Wiring Equality

The Impact of Internet on Wage Dispersion in Costa Rica

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September 2025

This paper shows that investment in internet infrastructure compresses lower-tail wage inequality. We present a monopsony model with heterogeneous firms in which better job search by workers, due to increased internet access, forcing wages to converge to the competitive wage. This results in larger wage increases for low-wage workers and a reallocation of workers from low-wage to high-wage firms, such that lower-tail wage inequality decreases. We then leverage the liberalization of the telecommunications market in Costa Rica as a natural experiment in a continuous treatment DiD design to show evidence in support of our model. We also show that lower-tail inequality in non-wage job characteristics decreases, and that minimum wages and collective bargaining are unlikely to be alternative explanations for our empirical results.

Keywords: internet adoption, monopsony, wage inequality, economic development
JEL: J3, J4, O1, O3

Helpful comments by Matías Cortés, Carlos Segura, F. Javier Rodríguez-Román, Bob Rijkers, César Ulate, Alberto Behar and Pujee Tuvaandorj are gratefully acknowledged. We thank conference participants of the *Conferencia de Economistas Costa Rica 2024* and numerous seminar participants for suggestions and discussions. We thank Instituut Gak for financial support. Corresponding author: Víctor Picado. E-mail address: v.a.picadoaraya@uu.nl.

1. Introduction

The relationship between development, technological change, and labor market outcomes has long been a central concern in economics. When developing countries invest in infrastructure, whether it is rails, dams, telephony, or internet connectivity, these investments shape the functioning of markets by altering transaction costs, information flows, and market power (Duflo and Pande 2007; Jensen 2007; Donaldson 2018; Hjort and Tian 2025). Infrastructure development can either exacerbate or reduce existing inequalities, depending on who gains access and how the new infrastructure affects relative bargaining positions among economic agents.

Recently, a literature has emerged that examines the relationship between GDP growth and the degree of competition in labor markets. One example is Armangué-Jubert et al. (2025), who argue that labor markets become more competitive as GDP per capita grows. By structurally estimating an oligopsony model with free entry across different development stages, they find that monopsony power decreases with GDP per capita. Wage markdowns vary from 54% in low-income countries to around 24% in the richest ones. If labor markets in poorer countries were as competitive as in more developed ones, their output per capita could increase by up to 44%. The intuition for this result is that, due to information and search frictions in labor markets, it takes time for workers to find and change jobs. Infrastructure investments reduce these frictions and therefore reduce poverty and increase consumption through increased participation in the labor force and salaried employment (Hjort and Poulsen 2019; Bahia et al. 2023, 2024).

This paper examines the relationship between economic development and the degree of competition in the labor market in Costa Rica, where the liberalization of the telecommunications market led to a significant variation in investments in internet infrastructure. Other papers have already focused on the importance of internet access for GDP growth and employment (Czernich et al. 2011; Chiplunkar and Goldberg 2022; Hjort and Poulsen 2019). Complementing these papers, this paper focuses on the importance of increased internet access for changes in wage inequality. To understand how increased internet access could affect changes in wage inequality, we build on recent papers that model imperfectly competitive labor markets (Card et al. 2018; Dustmann et al. 2022; Autor et al. 2023). In our framework, internet access reduces information frictions by enabling better job search, which increases the elasticity of firm-level labor supply. The model, which distinguishes between low-productivity (low-wage) and high-productivity (high-wage) firms, shows how the increase in the elasticity of firm-level labor supply not only increases the average real wage but also decreases lower-tail wage inequality. This decrease in lower-tail wage inequality results from higher wage growth at low-productivity firms and the reallocation of workers from low-productivity toward high-productivity firms.

This paper uses novel administrative data on the construction of internet towers after the liberalization of the telecommunications market in Costa Rica, combined with detailed household surveys. We first document that both internet infrastructure and internet access at home expanded rapidly with investments in towers. We then show that there was stronger relative wage growth in lower wage deciles in those counties where more towers were built, exploiting variation in the timing of internet roll-out using a difference-in-difference research design (Callaway et al. 2025; Baker et al. 2025). In addition and in line with our framework, we document that the decrease in lower-tail wage inequality operates through higher wage growth at smaller lower-paying firms as well as a reallocation of workers from smaller lower-paying firms toward larger higher-paying firms.

The remainder of the paper is organized as follows. Section 2 presents our theoretical framework. Section 3 describes the institutional context and the data. Section 4 outlines our empirical strategy. Section 5 presents the main results and explores the predicted mechanisms. Section 6 examines alternative explanations. Section 7 concludes.

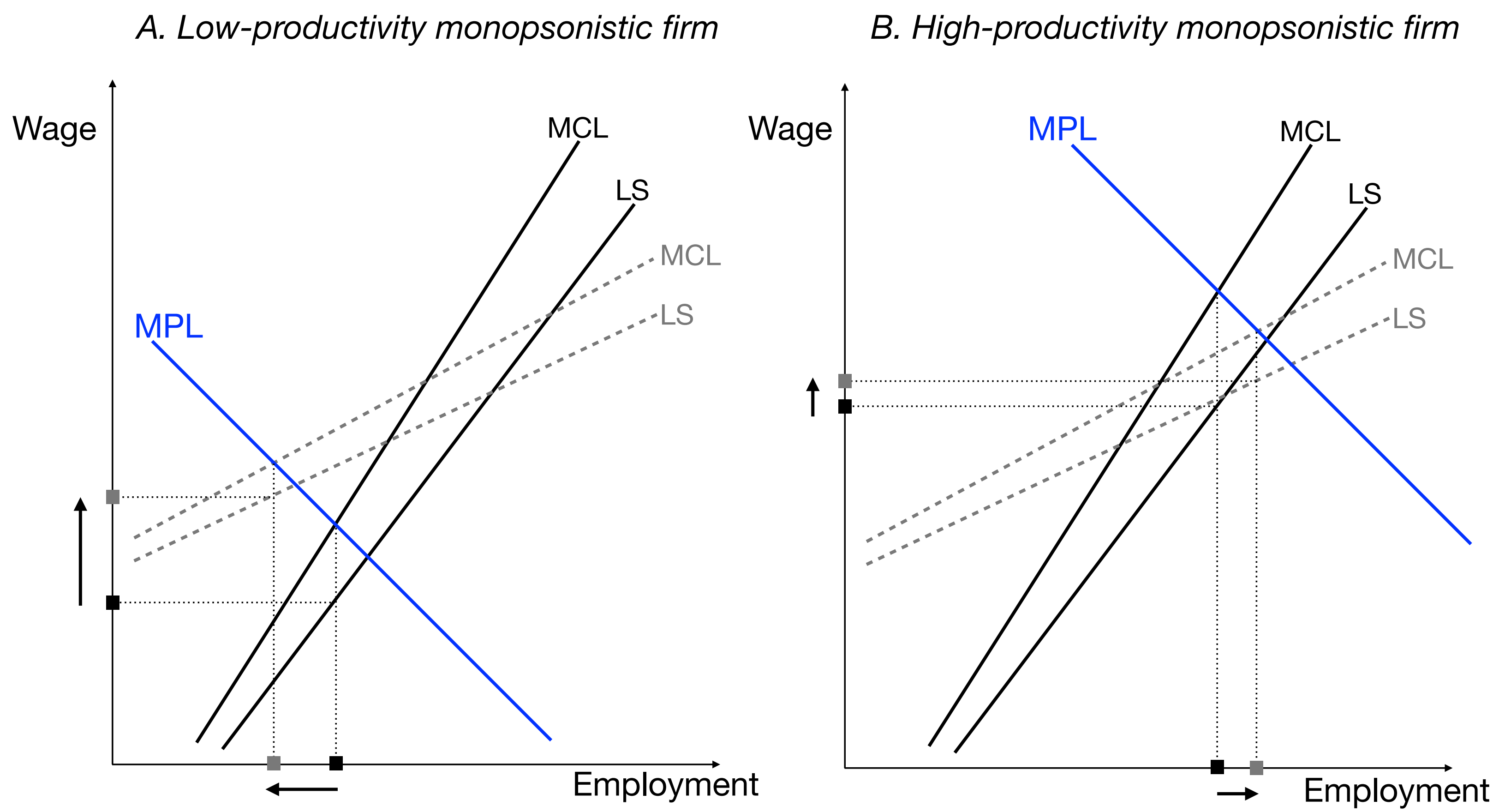
2. Model

2.1. Graphical summary and predictions

This subsection graphically summarizes our formal model below. Figure 1 illustrates how internet access at home changed the nature of competition in labor markets from being more monopsonistic to becoming more competitive, resulting in both average real wage growth as well as a decrease in lower-tail wage inequality.

Before the arrival of the internet, workers had lower chances of successful job applications due to poorer job search. Consequently, labor relations were characterized by substantial wage-setting power for firms. This is captured by the solid upward-sloping firm-level labor supply curves (LS) in panels A and B of Figure 1. The other solid upward-sloping curves draw the corresponding marginal cost of labor (MCL) for a non-discriminating monopsonist. Equilibrium employment, indicated with the

FIGURE 1. **Comparative statics when monopsonistic labor markets become more competitive**



black square on the x-axis, is then given by the intersection of the MCL-curve with the blue downward-sloping curve, capturing decreasing marginal labor productivity (MPL). The black square on the y-axis in panel A gives the equilibrium wage for smaller low-productivity monopsonistic firms, whereas the black square on the y-axis in panel B depicts the equilibrium for larger high-productivity monopsonistic firms.

An increase in workers' chances of successful job applications, due to better job search following increased internet access, implies that the balance of power between firms and workers shifts in favor of workers. Consequently, firms' wage-setting power decreases, which leads to an increase in the elasticity of firm-level labor supply. This more elastic labor supply is captured by the dashed LS curves in panels A and B of Figure 1. The figure further illustrates what happens to relative wages and employment. In panel A, the gray square on the x-axis gives the new equilibrium employment, and the gray square on the y-axis the new equilibrium wage for low-productivity firms. In panel B, the gray squares depict the corresponding changes in equilibrium employment and wages for high-productivity firms. While wages in both firms increase but more so in low-productivity firms, employment in smaller low-productivity firms declines, whereas employment in larger high-productivity firms increases.

In summary, our model shows that increased competition between firms for workers, following workers' increased internet access, causes a decrease in lower-tail wage inequality because wage growth is higher in low-wage than in high-wage firms. Moreover, lower-tail wage inequality decreases further due to the reallocation of workers from low-wage firms to high-wage firms. We will empirically test these predictions in the following sections. But first, the remainder of this section derives the equilibrium and comparative statics illustrated in Figure 1 more formally.

2.2. The balance of power between workers and firms

Following Card et al. (2018), assume that each firm j posts a single wage w_j to attract workers. Among all the posted wages, each worker then chooses to apply to a single firm. In addition, assume that the utility of worker i from working in firm j is given by:

$$u_{ij} = \epsilon[\ln(w_j) + \ln(\theta(w_j))] + \eta_{ij} \text{ with } \epsilon \geqslant 0 \tag{1}$$

with $w_j\theta(w_j)$ the expected wage at firm j, which is the product of two terms. First, w_j is the wage earned if worker i is hired by firm j. Second, $0 \leqslant \theta(w_j) \leqslant 1$ is the probability of getting a job offer from firm j given that worker i applied to that firm.

The term η_{ij} is an idiosyncratic preference term for the firm's non-wage characteristics. Examples are match-specific factors such as travel time or interactions with coworkers and supervisors. Finally, ϵ captures workers' preferences for expected wage income relative to the firm's non-wage characteristics.

We further assume that the probability of a successful application, $0 \leqslant \theta(w_j) \leqslant 1$, is decreasing in w_j as follows:

$$\ln(\theta(w_j)) = -\epsilon_{\theta w} \ln(w_j) \text{ with } \epsilon_{\theta w} \geqslant 0 \tag{2}$$

where the minus sign follows from the assumption that an increase in w_j reduces $\theta(w_j)$. The intuition for this is that a higher wage offer will attract more applications, which reduces each applicant's probability of receiving a job offer. $\epsilon_{\theta w}$ is the elasticity of a successful application with respect to the wage paid by firm j.

Importantly, we assume that $\epsilon_{\theta w}$ is greater when workers are less informed about possible employment opportunities. In particular, a greater $\epsilon_{\theta w}$ captures that workers value a job offer more when they are less informed about all possible job opportunities because they have limited access to online job ads. Intuitively, workers "feel lucky" when they receive a job offer when information about employment opportunities is scarce. We will show below that, therefore, firms will exploit workers' feelings of "being the chosen ones" when receiving a job offer by offering lower wages because the labor supply to the firm is more inelastic.

However, when workers are better informed about employment opportunities due to internet access, $\epsilon_{\theta w}$ decreases and the balance of power between workers and firms shifts towards workers, making the supply of labor to the firm more elastic. Consequently, increased competition between firms increases wages, and we show below that this wage increase is larger in smaller less-productive firms than in larger more-productive firms. In addition, we will also show that workers will reallocate from smaller lower-paying firms toward larger higher-paying firms. Taken together, our model predicts an increase in the average real wage as well as a decrease in lower-tail wage inequality following workers' improved online access. We assume that this is what happened with the rollout of internet towers in Costa Rica. In the extreme case of $\epsilon_{\theta w} = 0$, we have that $\theta(w_j) = 1$ such that every job application is successful.[1]

[1]Note that if $\epsilon_{\theta w} \to \infty$, we have that $\theta(w_j) \to 0$. In this case, no application is successful, which cannot be true. In the following, we exclude this possibility by assuming that $0 \leqslant \epsilon_{\theta w} \leqslant \epsilon/(1+\epsilon)$.

2.3. The elasticity of firm-level labor supply

This subsection formally shows that a decrease in $\epsilon_{\theta w}$ increases the elasticity of firm-level labor supply.

2.3.1. Firm-level labor supply

If $\{\eta_{ij}\}$ are independent draws from a type-I Extreme Value distribution, the number of applications to firm j is given by:

$$a_j = \frac{\exp\left(\epsilon[\ln(w_j) + \ln(\theta(w_j))]\right)}{\sum_{k=1}^{J} \exp\left(\epsilon[\ln(w_k) + \ln(\theta(w_k))]\right)} \tilde{L} \tag{3}$$

with $\tilde{L}$ the total number of job applicants.

To simplify the analyses and abstract from strategic interactions in wage setting, assume that the number of firms J is large such that we can write:

$$\ln(a_j) = \epsilon[\ln(w_j) + \ln(\theta(w_j))] + \ln(\lambda\tilde{L}) \tag{4}$$

where λ is a constant common across all firms. Using Equation (4) and the fact that firm-level employment can be defined as $l_j \equiv a_j \theta(w_j)$, labor supply to the firm is given by:

$$\ln(l_j) = [\epsilon(1 - \epsilon_{\theta w}) - \epsilon_{\theta w}] \ln(w_j) + \ln(\lambda\tilde{L}) \tag{5}$$

2.3.2. The elasticity of firm-level labor supply

Using Equations (2) and (4), the elasticity of firm-level applications w.r.t. wages is given by:

$$\epsilon_{aw} \equiv \frac{d\ln(a_j)}{d\ln(w_j)} = \epsilon(1 - \epsilon_{\theta w}) \tag{6}$$

which shows that ϵ_{aw} is decreasing in $\epsilon_{\theta w}$.[2]

[2] Estimates of ϵ_{aw} are around 0.5. See Manning (2021) for a discussion.

From Equation (5), the elasticity of firm-level labor supply is given by:

$$\epsilon_{lw} \equiv \frac{d\ln(l_j)}{d\ln(w_j)} = \epsilon(1-\epsilon_{\theta w}) - \epsilon_{\theta w} = \epsilon - (1+\epsilon)\epsilon_{\theta w} \tag{7}$$

which shows that ϵ_{lw} is decreasing in $\epsilon_{\theta w}$.[3] To ensure that $\epsilon_{lw} \geqslant 0$ or that firm-level labor supply is upward sloping, we assume that $0 \leqslant \epsilon_{\theta w} \leqslant \epsilon/(1+\epsilon)$. Note that a decrease in $\epsilon_{\theta w}$ increases ϵ_{lw}. That is, firm-level labor supply becomes more elastic if the balance of power shifts towards workers, as was graphically illustrated in Figure 1. If $\epsilon_{\theta w} = 0$ and $\epsilon \to \infty$, we get $\epsilon_{lw} \to \infty$. In this limiting case, the law of one wage holds because labor markets are perfectly competitive.

2.4. Wage setting by firms

Assume that firms have the following production function:

$$q_j = \psi_j \ln(l_j) \tag{8}$$

where ψ_j is firm-specific productivity. Firms maximize profits by posting a wage that minimizes labor costs given Equation (5):[4]

$$\max_{w_j} \left[\psi_j \ln(l_j) - w_j l_j\right] \quad \text{s.t.} \quad l_j = l_j(w_j) \tag{9}$$

The first-order conditions are given by:

$$\psi_j \frac{1}{l_j} \frac{dl_j(w_j)}{dw_j} = l_j + w_j \frac{dl_j(w_j)}{dw_j}$$

Using the definition of ϵ_{lw}, this can be written as:

$$w_j = \left(\frac{\epsilon_{lw}}{1+\epsilon_{lw}}\right) \frac{\psi_j}{l_j} \tag{10}$$

which shows that wages are a markdown of marginal labor productivity. Moreover, note

[3] Estimates of ϵ_{lw} are between 0 and 6. See Langella and Manning (2021).

[4] We assume employers do not observe worker preferences for firm-specific non-wage amenities. This implies that employers cannot discriminate between workers: if a firm wants to hire more workers, it needs to offer higher wages to all workers. Product markets are assumed to be perfectly competitive.

that Equation (7) implies that:

$$\frac{\epsilon_{lw}}{1+\epsilon_{lw}} = \frac{\epsilon - (1+\epsilon)\epsilon_{\theta w}}{(1+\epsilon)(1-\epsilon_{\theta w})}$$

Substituting this into Equation (10) and taking logs gives:

$$\ln(w_j) = \ln\left(\psi_j \frac{\epsilon - (1+\epsilon)\epsilon_{\theta w}}{(1+\epsilon)(1-\epsilon_{\theta w})}\right) - \ln(l_j) \tag{11}$$

Combining Equations (2), (4), (5) and (11), equilibrium expressions for wages and employment can be derived.[5] Firm-specific equilibrium wages are given by:

$$\ln(w_j) = \underbrace{\frac{1}{(1+\epsilon)(1-\epsilon_{\theta w})} \ln\left(\psi_j \frac{\epsilon - (1+\epsilon)\epsilon_{\theta w}}{(1+\epsilon)(1-\epsilon_{\theta w})}\right)}_{\equiv A} - \frac{1}{(1+\epsilon)(1-\epsilon_{\theta w})} \ln(\lambda \tilde{L}) \tag{12}$$

where the right-hand side only depends on the model's parameters. Firm-level employment in equilibrium is given by:

$$\ln(l_j) = \underbrace{\frac{\epsilon - (1+\epsilon)\epsilon_{\theta w}}{(1+\epsilon)(1-\epsilon_{\theta w})} \ln\left(\psi_j \frac{\epsilon - (1+\epsilon)\epsilon_{\theta w}}{(1+\epsilon)(1-\epsilon_{\theta w})}\right)}_{\equiv B} + \frac{1}{(1+\epsilon)(1-\epsilon_{\theta w})} \ln(\lambda \tilde{L}) \tag{13}$$

Note that terms A in Equation (12) and B in Equation (13) are firm-specific, showing that relatively more productive firms (i.e. firms with higher ψ_j) pay higher wages and employ more workers.

2.5. Comparative statics when the balance of power shifts towards workers

We first show that the average real wage grows when firms' wage-setting power decreases. We then show that our model also predicts that lower-tail wage inequality decreases because relative wages of low-wage workers increase and because workers relocate from low-wage to higher-wage firms.

[5] See Appendix A.1 for details.

2.5.1. Average real wage growth

The economy-wide average real wage is given by the employment-weighted average of firm-specific wages:

$$\bar{w} = \sum_j \frac{l_j}{L} w_j$$

with L the total number of jobs. Using Equation (10), this can be rewritten as:

$$\bar{w} = \frac{1}{L}\left(\frac{\epsilon_{lw}}{1+\epsilon_{lw}}\right)\sum_j \psi_j \tag{14}$$

If labor markets are perfectly competitive or $\epsilon_{lw} \to \infty$, the term in brackets in Equation (14) becomes unity. In this extreme case, technological progress directly results in average real wage growth. This result is consistent with the existence of a "productivity bandwagon" in competitive models.[6] Moreover, equation (14) shows that changes in the balance of power between firms and workers can either slow down (if ϵ_{lw} decreases because $\epsilon_{\theta w}$ increases) or speed up (if ϵ_{lw} increases because $\epsilon_{\theta w}$ decreases) this productivity bandwagon. Importantly, we argue that part of the growth in average real wages in Costa Rica was driven by an increase in ϵ_{lw}.

2.5.2. Changes in relative wages and employment

Our model also predicts that a decrease in $\epsilon_{\theta w}$ results in a decrease in lower-tail wage inequality because the relative wages of low-wage workers increase and low-wage workers relocate to high-wage firms, as illustrated in Figure 1.

To see what happens to relative wages and employment when $\epsilon_{\theta w}$ decreases, we can differentiate the firm-specific terms A in Equation (12) and B in Equation (13) w.r.t. $\epsilon_{\theta w}$.[7] Deriving term A in Equation (12) w.r.t. a decrease in $\epsilon_{\theta w}$ gives:

$$-\frac{\partial A}{\partial \epsilon_{\theta w}} = \frac{1}{(1+\epsilon)(1-\epsilon_{\theta w})^2}\left[\frac{1}{\epsilon-(1+\epsilon)\epsilon_{\theta w}} - \ln\left(\psi_j \frac{\epsilon-(1+\epsilon)\epsilon_{\theta w}}{(1+\epsilon)(1-\epsilon_{\theta w})}\right)\right] \tag{15}$$

which is decreasing in ψ_j.

From Equation (13) it is straightforward to see that a decrease in $\epsilon_{\theta w}$ will also increase

[6] Acemoglu and Johnson (2023) coin the term "productivity bandwagon" to describe the increase in the average real wage due to technological progress.

[7] See Appendix A.2 for details.

relative employment in firms with higher ψ_j. More formally, differentiating term B in Equation (13) w.r.t. a decrease in $\epsilon_{\theta w}$ gives:

$$-\frac{\partial B}{\partial \epsilon_{\theta w}} = \frac{1}{(1+\epsilon)(1-\epsilon_{\theta w})^2}\left[1+\ln\left(\psi_j \frac{\epsilon-(1+\epsilon)\epsilon_{\theta w}}{(1+\epsilon)(1-\epsilon_{\theta w})}\right)\right] \tag{16}$$

which is increasing in ψ_j.

In conclusion, our model predicts average real wage growth when increased internet access complements workers' job search and diminishes the wage-setting power of firms. Furthermore, it predicts that increased internet access compresses lower-tail wage inequality even among identical workers. This is due to an increase in the relative wages of workers in smaller low-wage firms and the relocation of workers from smaller low-wage to larger high-wage firms.

3. Data

3.1. Internet infrastructure investments

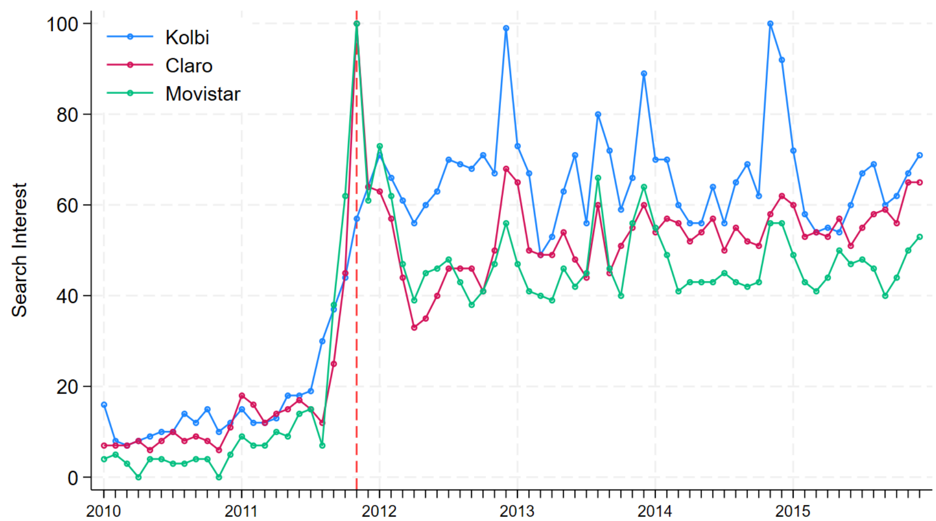
The liberalization of Costa Rica's telecommunications market emerged as a requirement of the Free Trade Agreement (FTA) with the United States. In October 2007, Costa Rica held a referendum on the FTA, which passed by a narrow margin of 51% to 49%. Before this reform, the market operated as a state monopoly under the Costa Rican Institute of Electricity (ICE), which served as the sole provider of telecommunications services in the country (PROSIC 2012, 2013).

The implementation of the liberalization of the telecommunications market involved several stages between 2008 and 2011. Opening this market to competition required the change of older legislation and the enactment of new legislation. This period also saw the establishment of the regulatory institution of the telecommunication sector. In addition, frequencies had to be auctioned, public contests had to be held, and legal disputes had to be settled. This process took years (PROSIC 2012, 2013).

In practice, it was until November 2011 that the market opened to competition, marking a significant shift in Costa Rica's telecommunications landscape. Following liberalization, three main providers served the market: Kölbi (ICE's commercial brand for telecommunication services), Claro, and Movistar. Consumers could then choose among several Internet service providers, a broader range of postpaid options was available, and prepaid sim cards were started being offered (PROSIC 2012, 2013). Figure

2 shows a sharp increase in the index of Google searches for internet providers after the market opened in November 2011.

FIGURE 2. **Interest in internet providers increased**



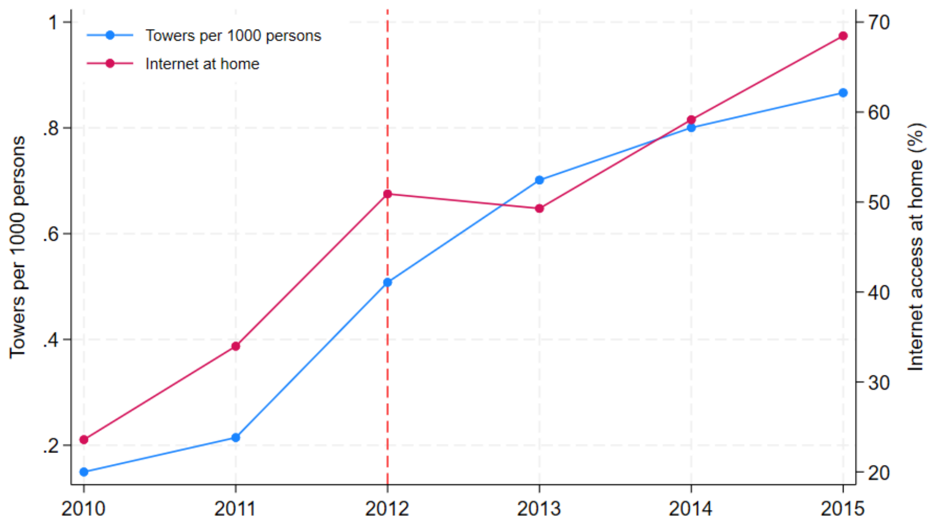
Source: Google Trends. *Notes:* Search index relative to the highest point on the chart.

Our first data source comes from the Telecommunications Superintendency (SUTEL), which maintains administrative records on the Internet infrastructure from Kölbi, Claro, and Movistar. The three telecommunications companies are required by law to provide SUTEL with comprehensive information about their infrastructure every year. This requirement ensures high-quality data on infrastructure investments in locations and over time. Internet infrastructure refers to infrastructure such as towers, monopoles, posts, and braced masts, among others. For simplicity, we will also refer to this internet infrastructure as towers.

This novel data set contains detailed information on towers, including their precise geographic coordinates, year of installation, and technology. We use the coordinates to assign each tower to a geographic county, the year of installation to determine how many towers are available in each county in each year, and the technology to eliminate towers only with 2G and keep those with 3G and higher. We discard 2G-only towers because 2G networks only allow access to basic cellphone network and texts, while 3G networks allow users to access the internet. For Costa Rica as a whole, Figure 3 shows that the supply of broadband infrastructure increased from 0.2 towers per 1000 persons in 2011 to just over 0.8 in 2015.

Figure 4 further illustrates how the expansion of towers spread geographically across counties between 2011 and 2015. Costa Rica consists of seven provinces that

FIGURE 3. **Expansion of internet in Costa Rica**



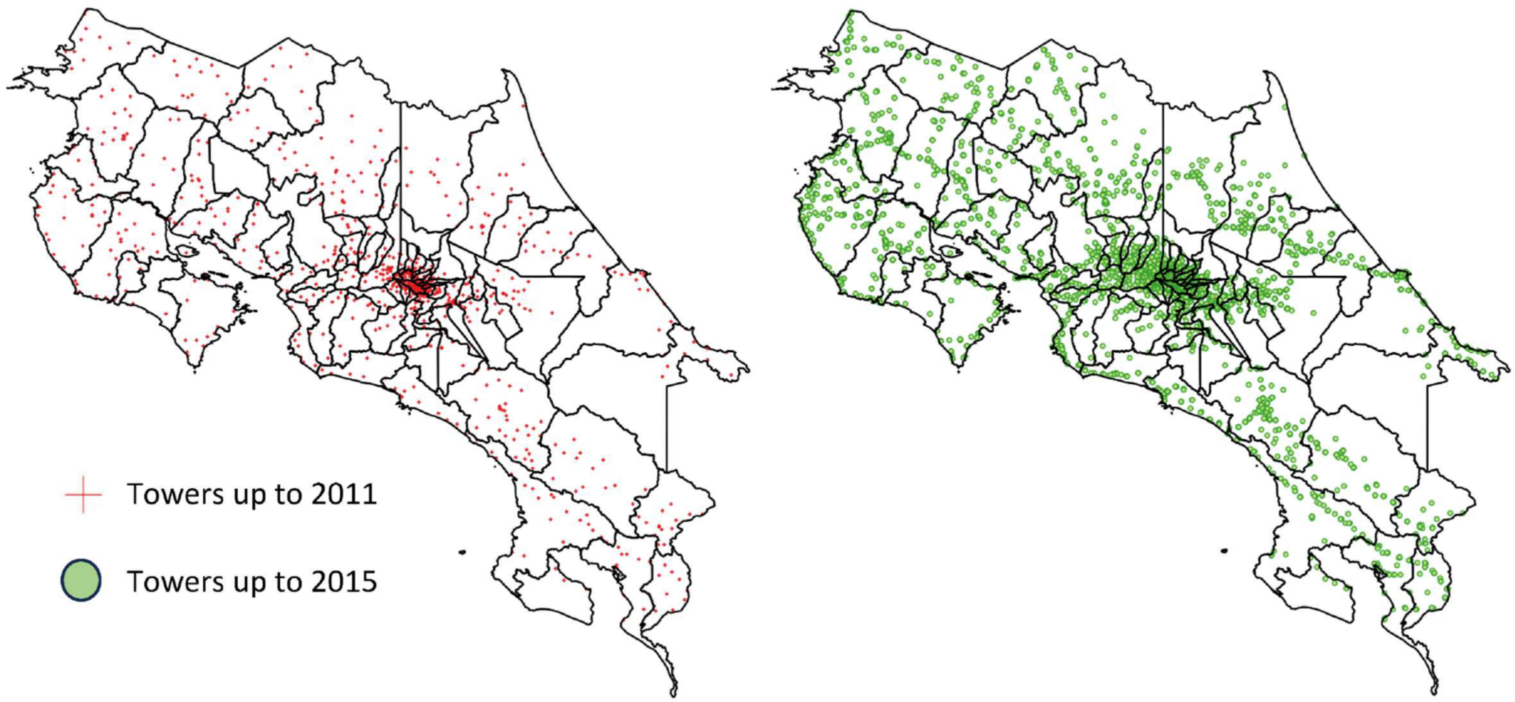
Source: ENAHO and SUTEL. *Notes:* Figure depicts the averages across counties. Left y-axis: number of towers per 1000 persons. Right y-axis: share of individuals at a county with internet access at home (in %).

are numbered 1 through 7, and each province consists of counties that are numbered accordingly: The San José counties go from 101 to 120, Alajuela from 201 to 215, Cartago from 301 to 308, Heredia from 401 to 410, Guanacaste from 501 to 511, Puntarenas from 601 to 611, and Limón from 701 to 706. There are 66 counties in our data. Counties function as the primary local governance units with elected municipal governments. For planning and development, the Ministry of National Planning and Economic Policy (MIDEPLAN) groups counties that are economically similar into six socioeconomic regions (INEC 2016).[8]

Liberalization of the telecommunications market mainly benefited households since firms were already highly connected to the internet. Firm-level survey data from PROSIC shows that in 2012, 71% of all firms had internet access (62% of micro firms, 94% of small and medium firms, and 100% of large firms), reaching 88% across all firms in 2013 (PROSIC 2012, 2013). These high levels of firm connectivity already in 2012 and 2013 help to isolate the hypothesis that the liberalization of the telecommunications market primarily improved workers' access to information about job opportunities.

[8]See Appendix B for details.

FIGURE 4. **Internet infrastructure across counties in Costa Rica**



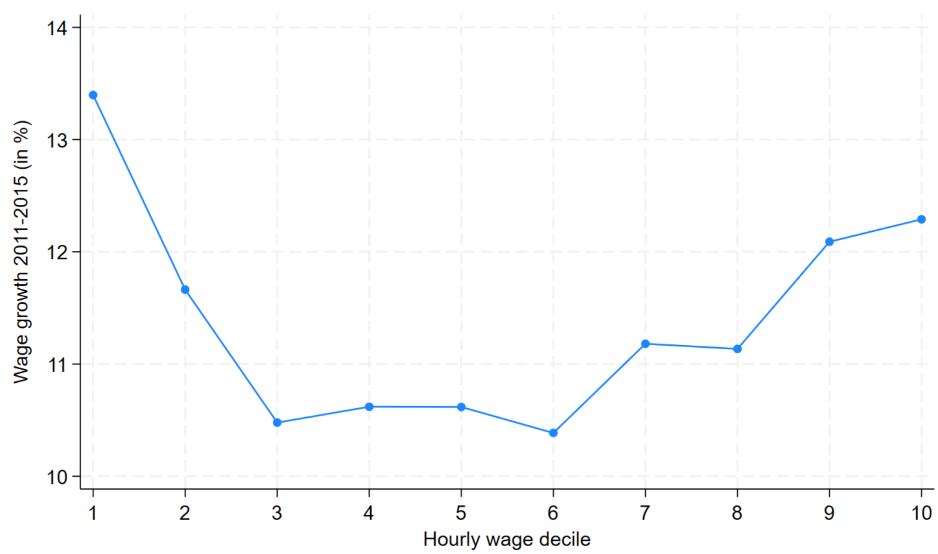
Source: SUTEL. Counties' limits shown in black. *Notes:* Figure shows internet infrastructure, such as non-tubular self-supporting towers, monopole, and posts, before the telecom market opened to competition (Towers up to 2011) and after (Towers up to 2015).

3.2. Labor market outcomes

Our source for labor market outcomes is the National Household Survey (ENAHO), a repeated cross-sectional survey conducted annually by Costa Rica's National Statistics and Census Bureau (INEC). We gained access to a novel version of this data set that includes geographic identifiers at the county level (instead of at the broader regional level), allowing us to link within-county changes in labor market outcomes to within-county changes in internet infrastructure over time. Our analysis focuses on salaried workers (men and women) aged 15 to 65 years over the period 2010-2015, encompassing years both before and after the liberalization of the telecommunications market.

The ENAHO provides comprehensive information on employment status, wages, the size of the firm that employs a worker, individual characteristics, and access to information and communication technologies (ICTs) such as internet access at home. Another strength of our unique data set, especially in the context of a developing country, is that our survey includes workers not only from the formal sector (as are only included in administrative data), but also from the informal sector. This is important since low-wage workers are more likely to have informal jobs.

FIGURE 5. **Wage growth by decile in Costa Rica, 2011-2015**



Source: ENAHO. *Notes:* Wage growth is computed for each hourly wage decile in each county and averaged across all counties.

Figure 5 illustrates the growth of real hourly wages by decile between 2011 and 2015. What is clear from this figure is that wage growth in the first and second deciles was higher than in the third to eighth decile. That is, lower-tail wage inequality decreased.

Turning to summary statistics on internet access at home, Figure 3 shows that internet access at home doubled from 35% in 2011 to 70% in 2015 as more towers were built.

For the Costa Rican economy as a whole, the rapid expansion of internet infrastructure is positively correlated with internet access at home, average real wage growth, and decreasing lower-tail wage inequality. The remainder of the paper aims to show that this correlation is also causal.

4. Difference-in-Differences design

To identify the causal impacts of investments in internet infrastructure on wage inequality, we use a Difference-in-Differences (DiD) design with continuous treatment intensity (Callaway et al. 2025). Our baseline specification is given by:

$$y_{ct} = \alpha_c + \tau_{r(c)t} + \beta \Delta Towers_c \times Post_t + \varepsilon_{ct} \tag{17}$$

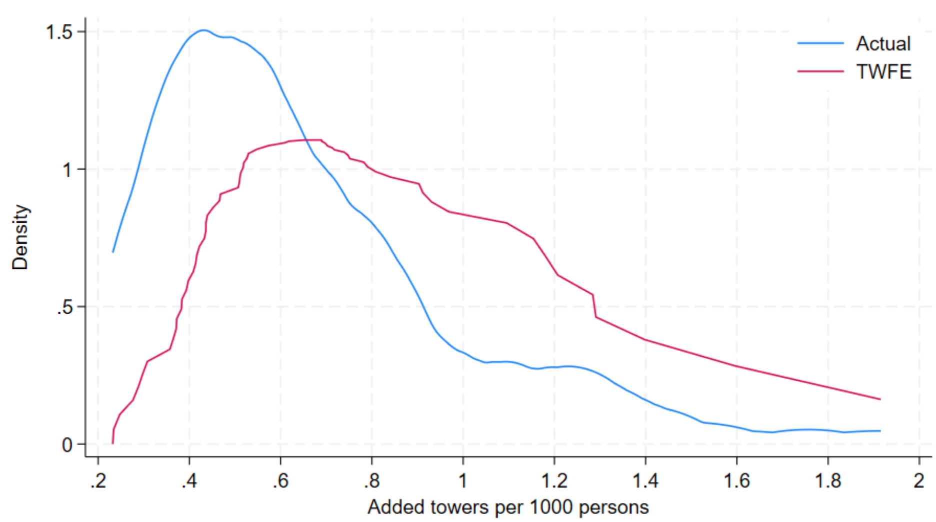
where y_{ct} is an outcome in county c in year t. There are 66 counties, indicated by subscript c, which can be grouped into 6 more aggregate regions, indicated by subscript $r(c)$. There are 6 years of data from 2010 to 2015, with 2010 and 2011 the pre-treatment years and 2012-2015 the post-treatment period.

Equation (17) includes a vector of county fixed effects (α_c) to control for time-invariant county characteristics, and a vector of year (τ_t) or region-year ($\tau_{r(c)t}$) time fixed effects to account for common and region-specific time trends. Because our measure of towers per 1000 people is cumulative, equation (17) uses $\Delta Towers_c$ which is a continuous treatment variable that measures the change in the number of towers per 1000 persons in county c between 2011 and 2015. The variable $Post_t$ is a dummy that is unity in each post-treatment year, and is zero in each pre-treatment year. The term ε_{ct} is an error term. All regressions are weighted by the number of workers in a county, and standard errors are clustered at the county level.

Our main parameter of interest is β. Upon imposing Strong Parallel Trends (SPT) because $\Delta Towers_c$ is a continuous variable, the TWFE estimates of β identify an Average Causal Response (ACR) of y_{ct} to a unit increase in towers per 1000 people. SPT is stronger than standard parallel trends because it also rules out that some counties invest more in internet access because the resulting change in outcomes is different in those counties (i.e., there can be no "selection-on-gains"). This ensures that the observed change in outcomes in a county due to its increase in internet access reflects what would have happened in all other counties if they had increased their internet access the same.

Even if SPT holds, TWFE estimates of β do not necessarily capture an aggregate ACR that is meaningful if causal responses vary between treatment intensities. Callaway et al. (2025) show that an ordinary least squares estimate of β in equation (17) is a weighted average of the causal responses for different treatment intensities, where the weights inherit their usual form from ordinary least squares. In particular, the weights are a hump-shaped density centered on the mean of $\Delta Towers_c$. Therefore, the weighting scheme that a regression of equation (17) implicitly uses to average the heterogeneity in causal responses between treatment intensities only results in a meaningful average if the actual density of $\Delta Towers_c$ is also hump-shaped. To see whether this is the case, the blue line in Figure 6 plots the actual density of $\Delta Towers_c$. In addition, the red line plots the TWFE weights calculated using the decomposition of the aggregate ACR into a weighted average of causal responses conditional on the intensity of treatment presented in Table 1 of Callaway et al. (2025). The figure shows that both are very similar, suggesting that TWFE estimates of β capture an aggregate ACR that is informative about the impact of increased internet access in the average county.

FIGURE 6. **Actual treatment density and TWFE weights**



Notes: Added towers per 1000 persons is the difference between the number of towers per 1000 persons in 2011 and 2015 in a county. The mean is 0.65 and the standard deviation is 0.34. The blue line plots a smoothed kernel density of actual added towers per 1000 persons across counties. The red line is a smoothed kernel density of TWFE decomposition weights using the the first formula in Table 1 of Callaway et al. (2025).

5. The impact of internet access on wage dispersion

5.1. Internet at home

To validate that investments in internet infrastructure effectively capture increased internet access, we first examine the relationship between the increase in towers per 1000 persons and workers' internet access. That is, we estimate equation (17) defining y_{ct} as the share of individuals who report having internet access at home.

Column (1) in the top panel of Table 1 shows that an additional tower per 1000 persons increases the share of individuals with internet access at home by approximately 3 percentage points when including fixed effects for county and year. This represents approximately a 12% increase relative to the mean prior to the period of 29% or one-fifth of the pre-period standard deviation of 15 percentage points in internet access at home. Taking into account regional-specific time trends in column (2), the effect doubles to approximately 7 percentage points. As a falsification exercise, the bottom panel of Table 1 uses the share of individuals who have a landline at home as the dependent variable, which should not be influenced by an increase in internet towers. As expected, the point estimates are smaller and not statistically significant.

TABLE 1. **Internet towers and internet access at home**

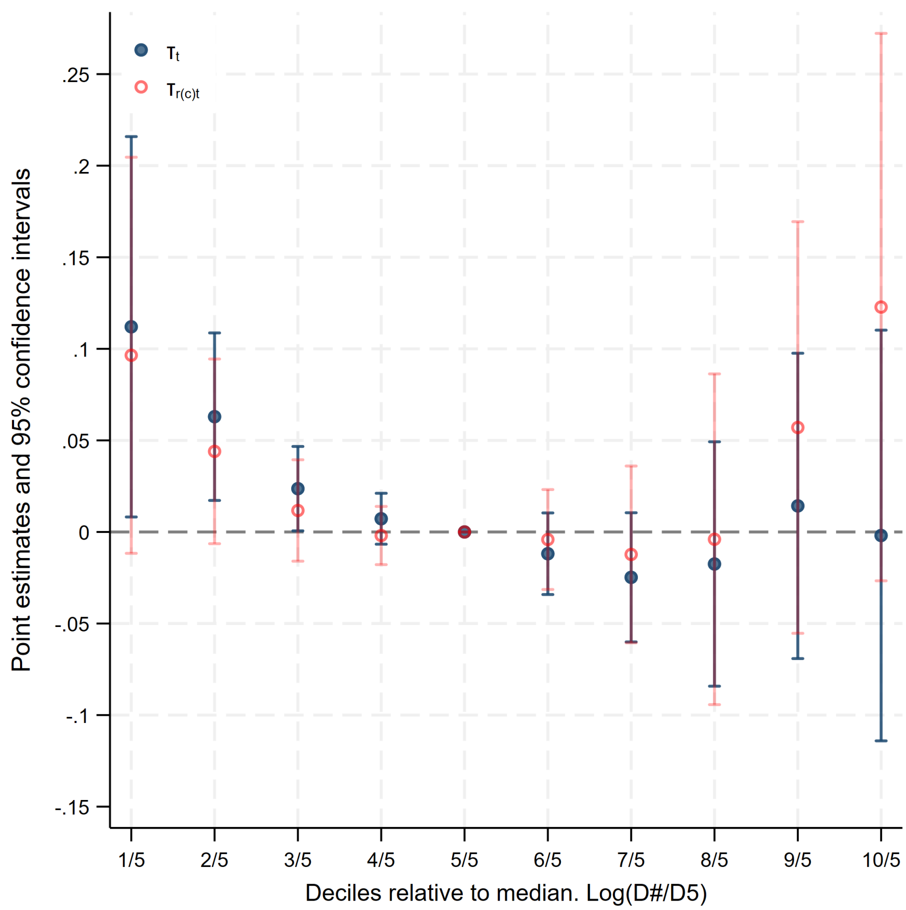
	(1)	(2)
	Dep. var.: % with internet at home	
$\Delta Towers_c$	3.31^{**}	6.92^{**}
	(1.42)	(2.66)
Time fixed effect	τ_t	$\tau_{r(c)t}$
	Dep. var.: % with landline at home	
$\Delta Towers_c$	-1.57	0.70
	(1.57)	(1.89)
Time fixed effect	τ_t	$\tau_{r(c)t}$

Notes: Estimates from equation (17). Top panel: the dependent variable is the percentage of individuals that have internet access at home in county c in year t. The pre-period mean is 29% and the standard deviation is 15%. Bottom panel: the dependent variable is the percentage of individuals that possess a landline telephone in county c in year t. The pre-period mean is 61% and standard deviation is 14%. Each regression is based on 396 observations. Regressions are weighted by workers per county. Standard errors in parentheses are clustered at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.2. Wage inequality

We estimate equation (17) using the logarithm of a wage decile relative to the median as a dependent variable. That is, we define $y_{ct} = \log(D_x/D_5)_{ct}$ with $x = 1, \ldots, 10$ and D_x a wage decile. The vertical axis of Figure 7 plots the estimated β and its 95% confidence interval for each decile on the horizontal axis. For each decile, we plot two estimates of β allowing for different time fixed effects in equation (17): only year fixed effects (τ_t) or the more flexible region-year fixed effects ($\tau_{r(c)t}$).

FIGURE 7. **Internet infrastructure investments and changes in wage inequality**



Notes: Estimates from equation (17). Each regression is based on 396 observations. Regressions are weighted by workers per county. Standard errors in parentheses are clustered at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

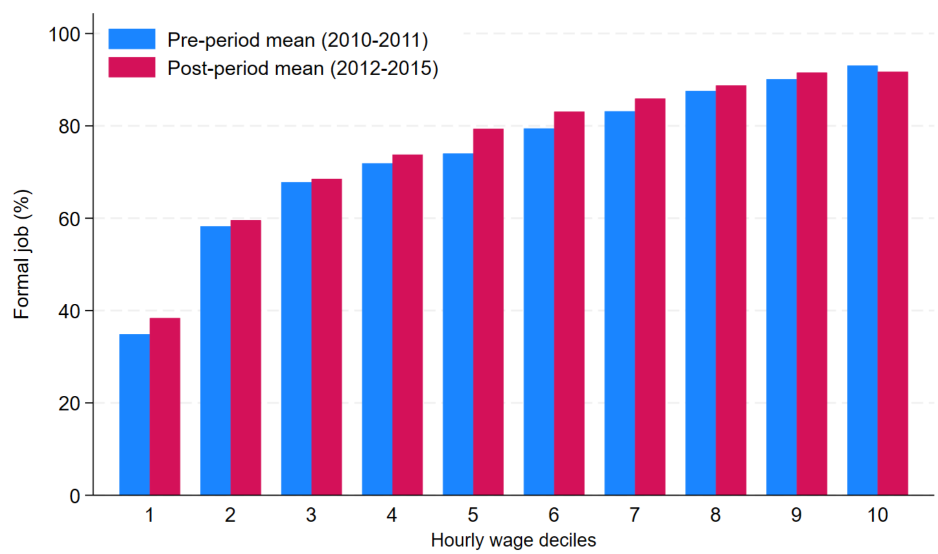
Estimates for the first decile (relative to the median) of approximately 0.1 predict a decrease of approximately 10 log points in $\log(D_1/D_5)$ for a unit increase in $\Delta Towers$. To gauge the size of this effect, a one-standard deviation increase in the number of towers per 1000 persons is approximately 0.3. Similarly, a standard deviation in $\log(D_1/D_5)$

equals 17 log points. Therefore, a one-standard deviation increase in towers per 1000 persons increases $\log(D_1/D_5)$ by approximately 18% (=3/17) of a standard deviation.

Turning to the treatment effects for other deciles, the estimates for β are decreasing up to $\log(D_7/D_5)$. This suggests that increased internet access reduced lower-tail wage inequality up to the seventh decile, in line with the predictions of our model. In contrast, the point estimates for the eight to tenth deciles do not seem to be strongly correlated with investments in internet infrastructure. If anything, an increase in internet infrastructure increased upper-tail wage inequality. These findings are robust for alternative measures of wage inequality.[9]

Our measure of hourly wages excludes additional pay components such as sick days, overtime pay, paid holidays, or receiving a 13th salary. In addition, not all workers have formal jobs. A job is considered formal if the worker receives at least one of the following: work-risk insurance, deduction of social security, or insured as a salaried worker. Work-risk insurance refers to insurance that protects the worker in case of injuries or illnesses related to their job. Deduction of social security refers to a salary deduction to opt for social security protection against disability, old age, death, or illness. Insured as a salaried worker refers to being insured as an employed salaried worker instead of being insured through a family member, self-insured, insured through pension, or not insured.

FIGURE 8. **Fraction of workers with formal jobs**



[9]See Appendix C.1 for details.

Figure 8 plots the percentage of workers with formal jobs within each decile for both the pre- and the post-period. It shows that workers in the lowest deciles are more likely to have informal jobs. One possibility could be that this likelihood increased over time due to increased internet access (e.g. by allowing firms to better search for workers, thereby increasing their monopsony power) and that the relative wage increases in low-wage deciles documented in Figure 7 are merely capturing a compensating wage differential. If this were the case, the reason for the compression in lower-tail wage inequality would not be more competition for workers between firms, as our model highlights, but less competition.

TABLE 2. **Internet towers and non-wage characteristics of jobs**

	Dep. var.: Additional pay		*Dep. var.: Formal job*	
	(1)	(2)	(3)	(4)
		Panel A: All workers		
$\Delta Towers_c$	1.47	2.82*	1.50	2.78**
	(1.19)	(1.57)	(1.07)	(1.23)
Time fixed effect	τ_t	$\tau_{r(c)t}$	τ_t	$\tau_{r(c)t}$
		Panel B: Workers paid below the median		
$\Delta Towers_c$	4.20*	4.97*	4.64**	5.29**
	(2.21)	(2.69)	(1.90)	(2.47)
Time fixed effect	τ_t	$\tau_{r(c)t}$	τ_t	$\tau_{r(c)t}$
		Panel C: Workers paid above the median		
$\Delta Towers_c$	0.17	-0.28	-0.63	-0.88
	(0.97)	(1.12)	(1.37)	(1.57)
Time fixed effect	τ_t	$\tau_{r(c)t}$	τ_t	$\tau_{r(c)t}$

Notes: Estimates from equation (17). Panel A: For Additional pay, the pre-period mean is 80 and standard deviation is 9. For formal jobs, the mean is 71 and standard deviation is 10. Panel B: For Additional pay, the pre-period mean is 74 and standard deviation is 12. For formal jobs, the mean is 61 and standard deviation is 13. Panel C: For Additional pay, the pre-period mean is 92 and standard deviation is 5. For formal jobs, the mean is 87 and standard deviation is 7. Each regression is based on 396 observations. Regressions are weighted by workers per county. Standard errors in parentheses are clustered at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

To further test our hypothesis, we therefore estimate equation (17) using *Additional pay* and *Formal job* as dependent variables in columns (1)-(2) and (3)-(4) of Table 2, respectively. *Additional pay* is the percentage of workers with at least one additional pay component (sick days, overtime, holidays, 13th salary) in county c in year t. *Formal job* is the percentage of workers who receive at least one component of formal work (work risk insurance, social security deduction, or insured as salaried worker) in county c in year t.

Panel A groups all workers together, while the other panels only consider workers with wages below (panel B) or above (panel C) the median. We expect positive effects for low-wage workers if our hypothesis is correct but negative effects if the compression in lower-tail wage inequality is a compensating differential.

Panel A shows estimates of β for the average worker. All estimates are positive and some are statistically significant. However, our model also predicts stronger effects for low-wage workers than for high-wage workers. Therefore, panel B only considers workers paid below the median, whereas panel C only uses workers paid above the median. In line with treatment effect estimates for wages, non-wage characteristics improved more for low-wage workers than for high-workers. We see this evidence as supportive of the hypothesis that increased competition for workers between firms not only decreased lower-tail wage inequality but also disproportionately improved non-wage characteristics of low-wage jobs.

5.3. Wage growth and job reallocation by firm size

The analyses so far provided evidence in support of the hypothesis that increased investment in internet infrastructure compresses lower-tail wage inequality. But our model is also informative about the precise channels through which this happens. If labor productivity differs between firms because they use different production technologies, the labor market will consist of smaller low-wage firms and larger high-wage firms. Increased competition between firms for workers forces wages to converge to the competitive wage. For smaller low-wage firms, this higher competitive wage implies that they must lay off workers to increase the marginal product of labor. For larger high-wage firms, the opposite holds. Consequently, wages in smaller low-wage firms grow relative to larger high-wage firms. In addition, employment in smaller firms decreases relative to larger firms. This subsection provides further evidence to support these predictions.

Table 3 shows some summary statistics. The ENAHO survey asks if a worker is employed in a firm with less than 10, 11 to 20, 21 to 30, 31 to 99, or more than 100 workers. The final row of column (1) shows that the overall average real hourly wage grew by 8.5% between 2010 and 2015. This is in line with our model's prediction of the productivity bandwagon in equation (14). Columns (2)-(5) illustrate the wage premium for working in larger firms, suggesting that smaller firms are less productive than larger firms. In addition, the final row shows that wage growth was decreasing in firm size, as predicted by the comparative statics of our model.

TABLE 3. **Average hourly wages and wage growth by firm size**

	All firms	By firm size			
	(1)	(2) 1-19 emp	(3) 20-29 emp	(4) 30-99 emp	(5) $\geq$100 emp
Mean log hourly wage					
2010-2011 (pre)	7.77	7.40	7.78	7.91	7.99
2012-2015 (post)	7.85	7.53	7.87	7.98	8.02
Wage growth (in %)	8.47	13.35	9.51	7.77	3.24

To provide causal evidence, Table 4 presents estimates of β in equation (17) for different categories of firm sizes. The top panel uses the logarithm of the average hourly wage in a firm size category relative to the largest category as the dependent variable. That is, $y_{ct} = \log(\bar{W}_x/\bar{W}_{\geq 100})$ with x a firm size category of 1-19, 20-29, or 30-99 employees. The bottom panel uses the employment share of a firm size category relative to the largest category as the dependent variable instead. That is, $y_{ct} = s_x/s_{\geq 100}$ with s_x the fraction of all workers employed in firm size category x.

Our hypothesis predicts positive coefficients for relative wages and negative coefficients for relative employment. In line with these predictions, the top panel of Table 4 shows that all but one of the point estimates are positive and largest for the smallest firms. The bottom shows that all but one of the point estimates are negative and more so for the smallest firms.

6. Alternative explanations

The discussion thus far has excluded the potential importance of changes in Costa Rica's labor market institutions. Perhaps the most obvious alternative explanation for our results would be an increase in minimum wages in those counties that also saw the largest investments in internet infrastructure. However, a large fraction of low-wage workers in our data have informal jobs that do not comply with minimum-wage laws. This is further illustrated in Figure 9. The figure shows the wage density of the average monthly wage of each worker earning below their county's first wage decile in the post-period (years 2012 to 2015). The red vertical line is the national minimum wage for unqualified workers in 2011. It is obvious from the figure that almost all of the ten percent lowest-paid workers in Costa Rica are earning less than the minimum wage.

TABLE 4. **Wage growth and worker reallocation by firm size**

	1-19 emp		20-29 emp		30-99 emp	
	(1)	(2)	(3)	(4)	(5)	(6)
	Dep. var.: Log relative mean hourly wage					
$\Delta Towers_c$	0.04	0.10	0.03	-0.01	0.02	0.04
	(0.11)	(0.12)	(0.10)	(0.11)	(0.08)	(0.09)
Time fixed effect	τ_t	$\tau_{r(c)t}$	τ_t	$\tau_{r(c)t}$	τ_t	$\tau_{r(c)t}$
	Dep. var.: Relative employment share					
$\Delta Towers_c$	-1.56**	-0.77	-0.05	0.06	-0.42**	-0.34**
	(0.63)	(0.62)	(0.06)	(0.09)	(0.13)	(0.11)
Time fixed effect	τ_t	$\tau_{r(c)t}$	τ_t	$\tau_{r(c)t}$	τ_t	$\tau_{r(c)t}$

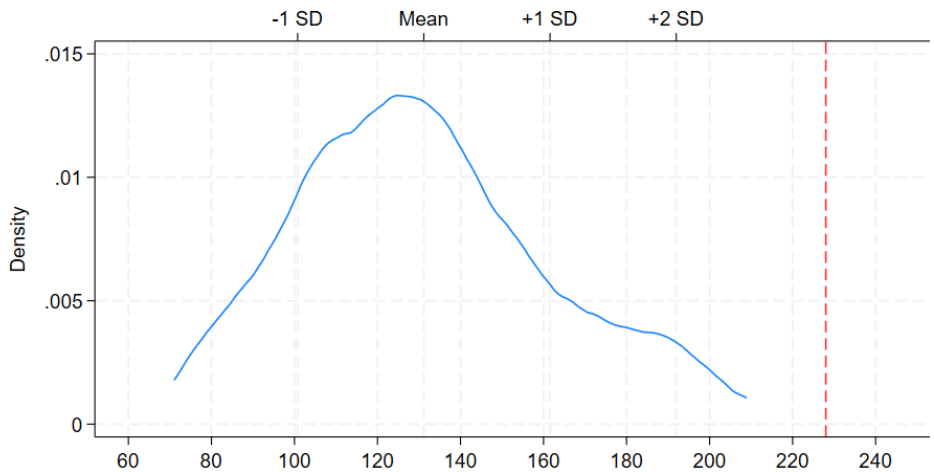
Notes: Estimates from equation (17). Top panel: dependent variable is the log average wage across workers in a firm size category relative to workers in firms with at least 100 employees. The pre-period mean (sd) is -0.5 (0.3) for 1-19 employees, -0.2 (0.4) for 20-29 employees, and -0.05 (0.3) for 30-99 employees. Bottom panel: dependent variable is the percentage of all workers in a firm size category relative to the percentage of workers in firms with at least 100 employees. The pre-period mean (sd) is 5 (4) for 1-19 employees, 0.4 (0.3) for 20-29 employees, and 0.7 (0.5) for 30-99 employees. Each regression is based on 396 observations. Regressions are weighted by workers per county. Standard errors in parentheses are clustered at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A related alternative explanation could be that relative wages changed because the collective bargaining strength of low-paid workers increased in those counties that also saw the largest investments in internet infrastructure. However, unions in Costa Rica do not mainly represent low-wage workers. As shown in Figure 10, union membership is concentrated among high-wage workers, with minimal representation in the lower deciles where we observe the strongest wage growth. Union membership was less than 1% for workers in the bottom decile compared to more than 25% in the top decile during our analysis period.

Finally, we examined other possible explanations for our results. For example, premature deindustrialization could have reduced the demand for middle-paid manufacturing jobs relative to low-paid service jobs (Rodrik 2016). However, this explanation seems unlikely for several reasons. First, it is inconsistent with our findings that relative wages increased, but relative employment decreased in low-wage jobs. Second, our data cover a relatively short 5-year time interval during which the distribution of workers between sectors within regions remained relatively stable. For example, the percentage of workers employed in the secondary sector averaged 18.2% in the pre-period (years

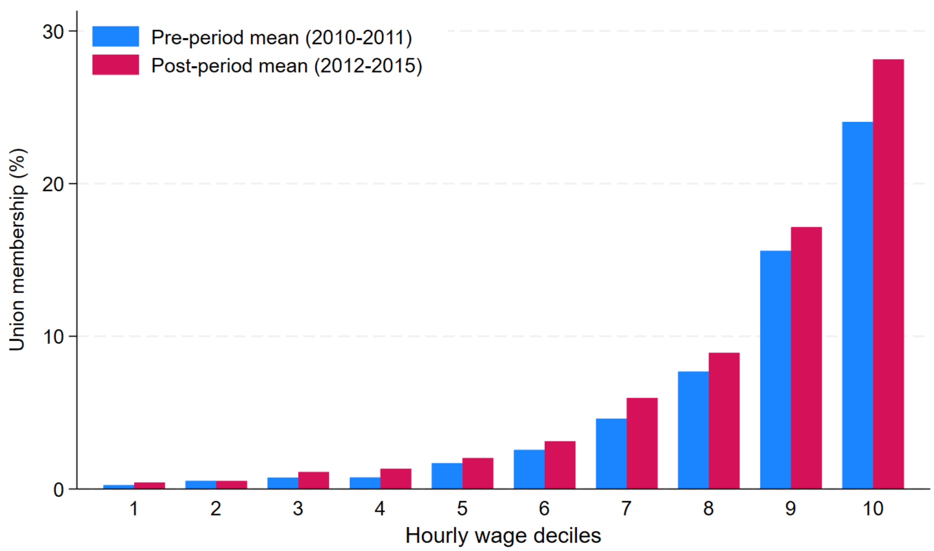
2010 and 2011) and 17.9% in the post-period (years 2012-2015).[10]

FIGURE 9. **Employees with lowest wages earn below minimum wage**



Source: ENAHO. *Notes:* The figure shows the wage density of the average monthly wage of each worker earning below their county's first wage decile in the post-period (years 2012 to 2015). X-axis is in thousands of real Costa Rican *colones*. The red vertical line is the federal minimum wage for unqualified workers in 2011.

FIGURE 10. **Union membership by hourly wage decile**



Source: ENAHO. *Notes:* A worker is classified as a union member if they answer "Yes" (instead of "No") to survey question: "Are you an active member of an union?"

[10]See Appendix C.2 for details.

7. Conclusions

This paper examines how investments in internet infrastructure affect wage inequality through their impact on labor market competition. Using the liberalization of the telecommunications market in Costa Rica as a natural experiment, we show that increased investment in internet infrastructure compresses lower-tail wage inequality. To explain this result, we start from a simple monopsony model in which labor productivity differs between firms, resulting in a labor market with smaller low-wage firms and larger high-wage firms. Increased internet access allows workers to better search for jobs, increasing competition between firms for workers and forcing wages to converge to the competitive wage. For smaller low-wage firms, this higher competitive wage implies that they must lay off workers to increase the marginal product of labor. For larger high-wage firms, the opposite holds. Consequently, wages in smaller low-wage firms grow relative to larger high-wage firms such that lower-tail wage inequality decreases. In addition, employment in smaller firms decreases relative to larger firms.

We find empirical support for these predictions using novel administrative data on internet infrastructure combined with detailed worker-level data. To test the predictions from our model, we leverage recent insights from the literature of Difference-in-Differences with continuous treatment. Our main result is that an increase in internet towers per 1000 persons by standard deviation decreases the gap between the first wage decile and the median by approximately 18% of a standard deviation. We also find that increased internet access reduces lower-tail wage inequality up to the seventh wage decile, although the effects taper off for higher deciles.

Additional evidence supports our main result. Using another strength of our unique data, we show that lower-wage workers also saw a relative improvement in non-wage job characteristics due to increased internet access for workers. These non-wage characteristics include paid sick days and holidays, overtime pay, receiving a 13th salary, or access to social security. The relative improvement in these non-wage characteristics is inconsistent with the idea that the relative wage increases in low-wage deciles are a compensating wage differential. If this were the case, the reason for the compression in lower-tail wage inequality would not be more competition for workers between firms, as our model highlights, but less competition.

Finally, confounding explanations are explored in a descriptive way. It is unlikely that our main results are explained by increases in minimum wages in those counties that also saw the largest investments in internet infrastructure because almost all workers earning less than the first wage decile are paid below the federal minimum wage for unqualified workers. Unionization is also unlikely as an explanation because union membership is concentrated among high-wage workers, with minimal representation in the lower deciles where we observe the strongest wage growth.

Our findings have implications for our understanding of how technological change affects inequality. Although much of the literature has emphasized technology's potential to exacerbate wage disparities through skill-biased technical change, our results highlight an important countervailing force: By reducing information frictions and promoting better directed search, information and communications technology can enhance labor market competition in ways that disproportionately benefit low-wage workers. Our findings suggest that investing in internet access might be particularly effective in shifting the balance of power from employers to workers in developing countries where informal employment is important.

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Appendices - for online publication only

Appendix A. Model

A.1. Equilibrium expressions

From the firm's maximization problem, we derived Equation (11):

$$\ln(w_j) = \ln\left(\psi_j \frac{\epsilon - (1+\epsilon)\epsilon_{\theta w}}{(1+\epsilon)(1-\epsilon_{\theta w})}\right) - \ln(l_j) \tag{A1}$$

and we want to solve for $\ln(w_j)$ by substituting out $\ln(l_j)$ to get Equation (12).

To get an expression for $\ln(l_j)$, first substitute Equation (2) into (4) to get:

$$\ln(a_j) = \epsilon(1-\epsilon_{\theta w})\ln(w_j) + \ln(\lambda L) \tag{A2}$$

Next substitute this expression into $\ln(l_j = \ln(a_j) - \epsilon_{\theta w}\ln(w_j)$:

$$\begin{aligned}
\ln(l_j) &= \epsilon(1-\epsilon_{\theta w})\ln(w_j) + \ln(\lambda L) - \epsilon_{\theta w}\ln(w_j) \\
\ln(l_j) &= [\epsilon(1-\epsilon_{\theta w}) - \epsilon_{\theta w}]\ln(w_j) + \ln(\lambda L) \qquad \text{(A3)}
\end{aligned}$$

which is Equation (5). Substitute Equation (5) into (11):

$$\begin{aligned}
\ln(w_j) &= \ln\left(\psi_j \frac{\epsilon - (1+\epsilon)\epsilon_{\theta w}}{(1+\epsilon)(1-\epsilon_{\theta w})}\right) - \ln(l_j) \\
\ln(w_j) &= \ln\left(\psi_j \frac{\epsilon - (1+\epsilon)\epsilon_{\theta w}}{(1+\epsilon)(1-\epsilon_{\theta w})}\right) - [\epsilon(1-\epsilon_{\theta w}) - \epsilon_{\theta w}]\ln(w_j) - \ln(\lambda L) \qquad \text{(A4)}
\end{aligned}$$

Rearranging terms gives Equation (12):

$$\ln(w_j) = \underbrace{\frac{1}{(1+\epsilon)(1-\epsilon_{\theta w})}\ln\left(\psi_j \frac{\epsilon - (1+\epsilon)\epsilon_{\theta w}}{(1+\epsilon)(1-\epsilon_{\theta w})}\right)}_{\equiv A} - \frac{1}{(1+\epsilon)(1-\epsilon_{\theta w})}\ln(\lambda L) \tag{A5}$$

Finally, substituting Equation (12) into (11) gives Equation (13):

$$\ln(l_j) = \ln\left(\psi_j \frac{\epsilon - (1+\epsilon)\epsilon_{\theta w}}{(1+\epsilon)(1-\epsilon_{\theta w})}\right) - \ln(w_j)$$

$$\ln(l_j) = \underbrace{\frac{\epsilon - (1+\epsilon)\epsilon_{\theta w}}{(1+\epsilon)(1-\epsilon_{\theta w})} \ln\left(\psi_j \frac{\epsilon - (1+\epsilon)\epsilon_{\theta w}}{(1+\epsilon)(1-\epsilon_{\theta w})}\right)}_{\equiv B} + \frac{1}{(1+\epsilon)(1-\epsilon_{\theta w})} \ln(\lambda L) \tag{A6}$$

A.2. Comparative statics

Deriving term A in Equation (12) w.r.t. a *decrease in* $\epsilon_{\theta w}$ gives:

$$-\frac{\partial A}{\partial \epsilon_{\theta w}} = \frac{1}{(1+\epsilon)(1-\epsilon_{\theta w})^2} \left[\frac{1}{\epsilon - (1+\epsilon)\epsilon_{\theta w}} - \ln\left(\psi_j \frac{\epsilon - (1+\epsilon)\epsilon_{\theta w}}{(1+\epsilon)(1-\epsilon_{\theta w})}\right)\right] \tag{A7}$$

which is decreasing in ψ_j such that wage growth is higher in low-wage firms.

Deriving term B in Equation (13) w.r.t. a decrease in $\epsilon_{\theta w}$ gives:

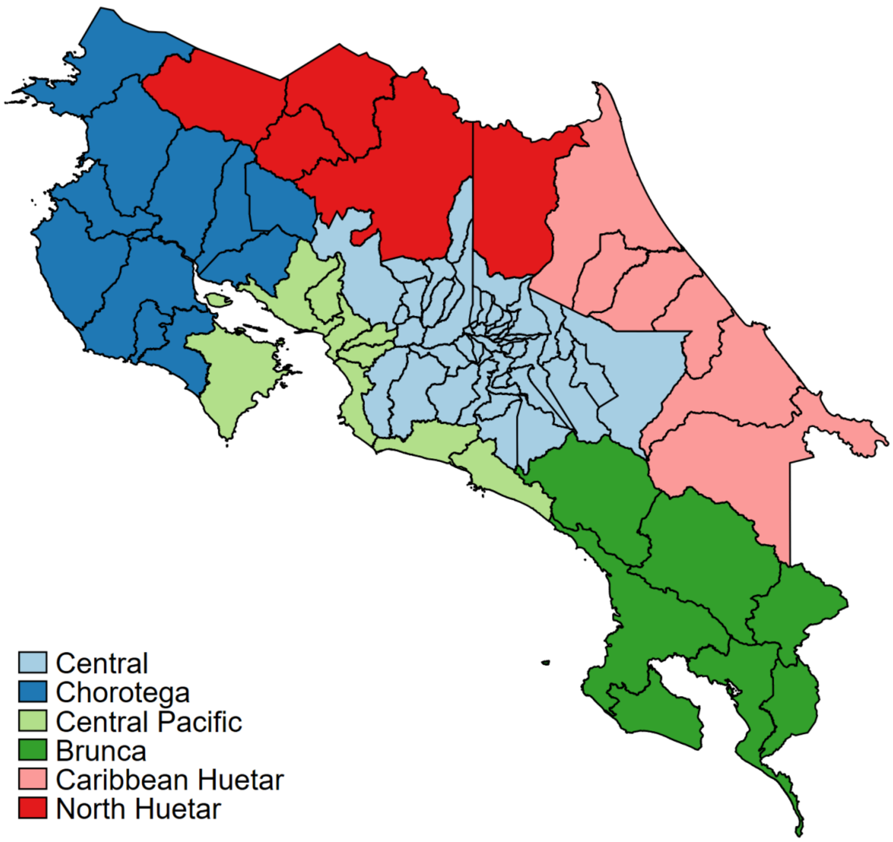
$$-\frac{\partial B}{\partial \epsilon_{\theta w}} = \frac{1}{(1+\epsilon)(1-\epsilon_{\theta w})^2} \left[1 + \ln\left(\psi_j \frac{\epsilon - (1+\epsilon)\epsilon_{\theta w}}{(1+\epsilon)(1-\epsilon_{\theta w})}\right)\right] \tag{A8}$$

which is increasing in ψ_j such that workers relocate from low-wage to high-wage firms.

Appendix B. Data

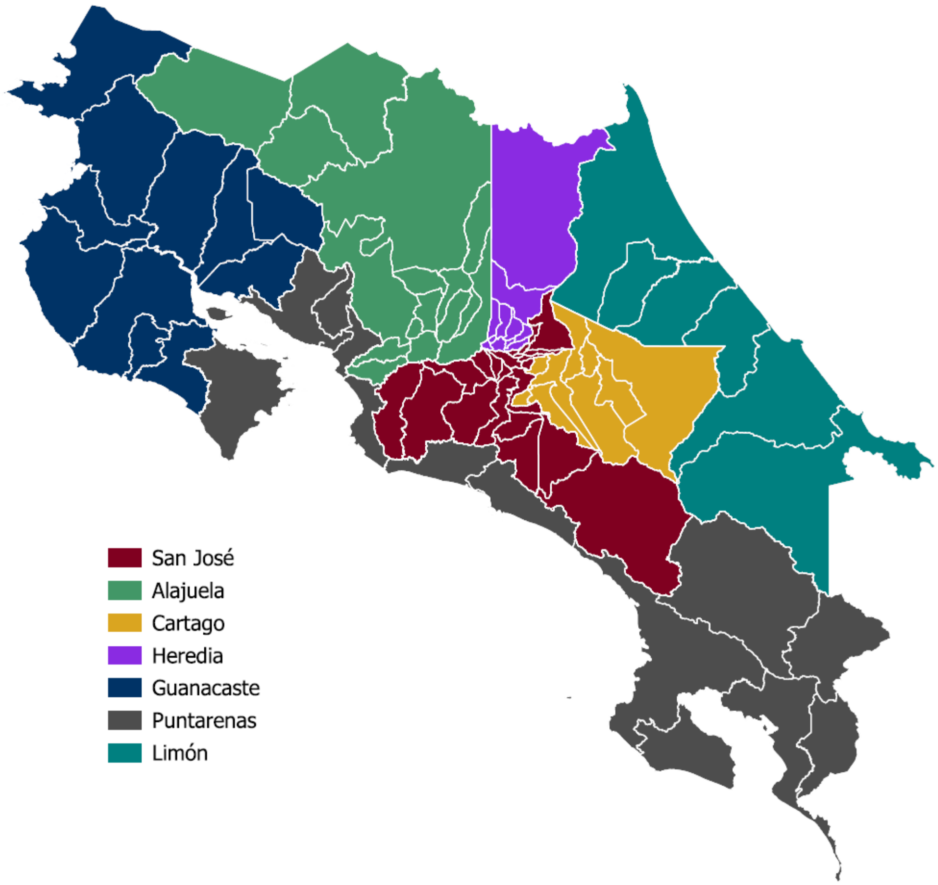
B.1. Geographic information

FIGURE B1. Six regions



Source: Chapter 1 Víctor (Primary source is INEC). *Notes:* Regions are used by the Ministry of National Planning and Economic Policy (MIDEPLAN) for planning and development. Costa Rica has six regions (central, chorotega, central pacific, brunca, atlantic huetar, north huetar). MIDEPLAN formed these regions based on areas with similar economic activities, development levels, and social indicators. Peripheral regions are the chorotega, central pacific, brunca, caribbean huetar, and north huetar regions. At the same time, Costa Rica is politically divided into districts which belong to counties (limits shown in black this figure) which belong to provinces. Counties are the local governance units; neither districts nor provinces are governance units. There are seven provinces (San José is 1, Alajuela is 2, Cartago is 3, Heredia is 4, Guanacaste is 5, Puntarenas is 6, and Limón is 7). Counties within each province are numbered with respect to their province such that counties in San José go from 101 to 120, counties in Alajuela go from 201 to 215, counties in Cartago go from 301 to 308, counties in Heredia go from 401 to 410, counties in Guanacaste go from 501 to 511, counties in Puntarenas go from 601 to 611, and counties in Limón go from 701 to 706. for planning and development, however, the Ministry of National Planning and Economic Policy groups the country into six regions shown in different colors in this map.

FIGURE B2. Seven provinces



Source: Author based on INEC. *Notes:* Costa Rica has seven provinces (San José, Alajuela, Cartago, Heredia, Guanacaste, Puntarenas, and Limón), which are political divisions and are shown in different colors in this map. Costa Rica is politically divided into districts which belong to counties (limits shown in white in this figure) which belong to provinces. Counties are the local governance units; neither districts nor provinces are governance units. There are seven provinces (San José is 1, Alajuela is 2, Cartago is 3, Heredia is 4, Guanacaste is 5, Puntarenas is 6, and Limón is 7). Counties within each province are numbered with respect to their province such that counties in San José go from 101 to 120, counties in Alajuela go from 201 to 215, counties in Cartago go from 301 to 308, counties in Heredia go from 401 to 410, counties in Guanacaste go from 501 to 511, counties in Puntarenas go from 601 to 611, and counties in Limón go from 701 to 706.

B.2. Grouping adjacent counties

In terms of counties and the ENAHO survey, we grouped together individuals from the following counties: Dota (117) and León Cortés (120) joined with Tarrazú (105); Turrubares (116) joined with Puriscal (104); San Mateo (204) joined with Orotina (209); Zarcero (211) and Valverde Vega (212, nowadays Sarchí) joined with Naranjo (206); Upala (213) joined with Guatuso (215); Jimenez (304) joined with Alvardo (306); Belén (407) joined with Flores (408); Abangares (507) and Bagaces (504) joined with Cañas (506); Nandayure (509) joined with Nicoya (502); and Montes de Oro (604) joined with Esparza (602). Lastly, we drop all individuals from counties of La Cruz (510) and Hojancha (511). Thus, the total number of counties in our final ENAHO sample is equal to 66.

Given that our analysis is at the county level, we applied the same grouping to towers from the SUTEL dataset. As a result, the total number of counties in our final tower sample is also equal to 66.

Appendix C. Results

C.1. Wage inequality

Columns (1) to (4) of Table C1 are the first four point estimates plotted in Figure 7. Columns (5) to (8) show similar patterns when examining other measures of lower-tail wage inequality. The dependent variable $\ln(Q1/Q3)$ is the log difference between the first and third quintile, and $\ln(T1/T2)$ is the log difference between the first and second tercile.

TABLE C1. **Different measures of lower-tail wage inequality**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log(D1/D5)		Log(D2/D5)		Log(Q1/Q3)		Log(T1/T2)	
$\Delta Towers_c$	0.112^{**}	0.096^{*}	0.063^{***}	0.044^{*}	0.093^{**}	0.070^{*}	0.062^{***}	0.045^{*}
	(0.052)	(0.054)	(0.023)	(0.025)	(0.036)	(0.039)	(0.023)	(0.025)
Region × Time	τ_t	$\tau_{r(c)t}$	τ_t	$\tau_{r(c)t}$	τ_t	$\tau_{r(c)t}$	τ_t	$\tau_{r(c)t}$
Pre-period mean	-0.885		-0.445		-0.720		-0.550	
Pre-period sd	0.166		0.090		0.125		0.098	

Notes: Estimates from equation (17). Each regression is based on 396 observations. Regressions are weighted by workers per county. Standard errors in parentheses are clustered at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C.2. Alternative explanations

TABLE C2. **Distribution of workers between sectors within regions**

	Region						
	Central	Chorotega	Cent. Pacific	Brunca	Atl. Huetar	North Huetar	Total
Pre-period							
Primary sector	9.69	11.45	12.65	24.97	47.32	27.80	17.54
Secondary sector	22.18	18.83	17.70	13.22	9.57	12.80	18.20
Tertiary sector	68.13	69.72	69.65	61.81	43.10	59.39	64.26
Post-period							
Primary sector	7.00	10.79	15.80	22.95	41.88	25.91	14.82
Secondary sector	21.53	16.69	14.01	13.44	11.22	13.57	17.94
Tertiary sector	71.47	72.52	70.19	63.60	46.90	60.52	67.24

Source: ENAHO. *Notes:* Pre-period years are 2010 and 2011. Post-period years are 2012 to 2015. The Primary sector is agriculture, the Secondary sector is manufacturing and construction, and the Tertiary sector are services.