct} \qquad (8)$$

[15] We examine differences in pre-Pix characteristics across municipalities by mobile-penetration level. Appendix Figure A6 shows unconditional differences (green estimates): Higher-penetration municipalities are larger and 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.

Here, 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—for example, 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, 5-9, 10-19, 20-49, 50-99, 100-249, 250-499, 500-999, and 1,000 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 preexisting 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-skill workers.

5.1 Pix Adoption

We begin by examining the relationship between our treatment variable—preexisting 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 (for example, 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 preexisting differences in mobile infrastructure significantly influenced the intensity of Pix adoption across municipalities. Appendix Table A2 quantifies this relationship, showing that a one standard deviation increase in mobile penetration is associated with 5.8 additional transactions per capita and approximately BRL 2,073 higher transaction value per capita following Pix introduction. 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 DID 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* × *Cash Intensive* × *Post*) captures Pix's wage effect by comparing cash-intensive and non-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 after 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 2020 as the baseline. Pre-Pix coefficients (2015–19) are small and statistically nonsignificant, and they show no evidence of any differential pre-trend, 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. As a robustness test, we present estimates using a continuous measure of cash intensity in Appendix Figure A7; the findings are qualitatively similar. The timing of this 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 DID 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 four 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 nine employees (columns (3)–(4)), the effects are 1.4 and 1.2 percent, respectively.

The monotonic pattern, with larger effects for smaller establishments, is consistent with our proposed mechanism: 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 nine employees), with coefficients normalized to 2020 as the baseline year. Overall, the pre-Pix coefficients (2015–19) remain small and do not suggest a persistent upward trend. After Pix is introduced, the wage differential emerges gradually, becoming more pronounced by 2022 and surpassing 2 percent at the end of the sample. For robustness, Appendix Figure A9 shows similar dynamic effects using the more restrictive definition of small establishments (up to four employees). These findings align with our cash-intensity results, further underscoring the robustness of our main conclusions about Pix's wage impacts.

5.2.3 Further Tests on Preexisting Trends

To strengthen confidence in our identification strategy, we perform DID analyses on the individual components of our triple-difference design to examine potential pre-trends before the introduction of Pix. Appendix Figure A8 decomposes our approach into two separate DID analyses. Panel A estimates dynamic effects from a DID specification comparing municipalities with higher versus lower mobile penetration. Panel B similarly examines wage trends comparing cash-intensive versus non-cash-intensive establishments. Panel A reveals no differential wage trends prior to Pix across municipalities based on mobile penetration, while Panel B demonstrates a similar absence of divergent wage patterns across establishments with varying cash intensity. These reassuring results provide evidence against systematic pre-trends, complementing our main test in Figure 3.

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 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 (Appendix 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.

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 as the difference in log of average wages between college and noncollege workers at the municipality level:

$$College\ Premium_c = \ln\left(avg.wage_{college}\right) - \ln\left(avg.wage_{non-college}\right) \qquad (9)$$

Panel A of Figure 6 confirms our model's prediction using a 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.

Panels B and C unpack these results further by separately examining wage dynamics for low- and high-skill workers. Panel B reveals a noticeable increase in low-skill wages following Pix adoption, consistent with increased labor demand in the cash-intensive sectors, which predominantly employ these workers. In contrast, Panel C shows no significant change in high-skill wages, further highlighting that the observed decline in wage inequality primarily arises from wage growth among low-skill workers rather than wage compression at the higher end of the skill distribution.

To examine whether the effect on the college wage premium originates primarily from cash-intensive industries, Figure 7 disaggregates the premium by industry cash intensity. Panel A shows that the decline in the college wage premium within high-cash sectors precisely coincides with Pix's introduction, with no evidence of preexisting trends.[16] In contrast, Panel B shows no corresponding change in low-cash industries, for which the estimates remain statistically nonsignificant and close to zero. This divergence aligns closely with our model, which predicts that Pix's reduction in transaction costs disproportionately benefits cash-intensive sectors employing more low-skill workers, thus specifically reducing wage inequality in those sectors.

Furthermore, the lack of effects in low-cash industries helps rule out alternative explanations involving general local economic shocks that could bias our estimates. Overall, this heterogeneity strongly supports the channel proposed by our model: Pix's inequality-reducing effects operate primarily through enhanced labor demand in cash-intensive sectors.

Table 5 further explores the underlying mechanisms behind the observed decline in the college wage premium by explicitly decomposing wage changes by worker skill level and industry cash intensity. The estimate in column (1) highlights a clear heterogeneity: Wages for low-skill workers in high-cash-intensity sectors significantly increase by approximately 1.9 percent following

[16] While the 2015 coefficient is marginally statistically significant, its modest magnitude does not suggest a persistent pattern leading up to Pix's introduction, as the coefficients for 2016–19 remain nonsignificant.

Pix's introduction. Conversely, there is no statistically significant wage effect for low-skill workers in low-cash-intensity sectors or for high-skill workers overall, as presented in columns (2) and (3), respectively.

The decline in the college premium is particularly notable given the canonical literature on skill-biased technical change, which finds 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, which disproportionately employ low-skill workers, digital payment technologies can generate more inclusive patterns of wage growth.

5.4 Challenges to Identification: COVID-19

Before proceeding, we consider potential alternative explanations arising from the concurrent timing of Pix's nationwide rollout and the COVID-19 pandemic. Specifically, one concern is that municipalities with higher preexisting mobile penetration might have been better prepared to adapt digitally during the pandemic, potentially driving differential economic recoveries unrelated to Pix.

We address this identification concern in several ways. First, our primary specification includes municipality-by-year fixed effects, absorbing any local time-varying shocks, such as differential pandemic severity, lockdown policies, or digital adaptation trends. We also incorporate industry-by-size-by-year fixed effects, capturing nationwide trends affecting specific combinations of industry and establishment size. These controls mitigate concerns regarding municipality- and industry-level confounding factors. We also verify the absence of differential pre-trends across all specifications, further supporting the parallel-trends assumption.

Second, we augment our baseline specification by adding industry-by-COVID-decile-by-year fixed effects. This approach addresses heterogeneous pandemic exposure across industries. Appendix Figures A10 and A11 confirm that our main estimates remain robust, further mitigating concerns about industry-specific pandemic-driven confounding.

Third, Table 6 incorporates direct COVID-19 policy controls, specifically government transfers and mobility restrictions. Columns (1) and (2) interact per capita transfers under Brazil's emergency aid program (Auxílio Emergencial) with the cash-intensity indicator, leaving the key instant payment coefficient virtually unchanged at about 1.5 percent (1.1 percent in column (2)). The additional triple interaction with transfers is smaller (0.5 percent), confirming that pandemic relief does not drive our observed wage effects. Columns (3) and (4) further control for municipal stay-at-home orders. Again, the coefficient remains robust (1.2 and 1.5 percent, respectively), while the coefficients on interactions with lockdown policies are negligible. Columns (5) and (6) explicitly control for cumulative COVID-19 cases per 100,000 population, and the main coefficient remains stable (1.5 and 1.0 percent, respectively), with small coefficients on interactions involving COVID-19 cases. These results reinforce our causal interpretation that instant payment adoption, rather than COVID-19 relief measures, drives the observed wage gains.

Fourth, that the pronounced reduction in the college wage premium is observed exclusively in cash-intensive sectors (Figure 7) aligns precisely with our model's predictions. If differential pandemic recovery driven by broader digital adaptation were driving our results, we would expect similar wage premium reductions in consumer-facing but low-cash-intensity industries. The sharp divergence we observe thus strongly supports Pix's specific role in reducing payment frictions, rather than reflecting a general pandemic-related digitalization effect.

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

6 Mechanisms

In this section, we 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-skill 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, 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, which are both cash intensive and heavily reliant on low-skill 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 DID approach comparing cash-intensive and non-cash-intensive industries. Figure 8 illustrates that cash-intensive sectors experienced significantly greater job growth after Pix. Table 7 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 9 presents entry patterns by sector and firm size. After Pix's introduction, municipalities with higher mobile penetration saw significant increases in entry of small retail firms (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 8 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-specific 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 that 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-skill 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 10 illustrates how the decline in the college premium varies systematically with local labor market scarcity. Panel A shows that in areas where low-skill workers are relatively scarce (above-median labor market scarcity), the college premium declines significantly by approximately 1 percentage point following Pix adoption. In contrast, Panel B reveals that areas with abundant low-skill workers experience a negligible and statistically nonsignificant effect. Table 4 quantifies how Pix adoption affects the college premium across labor market conditions. Column (2) shows that 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 scarcity 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, in which wage effects are amplified in tight labor markets (Pissarides, 2000).

6.3 Discussion of Alternative Mechanisms for Wage Gains

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 discussion.

One candidate explanation is rent-sharing, in which 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 because of 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 crucial for rent-sharing (Manning, 2011). Second, if rent-sharing were the primary channel, we would expect larger effects in establishments in which 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 in which 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, namely 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 Beyond Cost Savings: Evidence on Revenue and Credit Channels

Brazil's instant payment system has multiple effects. The most immediate and quantifiable impact is a sharp reduction in merchant payment costs (from roughly 2 percent to 0.22 percent), settlement lags (from 30 days to mere seconds), and cash-handling and security expenses. Yet this technology may also raise revenues by opening digital checkouts to customers who previously relied on cash and, over time, facilitate credit access through richer transaction records. Although our wage results align most directly with the economywide cost shock, these additional revenue and credit features could reinforce or complement the main mechanism. We therefore assess two complementary channels: sales expansion and credit supply.

7.1 Revenue-Gains Channel

In two ways, instant payment technology can enhance firm revenues by reducing transaction frictions previously constraining economic activity. First, by eliminating checkout frictions—such as the need for physical cash or expensive card processing—it potentially boosts conversion rates, especially for small-value transactions previously limited by high card fees. Second, the technology may expand the customer base, enabling digitally enabled consumers in regions with high smartphone penetration but limited point-of-sale infrastructure to engage in digital transactions.

To partially assess whether these revenue enhancements materialized, Figure 11 illustrates local micro-entrepreneur tax payment trends around the time of the technology's introduction. We find a rise in tax contributions following the introduction. While these data alone do not definitively separate higher aggregate sales from new registrations, they remain consistent with enhanced economic activity among micro-enterprises. Such revenue gains could plausibly stimulate labor demand and drive wage increases in cash-intensive sectors, complementing our primary findings regarding wage and inequality outcomes.

7.2 Credit-Access Channel

Another plausible channel through which instant payment systems could affect firms' labor demand is by improving access to credit. Digital transactions generate verifiable records of firms' sales, potentially mitigating the information asymmetries faced by lenders. In turn, enhanced financial transparency can boost lenders' willingness to extend credit, especially to more opaque or informal firms (Ouyang, 2021; Alok et al., 2024; Ghosh et al., 2024; Cramer et al., 2024).

To partially test this hypothesis, we examine whether municipalities with higher mobile penetration experience increased aggregate business lending after adoption. Figure 12 plots the evolution of per capita business loans across municipalities. We find no statistically significant rise in aggregate lending following the system's introduction, suggesting no credit expansion at the municipality level. However, this municipal-level analysis may mask heterogeneity—for example, any increase in lending to small, cash-intensive firms could be offset by reductions elsewhere.

An additional potential channel is that digital payments might enhance households' income verifiability, a significant constraint in emerging markets with large informal sectors. Improved verifiability could allow households to access more and better financial products after Pix. If the spending from these new loans is concentrated in high-cash industries, our observed results could be confounded by an increase in local demand rather than a supply-side response from firms.

To rule out this demand-side mechanism, we examine effect heterogeneity within high-cash industries based on their exposure to local demand shocks. We construct a Herfindahl-Hirschman Index of geographic concentration for each industry j as follows:

$$HHI_j = \sum_c \left(\frac{W_{jc}}{\sum_j W_{jc}}\right)^2$$

Here, W_{jc} represents total wages in industry j and city c. Following Mian and Sufi (2014), we interpret this measure as an indicator of an industry's tradability. Industries with high geographic concentration (high Herfindahl-Hirschman Index) are typically tradable, as production can be centralized. Conversely, industries with low concentration (low index) are nontradable and rely heavily on local demand, making them more susceptible to a credit-driven local demand shock.

We then compare the treatment effect for high-cash industries that are nontradable (and thus exposed to local demand) to the effect for high-cash industries that are tradable (less exposed). As shown in Figure 13, the estimated effects are statistically comparable across both groups. This result allows us to reject the hypothesis that a credit-driven demand shock is the primary mechanism behind our findings.

8 Conclusion

Our findings provide novel evidence on how financial technology adoption shapes labor markets and wage inequality. While the hypothesis of skill-biased technical change 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-skill 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, which 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-skill labor by mitigating frictions in sectors in which these workers are predominantly employed, thereby mitigating 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. In sum, the distributional impact of new technologies depends critically on which frictions they address: Instant payments reduce inequality by alleviating constraints faced by low-skill-intensive firms, while automation increases it by displacing routine labor.

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