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Labor Market Power, Self-Employment, and Development†

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This paper shows that self-employment shapes labor market power in low-income countries, with implications for industrial development. Using Peruvian data, we find that wage-setting power increases with employer concentration but less so where self-employment is more prevalent. A general equilibrium model shows that in oligopsonistic labor markets, self-employment raises the supply elasticity of wage labor, weakening employer market power. However, by the same mechanism, procompetitive policies aimed at expanding wage employment and reducing reliance on self-employment may unintentionally strengthen labor market power, undermining their objectives. (*JEL* J22, J23, J31, J42, L13, O14, O15)

A longstanding view in economic development holds that industrialization promotes economic growth in poorer countries, with self-employment declining as modern industrial firms expand (Lewis 1954; Rauch 1991). As a result, increasing wage employment in the manufacturing sector has become a cornerstone of industrial development strategies, prompting significant investments and targeted policy initiatives (UN General Assembly 2015). Despite these efforts, manufacturing self-employment remains widespread in emerging economies (La Porta and Shleifer 2014; Gollin 2008; Poschke 2025), and employment at large firms has stagnated (Hsieh and Olken 2014; McMillan and Zeufack 2022), even as GDP per capita increases.

Labor market structure is a potentially important yet often overlooked factor influencing these outcomes. Barriers such as high entry costs, a shortage of skilled labor, and inadequate infrastructure often lead to employment being concentrated

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among a few dominant firms (Djankov et al. 2002; Rud and Trapeznikova 2021; Hjort, Malmberg, and Schoellman 2022), which can reduce job opportunities and suppress wages to maximize profits. When wage jobs are scarce and unattractive, self-employment becomes a valuable alternative for workers (Blattman and Dercon 2018; Breza, Kaur, and Shamdasani 2021), acting as a buffer against employers' market power. However, by the same mechanism, policies that seek to expand wage employment and reduce reliance on self-employment may inadvertently strengthen employers' wage-setting power, making them less effective than intended.

This paper argues that understanding the interplay between labor market power and self-employment is essential to explaining persistently high rates of self-employment and why industrial development policies often fall short of their objectives. To support these claims, we provide new evidence from Peru, an original theoretical framework, and counterfactual policy experiments. Peru is a compelling case study due to its high employer concentration, high self-employment rates, and frequent worker transitions into and out of self-employment—characteristics shared by many emerging economies.

We begin by showing that labor market power is substantial across Peruvian manufacturing local labor markets.[1] We measure it as the inverse elasticity of the labor supply curve faced by individual firms, which directly captures their ability to set wages (Manning 2003). For estimation, we employ an instrumental variable strategy that leverages the staggered rollout of a rural electrification program across provinces and its differential impact on firms with high versus low ex ante constraints in accessing electricity, allowing us to isolate exogenous variation in labor demand across firms within a local labor market.

Our estimates indicate that the average firm-level inverse labor supply elasticity is positive and significant, indicating wage-setting power. The implied average wage markdown is 1.42, meaning that workers receive approximately 70 cents for each additional dollar they generate. Markdowns rise with market concentration, consistent with oligopsony power, though this gradient is weaker in markets with higher self-employment rates. We estimate the highest markdowns in highly concentrated markets with a low prevalence of self-employment, where workers receive only 57 cents per additional dollar they produce.

While these patterns indicate meaningful differences across markets, they do not necessarily reflect variations in underlying structural fundamentals. Our empirical strategy estimates *reduced-form* labor supply elasticities, which do not directly map to *structural* elasticities, as they may reflect competitors' equilibrium responses (Berger, Herkenhoff, and Mongey 2022). Disentangling equilibrium effects from structural features requires a theoretical model and is essential to fully characterize labor market dynamics and evaluate the scope and effectiveness of policy interventions.

We develop a general equilibrium model of Peruvian manufacturing labor markets in which employer concentration, self-employment rates, and labor market power are jointly determined. The model is built on two key features. First, it incorporates *oligopsony power*, where a finite number of heterogeneous firms in each

[1] We define a local labor market as the combination of a two-digit industry and a commuting zone. See Section I for further details and motivation for this definition.

local labor market internalize their influence on wages and make strategic employment decisions. Second, it embeds Roy's (1951) *self-selection* framework, where heterogeneous workers choose between wage employment and self-employment based on expected earnings.

This framework captures both *demand-* and *supply-side* determinants of labor market power. This is reflected in the average wage markdown in a local labor market, which depends on two key endogenous objects. The first is the Herfindahl-Hirschman Index (HHI) for employment, a measure of employer concentration that captures oligopsony power. The second is the aggregate supply elasticity of wage labor, which counteracts the employers' wage-setting power by increasing worker responsiveness to wage changes. These mechanisms interact in equilibrium: As concentration rises, markdowns increase, depressing wages and driving more workers into self-employment. This reallocation, in turn, raises labor supply elasticity, partially offsetting labor market power.

A key takeaway from our model is that self-employment serves a *dual role* in shaping labor market power dynamics. On the one hand, it provides a fallback option for workers, constraining firms' wage-setting power when wage opportunities are limited. On the other hand, when wage employment becomes more attractive, reduced reliance on self-employment reinforces oligopsony power, making it harder for industrial policies to increase employment and wages. Through counterfactual analyses, we show that the *variable elasticity channel* is quantitatively essential in explaining the limited effectiveness of industrial development policies.

A crucial factor influencing labor supply elasticity and its higher-order moments is the distribution of worker ability. Our identification strategy relies on parametric restrictions, specifically the assumption of log-normality. Standard in empirical Roy models (French and Taber 2011), this assumption is necessary in our setting for both estimation and tractability. It enables transparent estimation using worker-level data while providing the structure needed to embed the Roy block into our general equilibrium model and conduct counterfactual analyses. While our approach imposes a parametric structure, the log-normal distribution offers greater flexibility than the commonly used Fréchet, particularly by allowing comparative and absolute advantage to vary independently.[2]

Given the ability distribution, we employ a Method of Simulated Moments to estimate the remaining model parameters, including firm productivity, entry costs, average worker skills, and their variation across markets. We discipline them by targeting moments from the cross-sectional distributions of concentration, employment shares, earnings, and their correlations.

We validate the model by simulating the electrification program from our reduced-form analysis and assessing its ability to replicate the observed patterns of labor market power. First, we identify treated firms based on the observed correlation between the electricity wedge and productivity in the data. We then calibrate the productivity shock induced by electrification, apply it to the treated firms in the model, and simulate the resulting labor market responses. Specifically, we compute the model-implied reduced-form inverse labor supply elasticities as the ratio of the

[2] See Adão (2016) and Amodio, Alvarez-Cuadrado, and Poschke (forthcoming) for a discussion.

(log) wage to (log) employment responses of treated firms, aligning with the local average treatment effect (LATE) estimates from the reduced-form analysis.

The model closely matches the initial reduced-form estimates of labor market power, predicting an average inverse labor supply elasticity of 0.36, compared to 0.42 in the data, and accurately capturing the relationship between employer concentration and wage markdowns. It also replicates the mitigating effect of self-employment, revealing that the highest wage-setting power occurs in highly concentrated markets with low self-employment, with an estimated inverse elasticity of 0.62, compared to 0.75 in the data.

The model also allows for a comparison between reduced-form and structural inverse labor supply elasticities. Structural estimates tend to be more muted, as they account for the equilibrium responses of competing firms. However, the bias in reduced-form estimates does not account for the differences observed in market concentration and self-employment rates, as no consistent pattern emerges when comparing structural and reduced-form labor market power across these dimensions.

With the estimated model, we conduct two sets of counterfactual experiments. First, we assess the impact of labor market power on labor market outcomes by comparing our baseline economy to one in which employers are wage takers. Without labor market power, the average wage employment share across markets rises from 66 percent to 77 percent. Average earnings increase by 31 percent and 27 percent in the wage and self-employment sectors, respectively, suggesting that labor market power compresses the earnings gap between wage workers and the self-employed.

Second, we evaluate how labor market power influences the effectiveness of industrial development policies to expand wage employment. We consider policies that enhance firm productivity through market integration and infrastructure improvements (Volpe Martincus, Carballo, and Cusolito 2017; Fiorini, Sanfilippo, and Sundaram 2021), lower fixed entry costs for employers by streamlining business registration (Kaplan, Piedra, and Seira 2011; Bruhn 2011), and improve worker skills through off- and on-the-job training programs (McKenzie 2017; Alfonsi et al. 2020). To quantify their effects on labor market outcomes, we calibrate the policy shocks using empirical evidence from past implementations in Peru and Mexico and their estimated reduced-form impacts.

We find that the impact of industrial policies varies significantly across markets, mainly due to differences in labor market power. Changes in markdowns account for up to 99 percent of the variation in the policy's impact on wages and 88 percent of its effect on the wage employment share across markets, underscoring that a policy is only effective if it directly addresses labor market imperfections. These insights are crucial for policymakers aiming to design effective interventions for industrialization and inclusive economic growth.

Related Literature.—This paper contributes to several strands of the literature. First, we add to the work on informal self-employment in low-income countries. The traditional "dual" view posits that large formal firms and informal microenterprises operate in entirely separate economic spaces.[3] Our study challenges this perspective

[3] Early contributions include Lewis (1954); Harris and Todaro (1970); and Rauch (1991). See also La Porta and Shleifer (2014) for a review and Eslava et al. (2023, 2024) for evidence on Latin America.

by emphasizing the role of worker sorting and oligopsony power in shaping employment outcomes in emerging economies while offering an explanation for the persistently high prevalence of self-employment in manufacturing. In doing so, we align with Maloney (1999); Ulyssea (2018); and Donovan, Lu, and Schoellman (2023), among others, who show that formal and informal firms coexist within the same local labor markets, with frequent worker transitions between the two sectors.

Second, our paper contributes to the growing literature on labor market power by integrating self-employment into its analysis, highlighting its role in shaping labor supply elasticity to the wage employment sector and influencing policy effectiveness. This focus is particularly relevant for low- and middle-income countries, where self-employment rates are higher and research on labor market power remains relatively limited.[4] Our theory provides a novel microfoundation for the aggregate supply of wage labor, driven by the self-selection of heterogeneous workers, thereby explicitly incorporating supply-side determinants of wage-setting power. In doing so, we extend recent theories of monopsony power (Burdett and Mortensen 1998; Lamadon, Mogstad, and Setzler 2022; Kroft et al. 2019) and oligopsony power (Berger, Herkenhoff, and Mongey 2022). Our findings suggest that once worker sorting is accounted for, employer concentration exhibits a *nonlinear* relationship with labor market power, providing a potential explanation for the mixed results in the empirical literature.[5] Our theory also aligns with the findings in Felix (2022), which shows that firms in Brazilian markets with higher self-employment rates face *more elastic* labor supply curves.

Third, our analysis offers novel insights into the determinants of the earnings gap between self-employed and wage workers. In developing countries, self-employment accounts for nearly half of the workforce, yet wage employment generally pays more (Fields 2012). We quantify the role of labor market power for the size of the gap and how it changes with policy.

Finally, our work speaks to the extensive literature on informality in low-income countries.[6] Both Dix-Carneiro and Kovak (2019) and Ponczek and Ulyssea (2022) argue that informality acts as an "unemployment buffer" by reducing trade-induced adjustment costs in the labor market. Yet Dix-Carneiro et al. (forthcoming) shows that in the event of a negative economic shock, welfare declines more when informality rates are high. Our analysis adopts the notion of informal self-employment as a potential outside option for workers. It demonstrates that it plays a similar role in the presence of labor market power.

[4] Amodio and De Roux (2024) document substantial labor market power in Colombian manufacturing, while Felix (2022) finds similarly high labor market power in Brazil, with only limited effects of the 1990s trade liberalization. In Costa Rica, Alfaro-Ureña, Manelici, and Vasquez (2021) report minor wage effects from multinational expansion, suggesting low labor market power due to high worker mobility. Beyond Latin America, studies identify significant monopsony power in India (Brooks et al. 2021), China (Muralidharan, Niehaus, and Sukhtankar 2023), and South Africa (Bassier 2023). Finally, Armangué-Jubert, Guner, and Ruggieri (2025) and Amodio et al. (2024) leverage World Bank Enterprise Survey data to analyze labor market power and its relationship with development across multiple low- and middle-income countries.

[5] Several studies, mostly based on US data, use employer concentration as a proxy for labor market power, showing its negative correlation with wages (Azar, Marinescu, and Steinbaum 2022; Benmelech, Bergman, and Kim 2022). However, Bassier, Dube, and Naidu (2022) find no evidence that labor supply elasticities decrease with concentration, and Yeh, Macaluso, and Hershbein (2022) show that wage markdowns and employer concentration in US manufacturing followed different trends over recent decades.

[6] See Ulyssea (2020) for a review.

The remainder of the paper is organized as follows. Section I introduces the data and presents the empirical facts. The model and its properties are presented in Section II, while Section III discusses the model estimation procedure and results. Section IV presents the counterfactual policy analyses. Section V concludes.

I. Data and Facts

The empirical analysis relies on two main datasets on firms and workers. The first dataset is the Peruvian Annual Economic Survey (*Encuesta Económica Anual*, EEA), a nationwide firm-level survey conducted annually by the national statistical agency, Instituto Nacional de Estadística e Informática (INEI 2004–2011a). This dataset includes standard balance sheet information such as revenues, input expenditures, and plant locations. The survey is mandatory for firms with net sales above a certain threshold, while smaller firms are sampled. As a result, the EEA provides comprehensive coverage of medium and large firms, along with a representative sample of smaller firms. To ensure consistency across years and account for changes in the reporting threshold, we focus on manufacturing firms with net sales exceeding 2 million Peruvian soles (S/) per year—approximately US\$700,000 in 2010—over the period from 2004 to 2011. Our final dataset includes 2,473 firms and 8,138 firm-year observations.

The second data source is the Peruvian National Household Survey (*Encuesta Nacional de Hogares*, ENAHO), conducted annually by INEI (2004–2011b). This survey is nationally and regionally representative, covering urban and rural areas across the 24 Peruvian departments and the constitutional province of Callao. It provides information on household members' socioeconomic characteristics. Individuals aged 14 and older respond to a dedicated module with questions on employment status, pay, occupation, and industry. To align with the firm-level data, we focus on the years from 2004 to 2011 and restrict the sample to working-age individuals (25 to 65) who have completed their education and are not yet retired. ENAHO offers several panel versions where the same households are interviewed annually for five consecutive years; we use the 2007–2011 panel to track workers' transitions between employment states.

A. *Definitions*

We define a local labor market as a two-digit ISIC industry within a specific geographical area. These areas are primarily defined by Peruvian province boundaries, which correspond to level 2 administrative divisions and are subdivisions of departments. Excluding Metropolitan Lima—the province that includes the capital city—the average province has a population of approximately 114,000. Metropolitan Lima is a significant outlier, with a population of 10 million. Following Piselli (2013), we define five distinct local labor markets within Lima province. We analyze data from 199 geographical units and 23 manufacturing industries.

Our baseline measure of concentration is the Herfindahl-Hirschman Index for payroll, defined as $HHI_{kt}^{wn} = \sum_{i \in k} \left(s_{ikt}^{wn}\right)^2$, where $s_{ikt}^{wn} = \frac{w_{ikt} n_{ikt}}{\sum_{i \in k} w_{ikt} n_{ikt}}$ represents firm i's share of the total payroll in local labor market k in year t. Here, w_{ikt} and n_{ikt} denote the firm's wage and employment, respectively. Values near one indicate a few firms dominate the market payroll. We also consider the employment HHI, defined as $HHI_{kt}^n = \sum_{i \in k} \left(s_{ikt}^n\right)^2$, where $s_{ikt}^n = \frac{n_{ikt}}{\sum_{i \in k} n_{ikt}}$, along with the number of firms in the local labor market as alternative measures.

In the ENAHO survey, workers are classified into four categories: own-account workers, employers, auxiliary family workers, and employees. For our analysis, we group own-account workers and employers as *self-employed workers*, while employees are categorized as *wage workers*. We exclude auxiliary family workers from our classification, as they do not report monetary compensation. Additionally, ENAHO allows us to identify informal workers. A worker is classified as informal if they meet either of the following criteria: (i) they are a wage worker without employer-provided health insurance, which is legally mandated in Peru, or (ii) they are self-employed but are not registered with the national tax authority and employ five or fewer workers.

In Supplemental Appendix B, we perform a series of checks to validate our definitions and measures, demonstrating the robustness of the empirical findings presented below. These checks include validating the concentration measures with firm census data (INEI 2007), narrowing the self-employment category to include only informal self-employment or own-account workers, and broadening the geographical boundaries of local labor markets.

B. *Employer Concentration*

Employment and wages in Peruvian local labor markets are highly concentrated among a few medium and large firms. Panel A of Table 1 shows that the average local labor market includes about six firms, with unweighted and payroll-weighted mean wage bill HHIs of 0.65 and 0.37, respectively. Notably, 39 percent of these markets are dominated by just 1 medium-to-large firm, and these highly concentrated markets account for approximately 8 percent of the nationwide payroll. This highlights that, despite their smaller share, these concentrated markets exert a significant influence on the overall payroll. Importantly, location explains about 43 percent of the variation in wage bill HHI across markets, while differences across two-digit industries only account for an additional 14 percent.[7]

C. *Self-Employment and Flows into and from Wage Work*

In Peruvian manufacturing, as in other low- and middle-income countries, self-employment is widespread and primarily informal (Gollin 2008; La Porta and Shleifer 2014). Panel B of Table 1 shows that 40 percent of the manufacturing workforce is self-employed, 56 percent are wage workers, and the remaining 4 percent are auxiliary family workers. Over 90 percent of self-employment is informal, both across

[7] Peruvian manufacturing is less geographically clustered than in the United States or the United Kingdom. Using the Ellison-Glaeser index of geographic concentration over census data, we find that only 63 percent of industries in Peru exhibit some degree of localization, compared to 97 percent in the United States and 94 percent in the United Kingdom (Ellison and Glaeser 1997; Duranton and Overman 2005).

Table 1—Summary Statistics

Variable	Mean	SD
Panel A. Manufacturing local labor markets		
Number of firms	6.39	10.37
Wage bill HHI	0.65	0.33
Wage bill HHI (weighted by LLM payroll share)	0.37	0.03
Employment HHI	0.63	0.35
Employment HHI (weighted by LLM empl. share)	0.31	0.02
Percent of LLMs with 1 firm	38.78	2.27
Payroll share of LLMs with 1 firm	7.94	1.79
Employment share of LLMs with 1 firm	7.80	1.23
Panel B. Manufacturing workers		
Wage worker	0.56	0.50
Daily wage	31.84	31.85
Self-employed	0.40	0.49
Daily earnings from self-employment	23.06	41.31
W-S transition	0.06	0.24
S-W transition	0.04	0.21

Notes: This table reports summary statistics from EEA firm-level data across Peruvian local labor markets (panel A) and from ENAHO worker-level data (panel B), averaging across all years from 2004 to 2011. Transition rates are obtained using the 2007–2011 panel version of ENAHO. Worker-level statistics correspond to dummy variables indicating wage work and self-employment, wages and earnings expressed in soles ($S/1 \approx$ US\$0.35 in 2010), and annual transitions from the wage- to self-employment sector (W-S) and vice versa (S-W).

all industries and within manufacturing. Of the 40 percent classified as self-employed, 31 percent are own-account workers, and 9 percent are employers, with only 3 percent of self-employed individuals operating formally as registered businesses.

Informality reduces the costs of starting and operating a business, leading to variations in self-employment rates across industries. Self-employment is more prevalent in labor-intensive industries, constituting a substantial portion of Peru's manufacturing GDP. In these industries, physical capital is less critical, credit constraints are less severe, and the potential for informality is more significant. Self-employment is lower in more capital-intensive sectors, such as pharmaceuticals and metals, and virtually nonexistent in oil and petroleum manufacturing.

On average, earnings from self-employment are lower and more dispersed than wage work earnings. Panel B of Table 1 shows that daily earnings from self-employment are approximately 28 percent lower than daily wages, while their standard deviation is about 30 percent higher.

Transitions.—A defining feature of labor markets in low- and middle-income countries is the high level of worker mobility between wage work and self-employment (Maloney 1999; Donovan, Lu, and Schoellman 2023). This is also evident in Peru. Panel B of Table 1 shows that approximately 4 percent of self-employed manufacturing workers transition to wage work the following year, while 6 percent of manufacturing wage workers move to self-employment. Conditional on switching either employment status or industry, transitions between wage work and self-employment are about 20 percent more likely than industry changes that do not involve a status shift (56 percent versus 44 percent). Most of these transitions occur within the same geographical area. While ENAHO tracks only employment moves that do not involve a location change, the 2007 census shows that 85 percent

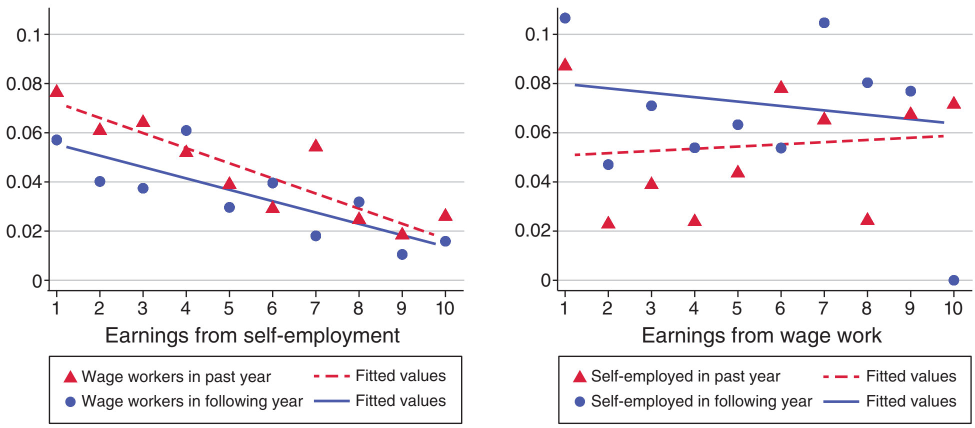

Figure 1. Transition Probabilities across the Earnings Distribution

Notes: The figures illustrate the relationship between the likelihood of transitioning from and into wage work and self-employment and earnings. The left panel plots average yearly transition probabilities into and from wage work across deciles of the self-employment earnings distribution. Similarly, the right panel plots average yearly transition probabilities into and from self-employment across the wage work earnings distribution deciles. The straight lines show the linear fit based on the underlying data.

of manufacturing workers lived in the same commuting zone as in 2002, indicating limited geographical mobility. Additionally, 70 percent of employment transitions occur within the same two-digit industry. This suggests that local labor markets provide a relevant unit for analyzing workers' employment transitions in the manufacturing sector.[8]

Worker transitions correlate with earnings. Figure 1 shows the likelihood of switching to or from wage and self-employment across deciles of the self-employment and wage earnings distributions. The left panel indicates that workers who have recently transitioned from wage work or are about to become wage workers are more likely to be among the lowest-earning self-employed individuals. In contrast, the right panel of Figure 1 shows that transitions to and from self-employment are not systematically correlated with earnings from wage work.

Thus, workers at the margin between self-employment and wage work consistently earn less than inframarginal self-employed workers and have similar earnings to inframarginal wage workers. These findings suggest positive selection into self-employment but no selection into wage work. We will elaborate on this point later.

D. *Concentration, Self-Employment Rates, and Earnings*

The final pattern in the data is the systematic relationship between concentration and self-employment across local labor markets. The left panel of Figure 2 shows that the average share of self-employment increases consistently across deciles of payroll HHI, indicating higher self-employment rates in more concentrated

[8] Supplemental Appendix Table A.1 shows that workers transitioning from manufacturing self-employment to wage work (or vice versa) are about four times more likely to remain in manufacturing compared to the average worker switching employment status across all sectors.

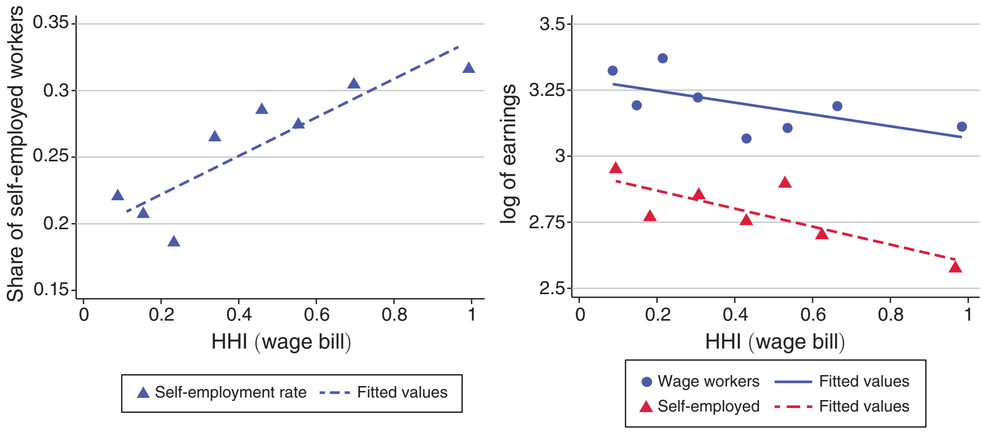

Figure 2. Concentration, Self-Employment Rate, and Earnings

Notes: The figures illustrate the relationship between employer concentration, rate of self-employment (left), and earnings from both wage work and self-employment (right) across local labor markets. The left panel plots the share of self-employed workers in each decile of the wage bill HHI distribution across local labor markets. The right panel plots the average log of daily earnings in each decile and separately for wage and self-employed workers. The straight lines show the linear fit based on the underlying data.

labor markets. Regression analysis further supports this correlation. We conduct a worker-level regression of a self-employment dummy on the log of wage bill HHI in the worker's local labor market for the same year. The results, presented in columns 1 to 3 of Supplemental Appendix Table A.2, reveal that the relationship between concentration and self-employment is positive and significant, even after controlling for individual characteristics, industry, and location fixed effects.

The right panel of Figure 2 together with columns 4 to 9 of Supplemental Appendix Table A.2 examine the correlation between concentration and earnings across markets. Where concentration is higher, wages are lower, and self-employment is less lucrative.

The decline in wage employment share and wages with increasing concentration is observed among formal and informal wage workers, as shown in Supplemental Appendix Figures A.1 and A.2. This suggests that in concentrated markets, self-employment is an alternative to formal and informal wage work. The right panels in both figures also show that, despite differences in earnings levels, the wages of both formal and informal wage workers decrease at the same rate as concentration increases.

These findings reinforce the sorting narrative proposed earlier: In highly concentrated markets, where wages are lower, more workers choose self-employment. As wage workers, these individuals would have earned similar wages to their peers. However, self-employed workers tend to earn less than their peers, decreasing average earnings from self-employment as market concentration increases.

E. *Labor Market Power*

The observed co-movements between concentration, self-employment, and earnings raise questions about the role of labor market power in Peruvian labor markets.

While employer concentration is negatively associated with wages, this relationship alone does not prove labor market power, as concentration and wages are equilibrium outcomes. To pin down labor market power, we estimate the inverse elasticity of labor supply faced by individual firms (Manning 2003b). By examining how this varies with labor market concentration and self-employment rates, we can gain deeper insights into the role of labor market power in this context and its determinants.

Empirical Strategy.—We estimate the following regression model:

$$\ln w_{i(j,g)t} = \beta \ln l_{i(j,g)t} + \alpha_i + \eta_{(j,g)t} + u_{i(j,g)t}, \tag{1}$$

where $w_{i(j,g)t}$ is the wage paid by firm i in year t in its local labor market, defined by a manufacturing industry j within a province or commuting zone g, and $l_{i(j,g)t}$ is employment at the same firm. α_i is a firm fixed effect that captures differences across firms that do not change over time. $\eta_{(j,g)t}$ is a market $\times$ year fixed effect that accounts for aggregate yearly shocks at the local labor market level. This allows β to measure the firm-specific inverse supply elasticity of wage work while holding the aggregate labor supply constant.

To estimate the parameters in equation (1) consistently, we require a firm-level labor demand shifter, as OLS estimates may be biased due to the interdependence of wages and employment. We address this by using the rollout of the Rural Electrification Program (Programa de Electrificación Rural, PER), launched by the Peruvian Ministry of Energy and Mining in 1993 to foster economic and social growth in rural areas (Dasso and Fernandez 2015a). Between 1994 and 2012, the program implemented 628 projects across rural Peru, prioritizing districts with high poverty rates, low electricity coverage, and high renewable energy potential, with a total investment of US\$657.5 million (Dasso and Fernandez 2015b; Dasso, Fernandez, and Ñopo 2015).

Our approach builds on the idea that electrification through the PER increased firms' marginal productivity and labor demand, especially for firms previously facing greater constraints in accessing electricity (Abeberese, Ackah, and Asuming 2021). To operationalize this approach, we first create the variable PER_{gt}, equal to the cumulative number of completed PER projects in location g up to year t. We then follow Bau and Matray (2023) to identify firms facing electricity access constraints at baseline.

For a firm i in market (j,g) producing output $y_{i(j,g)t}$ at time t and selling it in an imperfectly competitive market, the unit price $p_{i(j,g)t}$ is a markup $\mu_{i(j,g)t}$ over marginal cost. We assume that the firm uses a Cobb-Douglas production function with industry-specific input elasticities, where θ^e_j represents the output elasticity of electricity. The shadow cost of electricity, varying across firms and industries, is denoted by $\tau^e_{i(j,g)t}$. The electricity revenue share at firm i is given by $\alpha^e_{i(j,g)t} = \frac{e_{i(j,g)t}}{p_{i(j,g)t}y_{i(j,g)t}}$, where $e_{i(j,g)t}$ is total electricity bill.

Profit maximization implies $\frac{\theta^e_j}{\alpha^e_{i(j,g)t}} = \mu_{i(j,g)t}\left(1 + \tau^e_{i(j,g)t}\right)$, which we can rewrite as

$$\ln\left(\alpha^e_{i(j,g)t}\right)^{-1} = \ln\left(\mu_{i(j,g)t}\right) + \ln\left(1 + \tau^e_{i(j,g)t}\right) - \ln\theta^e_j. \tag{2}$$

This shows that we can estimate the firm-level wedge $\tau^e_{i(j,g)t}$ as the residual from a regression of the log of the inverse electricity share of revenues on industry fixed effects and firm-level markups.[9] We include four-digit ISIC Rev. 4 code fixed effects to control for industry-specific output elasticities and use second-degree polynomials of output market shares in both the local labor market and nationwide to flexibly account for firm-level markups.[10] To mitigate the impact of outliers and address measurement error, we define a dummy variable, $EC_{i(j,g)}$, which equals one for firms with an estimated wedge $\hat{\tau}^e_{i(j,g)t}$ above the median at baseline, indicating tighter constraints in accessing electricity.

The interaction $PER_{gt} \times EC_{i(j,g)}$ is our instrumental variable (IV). It combines variation in program rollout across geography and over time with variation across firms within industries in access to electricity at baseline. The first-stage regression specification is

$$\ln l_{i(j,g)t} = \gamma PER_{gt} \times EC_{i(j,g)} + \phi_i + \delta_{(j,g)t} + \nu_{i(j,g)t}, \tag{3}$$

with ϕ_i and $\delta_{(j,g)t}$ capturing firm fixed effects and local labor market $\times$ year fixed effects, respectively, following the second-stage regression specification in equation (1).

The validity of this IV approach relies on three key assumptions. First, the instrument must be strongly correlated with employment, which holds if the electrification program boosts labor demand, particularly for firms with limited electricity access. Second, the instrument must be orthogonal to the wage and employment trends of electricity-constrained firms within each local labor market. This is plausible since the Ministry did not consider local firms or industries when implementing the program. Finally, the instrument must satisfy the exclusion restriction, meaning that electrification should not differentially affect labor supply to electricity-constrained firms. This ensures that changes in employment and wages reflect movements along the labor supply curve, allowing us to trace its slope. To make this assumption more plausible, we include local labor market $\times$ year fixed effects in all specifications. These fixed effects capture and control for changes in labor supply common to all firms within a market, even if these vary locally across industries. Importantly, we demonstrate below that our estimates remain robust when accounting for differences across firms over time at a more granular geographical level.

The exclusion restriction also requires that the labor demand shock does not affect wages via other channels, such as rents captured by workers. While this could be a concern, it is unlikely in Peruvian manufacturing, where workers have minimal bargaining power. Union density remained consistently low throughout the analysis period, ranging from 1.9 percent to 3.2 percent, placing Peru among the bottom 5 percent of countries in terms of unionization rates (International Labour Organization 2020).

[9] Intuitively, in the absence of distortions, the electricity revenue share $\alpha^e_{i(j,g)t}$ should equal the output elasticity θ^e_j. However, a firm's electricity share can fall below this optimal level if the firm either has market power, which allows it to set a higher markup $\mu_{i(j,g)t}$, or if it faces a higher shadow cost of electricity, captured by $\tau^e_{i(j,g)t}$.

[10] Output markups can be expressed as an increasing function of a firm's output market share in many macroeconomic models, such as Atkeson and Burstein (2008). This approach also aligns with our theoretical model in Section II. The results are robust to (i) not controlling for output market shares (implicitly assuming no market power), (ii) controlling only for local labor market shares, and (iii) controlling only for national shares.

Another concern is whether the electrification program induced sufficient variation across Peruvian local labor markets. To explore this, we use districts as the geographical unit of analysis. Peru has 1,838 districts, each a subdivision of a province, with an average of about 9 districts per province. We find that 15 percent of districts in the firm-level IV estimation sample were affected by the program. These districts account for 41 percent of firm-level observations and 17 percent of the manufacturing workforce (based on ENAHO data). Supplemental Appendix Figure A.3 offers additional details on the program's implementation. Initially, the targeted districts had a relatively low share of manufacturing employment. By the end of the period, however, the program had touched districts with a higher proportion of manufacturing employment, possibly due to the program spurring growth in these areas.

Results.—Table 2 presents the inverse elasticity IV estimates and standard errors. We report for each estimate the *F-statistic* associated with the Sanderson-Windmeijer multivariate test of excluded instruments, confirming that the instrument provides meaningful identifying variation throughout. Supplemental Appendix Table A.3 reports the first-stage regression results.

Column 1 reports the results for the total sample of manufacturing firms. The firm-level inverse labor supply elasticity is estimated at 0.42, corresponding to a labor supply elasticity of 2.36, which is statistically significant at the 1 percent level. This elasticity implies a markdown of 1.42 between the marginal revenue product of labor and the wage paid. In other words, workers generate 42 percent more as value than what they earn at the margin, taking home 70 cents for every marginal dollar they produce.[11]

Columns 2 to 4 focus on different subsamples.[12] In column 2, we estimate labor market power separately for markets with varying levels of labor market concentration.[13] For firms in the least concentrated labor markets ($HHI \leq 0.18$), we estimate an inverse labor supply elasticity that is statistically and economically insignificant. As concentration increases, labor market power rises. In moderately concentrated markets ($0.18 < HHI \leq 0.25$), workers take home nearly 80 cents for every marginal dollar they generate. In highly concentrated markets ($HHI > 0.25$), the wage take-home share drops to 63 percent.

Columns 3 and 4 further divide markets based on whether the self-employment rate is below or above the national average. In less concentrated markets, labor market power remains insignificant regardless of the self-employment rate. However, in highly concentrated markets, the degree of labor market power is influenced by the availability of self-employment opportunities. The highest level of labor market power

[11] These figures closely align with those reported by Amodio and De Roux (2024) for Colombian manufacturing plants (inverse elasticity of 0.4) and by Deb et al. (2022) and Yeh, Macaluso, and Hershbein (2022) for US manufacturing (ranging from 0.37 to 0.4 and 0.53, respectively). They are slightly lower than what Felix (2022) finds for Brazil before the 1990s trade liberalization (50 percent wage take-home share).

[12] These estimates are derived using more flexible second- and first-stage specifications, where both the log of firm-level employment $\ln l_{i(j,g)t}$ and the instrument $PER_{gt} \times EC_{i(j,g)}$ are interacted with dummy variables that identify the different subsamples.

[13] This analysis uses contemporaneous wage bill HHI values. Although potentially endogenous, the contemporaneous HHI determines the wage markdown size at a specific time. When we instrument contemporaneous HHIs with their lags, the resulting pattern closely mirrors the one discussed here. Similarly, when we use the previous year's self-employment rates as instruments and categorize markets by self-employment rate, the robustness of the estimates in columns 3 and 4 is confirmed.

TABLE 2—ESTIMATES OF LABOR MARKET POWER

			Self-employment rate	
			Low	High
	(1)	(2)	(3)	(4)
All markets	0.423 (0.052)			
$HHI^{wn} \in (0, 0.18]$		−0.006 (0.148)		
$HHI^{wn} \in (0.18, 0.25]$		0.262 (0.105)		
$HHI^{wn} \in (0, 0.25]$			−0.108 (0.087)	−0.061 (0.128)
$HHI^{wn} \in (0.25, 1]$		0.600 (0.150)	0.752 (0.112)	0.104 (0.067)
SW F-statistics	178.78	222.58 142.80 3,370.22	215.80 686.18	130.01 725.92
Observations	6,191	6,191	3,987	2,204

Notes: The unit of observation is a medium to a large firm in EEA. The table reports 2SLS estimates of the firm-level inverse elasticity of supply of wage labor as captured by β in equation (1). The instrumental variable is the interaction of the cumulative number of PER projects completed in each location g up to year t (PER_{gt}) and a dummy equal to one for firms with higher than median constraints to accessing electricity at baseline ($EC_{i(j,g)}$). Estimates in columns 2 to 4 are obtained by interacting both the log of firm-level employment $\ln l_{i(j,g)t}$ and the instrument $PER_{gt} \times EC_{i(j,g)}$ with dummy variables that identify the different subsamples as discussed in the text. Low and high self-employment rates are defined as below and above the average self-employment rate across local labor markets, respectively. We report the F-statistic associated with the Sanderson-Windmeijer multivariate test of excluded instruments for each estimate. Following equation (1), firm fixed effects and local labor market $\times$ year fixed effects are included in all specifications. Standard errors are clustered at the level of location g, that is, province or commuting zone.

is observed in highly concentrated markets with low self-employment rates, where the firm-level inverse labor supply elasticity is estimated at 0.75 and is statistically significant at the 1 percent level, corresponding to a 57 percent wage take-home share.[14] In contrast, in highly concentrated markets with higher self-employment rates, the estimated inverse labor supply elasticity is positive but much lower in magnitude and not statistically significant at conventional levels. Nevertheless, this estimate is statistically different at the 5 percent level from the corresponding estimate in less concentrated markets. Additionally, the difference between the inverse labor supply elasticity in markets with high versus low self-employment rates among highly concentrated markets is statistically significant at the 1 percent level, as is the difference-in-differences estimate between highly concentrated and less concentrated markets with varying self-employment rates.

[14] These markets account for a significant portion of manufacturing employment, representing 24 percent of the manufacturing workforce across all markets for which we have firm-level data. Overall, 66 percent of all manufacturing workers are in provinces or commuting zones with at least one highly concentrated manufacturing labor market that features low self-employment rates. These areas tend to be less rural and have a higher share of manufacturing employment compared to agriculture.

Discussion.—A potential concern with our findings is that the local labor market $\times$ year fixed effects in our specification may not fully capture variations in labor supply or other general equilibrium effects of electrification that impact all firms equally within markets. For example, if firms facing tighter ex ante constraints on accessing electricity are located in more rural areas, workers in those areas might respond differently to electrification, potentially violating the exclusion restriction. To address this, we redefine local labor markets as two-digit industries j within districts d, substantially increasing the granularity of the local labor market $\times$ year fixed effects. This refinement enables us to control for changes in labor supply and general equilibrium effects at a geographical level approximately 10 times finer than in the baseline analysis. Results are presented in Supplemental Appendix Table A.4, and all first-stage regression results are reported in Supplemental Appendix Table A.5. The point estimates of the inverse elasticity of labor supply remain broadly consistent with those in Table 2, exhibiting similar patterns of market heterogeneity. Although the estimates are somewhat higher, the standard errors also increase, reflecting the reduced identifying variation caused by the more granular fixed effects.

Finally, a critical consideration is that the labor supply to a given firm is not independent of the one faced by other firms in the same market. By affecting more those firms facing tighter constraints on accessing electricity at baseline, electrification leads to labor reallocation across firms due to both supply and demand effects. In other words, the *reduced-form* inverse elasticity obtained through our identification strategy does not directly translate into the *structural* inverse elasticity, which measures the elasticity of firm-level wages to employment changes, while holding competitors' wages and employment constant. Berger, Herkenhoff, and Mongey (2022) study this issue in detail, showing that in granular labor markets, there is no closed-form mapping between the two elasticities; thus, a model is needed to determine the structural, welfare-relevant elasticity. Furthermore, the bias could be either negative or positive depending on the number of treated firms, their market shares, and those of their competitors. Our approach involves replicating the electrification quasi-experiment within the estimated model and comparing the implied reduced-form inverse elasticities with those in Table 2 as a means of testing the model's validity. We then derive the corresponding structural elasticities and rule out the possibility that the observed heterogeneity across markets, related to concentration and self-employment rates, is driven by bias rather than by the underlying structural features of the economy.

The evidence in this section reveals significant interactions between concentration, self-employment opportunities, and wage-setting power. Workers shift between wage employment and self-employment based on earnings. High concentration levels lead to increased oligopsony power, which results in fewer wage jobs and lower wages, thus pushing more workers toward self-employment. As wages fall, more workers are displaced from wage employment, making wage workers more responsive to wage changes and, in turn, reducing employers' labor market power. The following section provides a theoretical characterization of these dynamics.

II. Model

This section introduces a general equilibrium model of Peruvian manufacturing, where employer concentration, self-employment rates, and labor market power are jointly determined. The model aims to reconcile the empirical evidence discussed in the previous section and to conduct counterfactual analyses, specifically concerning industrial development policies.

A. *Environment*

The economy consists of a continuum of local labor markets, indexed by $k \in [0,1]$, each characterized by M_k heterogeneous firms and a fixed measure of workers, L_k. Workers choose employment in one of two sectors: wage employment (sector F) or self-employment (sector S). Workers are immobile across local labor markets and make employment decisions within their respective markets. Although workers differ in their sector-specific abilities, they share preferences over consumption goods and incur no disutility from labor. In addition to their labor earnings, workers hold equity in firms and receive income from profit distributions.

Preferences.—Workers' preferences over the consumption of market-level goods $\{C_k\}_{k\in[0,1]}$ are of the Cobb-Douglas form:

$$C = \exp\left\{\int_0^1 \alpha_k \log C_k \, dk\right\},$$

where C_k is market k's output and $\{\alpha_k\}_{k\in[0,1]}$ are nonnegative parameters determining the shares of income spent on each market, such that $\int_0^1 \alpha_k \, dk = 1$.

Each good C_k is an aggregate of two sectoral goods: $C_{F,k}$, produced by firms in sector F, and $C_{S,k}$, produced by self-employed workers in sector S. Within sector F, each firm $i \in \{1, \ldots, M_k\}$ produces a unique variety of $C_{F,k}$, denoted $c_{iF,k}$. The corresponding CES aggregators are given by

$$C_k = \left[\zeta C_{F,k}^{\frac{\rho-1}{\rho}} + C_{S,k}^{\frac{\rho-1}{\rho}}\right]^{\frac{\rho}{\rho-1}}, \text{ where } C_{F,k} = \left(\sum_{i=1}^{M_k} c_{iF,k}^{\frac{\eta-1}{\eta}}\right)^{\frac{\eta}{\eta-1}}. \tag{4}$$

Consumers substitute between $C_{F,k}$ and $C_{S,k}$ with a constant elasticity ρ, and among firm-level varieties within sector F with a constant elasticity η. We impose $\eta > \rho > 1$, implying that consumers are more willing to substitute within than across sectors. Additionally, we allow for a preference shifter for good F, denoted as $\zeta > 0$.

Given this demand structure, consumer expenditure on market k's goods is

$$P_{F,k} C_{F,k} = \gamma_{F,k} \alpha_k Y \text{ and } P_{S,k} C_{S,k} = (1 - \gamma_{F,k}) \alpha_k Y, \tag{5}$$

where $\gamma_{F,k} = \zeta^{\rho} (P_{F,k}/P_k)^{1-\rho}$ represents the share of expenditure on variety F of good k relative to total expenditure in market k, with the sector- and market-level price indices defined as $P_{F,k} = \left(\sum_{i=1}^{M_k} p_{iF,k}^{1-\eta}\right)^{\frac{1}{1-\eta}}$ and $P_k = \left(\zeta^{\rho} P_{F,k}^{1-\rho} + P_{S,k}^{1-\rho}\right)^{\frac{1}{1-\rho}}$, respectively.

Similarly, expenditure on firm-level varieties within sector F is given by

$$p_{iF,k} c_{iF,k} = s_{iF,k} \gamma_{F,k} \alpha_k Y, \tag{6}$$

where $s_{iF,k} = \left(p_{iF,k}/P_{F,k}\right)^{1-\eta}$ is the share of expenditure on variety i of good k in sector F over the total expenditure on sector F in market k.

Labor Supply.—Each worker h is endowed with sector-specific efficiency labor units, $\mathbf{a}^h \equiv \left(a_F^h, a_S^h\right)$, drawn from a joint distribution G_k, whose parameters may vary across markets.

Workers self-select into wage employment or self-employment to maximize their earnings. In sector F, workers perceive all M_k firms as identical despite underlying productivity differences. As a result, the wage per efficiency unit, $W_{F,k}$, is uniform across all firms. In sector S, workers earn a distinct wage per efficiency unit, $W_{S,k}$. Given their abilities, worker h's earnings in sector $J \in \{F, S\}$ are given by $W_{J,k} a_J^h$. Worker h chooses sector F if and only if

$$\hat{W}_k \geq \left(\frac{a_F^h}{a_S^h}\right)^{-1}, \tag{7}$$

where $\hat{W}_k \equiv W_{F,k}/W_{S,k}$ denotes the relative wage in market k.

The sorting rule in equation (7) determines how workers allocate themselves across sectors based on their relative abilities and the relative wage $\hat{W}_k$. It implies that the aggregate supply of efficiency labor units in sector F is

$$N_{F,k} \equiv N_{F,k}\left(\hat{W}_k\right) = L_k \int_0^\infty \int_0^{a_F \hat{W}_k} a_F\, g_k\left(a_F, a_S\right) da_F\, da_S, \tag{8}$$

where L_k is the total labor force in market k and $g_k\left(a_F, a_S\right)$ represents the joint density of sector-specific abilities. The labor supply $N_{F,k}$ is an increasing function of the relative wage, that is, $N'_{F,k} > 0$, since a higher $\hat{W}_k$ leads more workers to choose wage employment.

The sensitivity of labor supply to changes in $\hat{W}_k$ is captured by the wage labor elasticity,

$$\epsilon_{F,k} \equiv \epsilon_{F,k}\left(\hat{W}_k\right) = \frac{\hat{W}_k \int_0^\infty a_F^2\, g_k\left(a_F, a_F \hat{W}_k\right) da_F}{\int_0^\infty \int_0^{a_F \hat{W}_k} a_F\, g_k\left(a_F, a_S\right) da_F\, da_S} > 0, \tag{9}$$

which depends on the relative wage $\hat{W}_k$ and is thus determined in equilibrium. In what follows, we will show how adjustments in $\epsilon_{F,k}$ play a central role in shaping the dynamics of labor market power in this economy.

Technology.—Production technology in sectors S and F is linear in efficiency units of labor. Total output in sector S equals the efficiency labor units allocated to it:

$$Y_{S,k} = N_{S,k}, \tag{10}$$

where $N_{S,k}$ denotes labor supply in sector S.

In sector F, each firm i produces output according to $y_{iF,k} = z_{iF,k} n_{iF,k}$, where $z_{iF,k}$ is a productivity term, and $n_{iF,k}$ is labor demand. Aggregating across firms according to (4) leads to the following expression for total output in sector F:

$$Y_{F,k} = Z_{F,k} N_{F,k}, \tag{11}$$

where $N_{F,k} \equiv \sum_{i=1}^{M_k} n_{iF,k}$ and $Z_{F,k}\left(\sum_{i=1}^{M_k} s_{iF,k}^{\frac{\eta}{\eta-1}} z_{iF,k}^{-1}\right)^{-1}$ is a productivity index, with $s_{iF,k}$ defined above. Labor market clearing ensures that $N_{F,k}$ in (11) equals aggregate labor supply to sector F from equation (8). $N_{S,k}$ in (10) can be derived analogously.

Market Structure.—Sector S operates under perfect competition, while firms in sector F engage in Nash-Cournot competition in both the product and labor markets.

Firms in sector F produce differentiated varieties of the final good, leading to heterogeneous markups and prices in the output market. However, because workers perceive these firms as perfect substitutes, the labor market features oligopsonistic competition among effectively homogeneous employers, resulting in a uniform wage.

Firm's Problem.—Each firm i chooses its labor demand to maximize profits, taking as given the aggregate prices P_k and $P_{S,k}$, the self-employment wage $W_{S,k}$, and the employment decisions of its competitors, $N_{F,k/\{i\}}$. Firms internalize the impact of their labor demand on the sector F price index $P_{F,k}$, labor supply $N_{F,k}$, and the aggregate wage $W_{F,k}$.

The first-order necessary condition of the firm problem determines its labor demand:

$$W_{F,k} = \frac{MRPL_{iF,k}}{\psi_{iF,k}}, \tag{12}$$

where $MRPL_{iF,k} \equiv \partial R_{F,k}/\partial n_{iF,k} = p_{iF,k} z_{iF,k}/\mu_{iF,k}$ is the firm's marginal revenue product of labor. The term $\psi_{iF,k}$ captures the wage markdown and is expressed as

$$\psi_{iF,k} = 1 + \frac{s_{iF,k}^N}{\epsilon_{F,k}} \geq 1, \tag{13}$$

where $s_{iF,k}^N \equiv n_{iF,k}/N_{F,k}$ denotes the firm's employment share in market k and $\epsilon_{F,k}$ is the wage labor supply elasticity defined in (9). A markdown above one indicates that the equilibrium marginal revenue product of labor exceeds the wage, reflecting wage-setting power. This outcome requires two conditions: (i) a positive employment share for the firm ($s_{iF,k}^N > 0$) and (ii) a finite labor supply elasticity ($\epsilon_{F,k} < \infty$).[15]

[15] The markdown can also be expressed as $\psi_{iF,k} \equiv 1 + \epsilon_{iF,k}^{-1}$, where $\epsilon_{iF,k} \equiv \frac{\partial \ln n_{iF,k}}{\partial \ln W_{F,k}}$ is the firm residual labor supply elasticity, holding other firms' employment fixed. This is found as

$$\epsilon_{iF,k} = \frac{\partial \ln n_{iF,k}}{\partial \ln N_{F,k}} \cdot \frac{\partial \ln N_{F,k}}{\partial \ln W_{F,k}} = \frac{\epsilon_{F,k}}{s_{iF,k}^N},$$

where we derived $\frac{\partial \ln n_{iF,k}}{\partial \ln N_{F,k}} = \frac{1}{s_{iF,k}^N}$, from $N_{F,k} = \sum_{i=1}^{M_k} n_{iF,k}$.

The optimality condition in (12) can be rearranged to express the firm i's output price as

$$p_{iF,k} = \mu_{iF,k} \psi_{iF,k} \frac{W_{F,k}}{z_{iF,k}}, \tag{14}$$

where $\mu_{iF,k}$ represents the firm's markup over marginal cost. This is defined as

$$\mu_{iF,k} = \frac{\varepsilon_{iF,k}}{\varepsilon_{iF,k} - 1}, \text{ where } \varepsilon_{iF,k} = \varepsilon\left(s_{iF,k}\right) = \left[\frac{1}{\eta}\left(1 - s_{iF,k}\right) + \frac{1}{\rho} s_{iF,k}\right]^{-1} \tag{15}$$

is the firm's price elasticity of demand. This elasticity depends on the firm's output market share $s_{iF,k}$, as is standard in models of oligopolistic competition and product differentiation (e.g., Atkeson and Burstein 2008).

B. *Equilibrium*

With segmented labor markets and Cobb-Douglas preferences across market-level goods, interactions across markets occur solely through changes in expenditures $Y_k \equiv \alpha_k Y$, where $\left\{\alpha_k\right\}_{k \in (0,1)}$ are the constant expenditure shares. This means that given Y, each market's equilibrium can be determined independently of the others.

This setup simplifies the model's solution into two distinct components: market equilibrium and general equilibrium. Below, we briefly outline these components while detailing the algorithm and numerical implementation in Supplemental Appendix C.1.

Market Equilibrium.—The market equilibrium refers to the equilibrium in each local labor market, given aggregate income Y and the model's fundamentals. It is characterized by a vector $\hat{\mathbf{K}}_k \equiv \left(M_k, \hat{W}_k, \mathbf{\Lambda}_k\right)$ for each market k, where M_k is the number of active firms; $\hat{W}_k$ is the relative wage; and $\mathbf{\Lambda}_k = \left(s_{iF,k}, s^N_{iF,k}, \mu_{iF,k}, \psi_{iF,k}\right)_{i=1}^{M_k}$ is the vector of output and employment shares, markups, and markdowns for each firm.

To solve for $\hat{\mathbf{K}}_k$, we first assume that the set of employers M_k and their productivity are known for each k. Given M_k and a guess for $\hat{W}_k$, equations (6), (13), (14), and (15) define a fixed-point problem that determines the vector $\mathbf{\Lambda}_k$. In turn, given $\mathbf{\Lambda}_k$, the relative wage $\hat{W}_k$ is updated using equations (5), (10), and (11). The resulting fixed point in each market k constitutes the vector of market equilibria for a given guess of M_k.

Solving for the Number of Entrants.—We model firm entry as a sequential game in which, upon entry, firms incur a fixed cost $f^e_{i,k}$, measured in units of the final good, with more productive firms entering first. This process uses a fixed-point algorithm to solve for equilibrium wages and market shares iteratively. The equilibrium is reached when the marginal entrant's profits are nonnegative, and any additional entrants would incur losses, leading to a unique and stable cutoff equilibrium where only firms above a certain productivity threshold enter.

To reduce the computational load of solving the fixed-point algorithm for each candidate M_k, we employ a simplified entry model for baseline calibration, similar to Gaubert and Itskhoki (2021). In this model, firms at the entry stage are assumed to behave "naïvely," anticipating atomistic markups and markdowns, which considerably streamlines the computation of market shares and equilibrium conditions. In Section IIIE, we examine the robustness of our findings to a more comprehensive entry game, which produces quantitatively similar results.

General Equilibrium.—The general equilibrium of the economy is given by a vector of expenditures and prices, $\mathbf{X} = (Y, P)$, such that aggregate income equals aggregate expenditure and that product markets clear. The first condition can be formulated as

$$Y = W + F, \tag{16}$$

where W denotes total workers' income, equal to the sum of labor income and profits:

$$W = \int_{k \in (0,1)} \left(W_{S,k} N_{S,k} + W_{F,k} N_{F,k} + \sum_{i \in [1, M_k]} \pi_{iF,k} \right) dk, \tag{17}$$

and $F = \int_{k \in (0,1)} \left(\sum_{i=1}^{M_k} f_i^e \right) dk$ are total entry costs.[16]

To ensure that product markets clear, the real aggregate expenditure must also be equal to aggregate output, which leads to the second equilibrium condition:

$$\frac{Y}{P} = C. \tag{18}$$

With P normalized to 1, the conditions (16), (17) and (18) yield the general equilibrium vector $\mathbf{X}$, given a market equilibrium $\mathbf{K}$.[17] In turn, given $\mathbf{X}$, the algorithm for the market equilibrium described above yields $\mathbf{K}$. The fixed point $(\mathbf{X}; \mathbf{K})$ is the economy equilibrium.

C. *Characterization*

Table 2 indicates that labor market power increases with employer concentration but less so in areas with higher self-employment rates. As noted in Section I, reduced-form evidence alone makes it challenging to disentangle these patterns, as the estimates in Table 2 capture both direct and equilibrium effects. We now turn to our structural model for deeper insights.

Define $\bar{\psi}_{F,k} \equiv \sum_{i \in M_k} s_i^N \psi_{iF,k}$ as the employment-weighted average markdown in local labor market k. Substituting for $\psi_{iF,k}$ using equation (13), we obtain

$$\bar{\psi}_{F,k} = 1 + \frac{HHI_{F,k}^n}{\epsilon_{F,k}}, \tag{19}$$

[16] Here, W also captures aggregate welfare. In our counterfactual analysis, we will focus on local labor income $W_{S,k} N_{S,k} + W_{F,k} N_{F,k}$, which serves as a direct and relevant indicator of welfare that varies significantly across local labor markets.

[17] Walras' law implies that one of the two general equilibrium conditions is redundant.

where $HHI^n_{F,k}$ is the employment-based HHI in sector F of market k, which also coincides with the wage bill HHI in our model. This equation reveals that while employer concentration increases average labor market power, reflecting more substantial oligopsony power, the aggregate labor supply elasticity $\epsilon_{F,k}$ weakens this effect. It also shows that this elasticity depends on the relative wage $\hat{W}_k$ and the joint distribution of workers' abilities G_k.

To further examine these relationships, we impose structure on the distribution by assuming a log-normal functional form—a common choice in empirical Roy models due to its desirable identification properties, as discussed in Section III.

Let the random variable $Z \equiv a_F - a_S$ represent workers' comparative advantage, with mean $\hat{\mu}$ and standard deviation σ^*, both assumed constant across markets for simplicity. Under the log-normal assumption, and using parameter values consistent with our data and prior empirical studies, the aggregate wage labor supply elasticity $\epsilon_{F,k}$ can be approximated as

$$(20) \qquad \epsilon_{F,k} \approx \frac{\lambda(c_{F,k})}{\sigma^*}, \quad \text{where} \quad c_{F,k} \equiv \frac{\ln \hat{W}_k + \hat{\mu}}{\sigma^*}.$$

Here, $\lambda(x) = \phi(x)/\Phi(x)$ is the inverse Mills ratio, where $\phi(x)$ and $\Phi(x)$ denote the standard normal probability density and cumulative distribution functions, respectively. Notably, since $\lambda'(x) < 0$, the labor supply elasticity decreases as the relative wage $\hat{W}_k$ rises.[18]

Equation (20) shows that under the log-normal assumption, the elasticity function $\epsilon_F(\cdot)$ depends only on a few parameters of the ability distribution. In Section IIIB, we demonstrate how these parameters can be identified from cross-sectional earnings data, allowing us to estimate $\epsilon_F(\cdot)$ using worker-level data alone.

Letting $\chi_{S,k}$ denote the self-employment share, we derive the following relationship:

$$(21) \qquad c_{F,k} = \Phi^{-1}(1 - \chi_{S,k}),$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function, with $\Phi' > 0$. This result implies that, in the log-normal case, the wage labor supply elasticity is directly linked to the self-employment share, which serves as a sufficient statistic for labor supply responsiveness to wage changes.

Equations (19)–(21) illustrate a key takeaway from our model: Greater employer concentration increases average markdowns by strengthening oligopsony power, which suppresses wages. As wages fall, more workers shift into self-employment, altering the sectoral workforce composition. This, in turn, raises labor supply elasticity, mitigating labor market power.

The Pass-Through of Shocks to Average Earnings.—We now use our theory to characterize the effects of shocks to the economic environment on labor market outcomes. For illustration, we focus on average sectoral earnings, a central policy

[18] See Supplemental Appendix C.2.1 for a detailed discussion.

outcome in the counterfactuals below. In sector F, we can decompose the change in (log) average earnings, $\ln \bar{E}_{F,k}$, as

$$(22) \qquad d\ln \bar{E}_{F,k} = -\underbrace{d\ln \bar{\psi}_{F,k}}_{\text{labor market power}} + \underbrace{d\ln Z_{F,k} + d\ln P_{F,k} - d\ln \bar{\mu}_{F,k}}_{\text{labor revenue productivity}\left(\overline{MRPL}_{F,k}\right)} + \underbrace{d\ln \bar{A}_{F,k}}_{\text{selection}},$$

where $P_{F,k}$ is the sectoral price index and $\bar{\mu}_{F,k}$ is the average markup, defined as $\bar{\mu}_{F,k} \equiv \left(\sum_i s_{iF,k} \cdot \left(\mu_{iF,k}\right)^{-1}\right)^{-1}$.

Shocks influence average earnings in sector F through two channels: a *direct* effect on the wage per efficiency unit, captured by the first two bracketed terms, and a *selection* effect, which reflects how changes in worker composition alter average ability in response to the shock. The sign and size of the selection effect depend on the distribution of worker abilities.

The direct effect itself consists of two components. The *labor market power* channel captures how the average markdown responds to the shock, while the *labor revenue productivity* channel reflects how the average marginal revenue product of labor changes through adjustments in aggregate productivity $(Z_{F,k})$, prices $(P_{F,k})$, and average markups $\left(\bar{\mu}_{F,k}\right)$.

Changes in earnings in the self-employment sector can be decomposed in a similar way, but with perfect competition, the expression simplifies to

$$(23) \qquad d\ln \bar{E}_{S,k} = \underbrace{d\ln P_{S,k}}_{\overline{MRPL}_{S,k}} + \underbrace{d\ln \bar{A}_{S,k}}_{\text{selection}}.$$

The sorting of heterogeneous workers across sectors influences how shocks affect average earnings by altering the average ability of workers in each sector, that is, through the *selection* channel. These effects depend on the correlation between workers' abilities in wage work and self-employment and their relative dispersion (Adão 2016; Amodio, Alvarez-Cuadrado, and Poschke 2020). In Supplemental Appendix C.2.2, we show that, when the two abilities are strongly positively correlated and more dispersed in self-employment than in wage work, the mean ability of workers in both sectors increases when the relative wage $\hat{W}_k$ rises in response to shocks. This is because absolute and comparative advantage are negatively correlated in wage work but positively correlated in self-employment: As more workers select into wage employment, average ability increases everywhere. Vice versa, if abilities are negatively or weakly positively correlated, the mean ability of wage workers decreases, and the one of self-employed workers increases when more workers choose wage employment.

D. *Model Discussion*

We conclude with a discussion of four critical assumptions in our model. First, we assume that workers perceive all firms in sector F as homogeneous, enabling us to model the labor market as a standard Cournot oligopsony. Firms strategically choose labor demand but offer a uniform wage despite productivity differences. This simplifies our model compared to recent oligopsony theories where firms are imperfect substitutes, leading to wage variation.[19] This choice is motivated by two key factors: (i) it ensures analytical tractability, allowing us to examine the sources of market-level differences in labor market power, an essential aspect of both the theoretical and empirical analysis; and (ii) it is crucial for model estimation, as discussed in the next section. However, a caveat is that in our framework, only Cournot competition generates markdowns, whereas Bertrand competition would lead to efficient outcomes.

The second key assumption is that we restrict worker mobility across markets, effectively segmenting labor markets. This assumption is supported by the evidence in Section I showing that transitions between wage work and self-employment are more frequent than movements between local labor markets within wage work, a common focus in the literature. The main advantage of this assumption is that it simplifies worker sorting into a binary decision, as in the classic Roy (1951) model. Together with our assumptions about labor market structure and the log-normal parameterization of the ability distribution, this facilitates mapping the ability distribution to cross-sectional earnings data for identification. As discussed in Section IIC, an important implication is that we can use worker-level data to discipline the labor supply determinants of labor market power in the model.

Finally, a notable feature of our model is that it incorporates oligopoly power in the output market, oligopsony power in the labor markets, and endogenous entry. This sets our approach apart from much of the existing literature, which often assumes fixed entry due to the computational challenges of modeling entry games with oligopsony. Notable difficulties in modeling endogenous entry include accounting for existing competitors, which can lead to multiple equilibria, and determining entry patterns across interdependent markets (MacKenzie 2021).

Two assumptions make the entry problem tractable in our model. First, the boundaries of the product and labor markets align, with product varieties and worker decisions being determined within both industry and location.[20] Second, we assume Cobb-Douglas preferences across market-level goods. Combined with segmented labor markets, these assumptions ensure that a firm's market share depends only on local competitors, allowing firms to make independent entry decisions across different markets.

III. Model Identification and Estimation

This section explains how the model is identified using Peruvian firm- and worker-level data. First, we set up the model for quantitative analysis by imposing parametric assumptions. Next, we outline how the parameters are identified using direct and indirect methods. Finally, we present the estimation results.

[19] See, e.g., MacKenzie (2021); Berger, Herkenhoff, and Mongey (2022); Felix (2022); Gutiérrez (2023).

[20] While this is common for labor markets, it is less typical for product markets, which are often defined at the national level. Berger, Herkenhoff, and Mongey (2022) assume perfect competition in the output market. Gutiérrez (2023) discusses the challenges that arise when product and labor market boundaries do not align in a theory of oligopoly and oligopsony with fixed entry.

A. *Parameterization*

We parameterize the model to capture heterogeneity across local labor markets in several factors affecting firms' and workers' decisions, such as firm productivity, entry costs, and worker skills. Since our model's structure does not permit a straightforward inversion—where each labor market or firm in the data can be directly matched to a counterpart in the model—we treat each local labor market as a multidimensional draw from the structural data-generating process defined by the model, focusing on the estimation of common parameters shared across markets.

Firm Productivity.—Firm productivity is influenced by both idiosyncratic factors and broader market characteristics. We adopt a parameterization that incorporates both types of variation.

Let M_k^* denote the potential (shadow) entrants in the wage sector of local labor market k, assumed to follow a Poisson distribution with $\mathbb{E}[M_k^*] = \bar{M}_k^*$. Each potential entrant independently draws a productivity level from a Pareto distribution with a lower bound $\underline{z}_k$ and shape parameter θ, where a smaller θ implies a more dispersed and skewed productivity distribution. Under this Poisson-Pareto framework, the parameter $T_k \equiv \bar{M}_k^* \cdot \underline{z}_k^{\theta}$ acts as a sufficient statistic for expected productivity in a local labor market, provided the least efficient firm remains inactive (Gaubert and Itskhoki 2021).[21]

To capture heterogeneity in productivity across local labor markets, we assume that the T_k values are drawn from a log-normal distribution with parameters μ_T and σ_T:

$$T_k \sim \log \mathcal{N}(\mu_T, \sigma_T).$$

This parsimonious productivity structure generates a realistic cross-sectional distribution of sales. Supplemental Appendix Figure A.5 illustrates this, showing that a log-normal distribution closely approximates the distribution of log sales across local labor markets.

Firm Entry Cost.—In many models, entry costs are assumed to be constant across firms. We make two critical adjustments in our baseline specification. First, we set the entry cost for the first firm to zero, $f^e(1) = 0$, ensuring that at least one firm operates in every local labor market. This is essential to maintain a fixed number of active local labor markets. Second, we allow entry costs to increase with the number of active firms, specified as

$$f^e(n) = f_0 + f_1\sqrt{n}, \quad \text{for } n \geq 2,$$

where n denotes the rank of an entrant. While not critical for the main results, this adjustment prevents the least productive shadow firm from becoming active.

[21] Specifically, the number of shadow firms with productivity exceeding $z > \underline{z}_k$ follows a Poisson distribution with mean $T_k z^{-\theta}$(Eaton, Kortum, and Sotelo 2012).

As discussed earlier, this is necessary to ensure that the parameter T_k accurately reflects average market productivity.

Section IIIE demonstrates that our results remain robust under an alternative parameterization in which the fixed cost f_k^e is a constant that may vary across labor markets.

Worker Ability.—For workers' ability, we assume that each worker's ability vector $\mathbf{a} = (a_F, a_S)$ is drawn from a joint log-normal distribution:

$$\log \mathbf{a} \sim \mathcal{N}(\boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k), \text{ where } \boldsymbol{\mu}_k = \begin{pmatrix} \mu_{F,k} \\ \mu_{S,k} \end{pmatrix}, \; \boldsymbol{\Sigma}_k = \begin{pmatrix} \sigma_{F,k}^2 & \varrho_k \sigma_{F,k} \sigma_{S,k} \\ \varrho_k \sigma_{F,k} \sigma_{S,k} & \sigma_{S,k}^2 \end{pmatrix}, \tag{24}$$

where $\boldsymbol{\mu}_k$ represents the mean efficiency labor units in wage work and self-employment, while $\boldsymbol{\Sigma}_k$ is the variance-covariance matrix.

The log-normal assumption for G_k is common in empirical Roy models, as it facilitates the identification of the underlying parameters (French and Taber 2011). In Section IIIB, we explain how, within our framework, the variance-covariance parameters $\boldsymbol{\Sigma}_k$ and the relative comparative advantage $\hat{\mu}_k \equiv \mu_{F,k} - \mu_{S,k}$ can be identified on a market-by-market basis using cross-sectional earnings data from both wage and self-employment sectors. However, the absolute advantage parameters $\mu_{F,k}$ and $\mu_{S,k}$ cannot be directly identified. To address this, we employ an indirect approach by assuming that $\mu_{S,k}$ is drawn from a normal distribution:[22]

$$\mu_{S,k} \sim \mathcal{N}(\mu_{\mu_S}, \sigma_{\mu_S}),$$

where the parameters μ_{μ_S} and σ_{μ_S} are estimated using the procedure described in Section IIIB. Given a draw for $\mu_{S,k}$ and an estimate for $\hat{\mu}_k$, we can then recover $\mu_{F,k}$ as $\mu_{F,k} = \mu_{S,k} + \hat{\mu}_k$. Later, we will show that this parameterization of the ability distribution yields a plausible distribution of workers' abilities and earnings.

B. *Identification*

We now discuss the identification of all model parameters, beginning with the parameters governing the distribution of workers' abilities, $\boldsymbol{\Sigma}_k$ and $\hat{\mu}_k$. For brevity, we provide only a high-level overview here, while Supplemental Appendix D.1 offers a detailed explanation of our approach. Section IIIB then discusses identification via indirect inference.

Workers' Ability Distribution.—Identification of the variance-covariance parameters $\boldsymbol{\Sigma}_k = \{\sigma_{F,k}, \sigma_{S,k}, \varrho_k\}$ builds on the approach in Heckman and Sedlacek (1985) and relies on the relationship between observed labor market outcomes and the underlying ability distribution of workers. Assuming log-normality, these relationships can be expressed in a tractable form, yielding a system of three equations that

[22] The assumption of normality for $\mu_{S,k}$ is supported by the evidence in Supplemental Appendix Figure A.5 showing that a normal distribution well approximates the distribution of years of education across local labor markets.

map the three parameters of interest to observed employment shares and sectoral earnings data on a market-by-market basis.

Mean Comparative Advantage.—The mean comparative advantage $\hat{\mu}_k$ governs the relationship between the average ability gap across sectors, sectoral shares, and the parameters $\boldsymbol{\Sigma}_k$. While the log-normal assumption provides an analytically tractable way to express this relationship, the lack of data on worker abilities still presents an identification challenge for $\hat{\mu}_k$.

To address this, we impose an additional restriction by assuming that mean log ability across sectors can be mapped to the ratio of log years of education across sectors, with this mapping governed by an unknown elasticity β, which we assume to be constant across markets. This parameter captures how differences in average (log) education levels between wage and self-employed workers translate into differences in average (log) abilities across sectors.

We then use the model equations to derive an expression that maps differences in log earnings across sectors to differences in abilities. Using education as a proxy for ability, we can infer the value of β. To address concerns about measurement error in earnings data or potential violations of the exclusion restriction, we also experiment with alternative regressors and different values of β. With estimates for β and $\boldsymbol{\Sigma}_k$, we infer $\hat{\mu}_k$ for each market using the expression for the mean log ability gap under the log-normal assumption.

This approach allows us to integrate the education-based proxy into the structural model and estimate the ability gap. While Heckman and Sedlacek (1985) address the challenge of identification of mean absolute advantages using instrumental variables with time series wage data, our method combines direct and indirect estimation techniques, leveraging the specific structure of our model for identification.

Setting Parameters to Constant.—Despite our ability to recover market-specific parameters, we maintain a constant variance-covariance matrix and mean comparative advantage across markets in our baseline model for two reasons. First, this parsimonious approach enhances transparency by minimizing market heterogeneity and the impact of measurement error in earnings data. Second, it aligns with our method of matching the model to the data, where the mapping between markets in the data and the model is indirect. In Section IIIE, we discuss an extension of the model that allows for heterogeneity in these parameters.

Discussion.—Our approach to the identification of the workers' ability distribution relies on parametric restrictions, a common but not fundamental feature of empirical Roy models. In our setting, these restrictions allow for transparent estimation using worker-level data while providing the necessary structure to embed the Roy block into our general equilibrium model and conduct counterfactual analysis.

In principle, one could relax parametric assumptions if valid instruments that shift skill distributions without directly affecting wages were available (Heckman and Honoré 1990; French and Taber 2011). A recent application by Adão (2016) demonstrates how nonparametric identification can be obtained using cross-regional variation in sectoral responses to industry-specific price shocks. While this approach avoids strong parametric assumptions, it relies on exogenous variation in labor demand shifters and additional model restrictions, such as price-taking behavior, which are inconsistent with our setting. Given these challenges, implementing a similar approach is beyond the scope of this paper.

Crucially, while our assumption of log-normality imposes parametric structure, it avoids the strict selection patterns that would arise under the more widely used Fréchet distribution (Hsieh et al. 2019; Burstein, Morales, and Vogel 2019). In contrast, as explained in Section IIC, the log-normal specification allows comparative and absolute advantage to vary independently, offering sufficient flexibility to capture the core mechanism of the Roy model while maintaining tractability within a general equilibrium framework.

In sum, our parametric approach strikes a balance between flexibility and tractability, making it both empirically reasonable and methodologically appropriate for our analysis. Nevertheless, we acknowledge its limitations. As Heckman and Honoré (1990) emphasizes, relying solely on normality for identification can introduce biases if the assumption does not hold.

Targeted Moments and Identification of Remaining Parameters.—We now describe the procedure used to estimate the remaining parameter vector, given by $\Phi = \left(\mu_T, \sigma_T, \theta, f_0, f_1, \mu_{\mu_S}, \sigma_{\mu_S}, \eta, \rho, \zeta\right)$. We target 27 empirical moments that capture key local labor market outcomes, informed by the empirical findings in Section I. These moments characterize the cross-sectional patterns of concentration, self-employment, and their co-movements. While all parameters influence every moment to some extent, certain parameters are more directly linked to specific moments, which plays a crucial role in identification, as discussed below.

Targeted Moments.—First, we focus on capturing the prevalence of concentration across local labor markets. From Table 1, we target the mean and standard deviation of the (log) number of firms in each market and the employment-based HHI, both weighted and unweighted. We also target the share of local labor markets with a single employer and the corresponding percentage of total wage employment.[23]

These moments are essential for identifying productivity parameters and the fixed cost distribution. Intuitively, fixed cost parameters (f_0 and f_1), along with productivity parameters for firms and workers (θ and μ_{μ_S}), determine the incidence of concentration across markets. A market can feature fewer firms due to high fixed costs or high firm or worker productivity.

We also target moments of the distribution of log total sales across markets, specifically the interquartile ratio and the 90–10 ratio, along with the mean and standard deviation of the sales concentration ratio (CR1 and CR4) within markets. These moments help identify the average market productivity parameters (μ_T and σ_T) and within-market productivity variation (θ).

[23] We specifically target the moments presented in Supplemental Appendix Table A.6, which replicates Table 1 for the merged sample of local labor markets where both firm-level and worker-level data are available across sectors.

Next, we aim to capture self-employment patterns across local labor markets. We target the mean and standard deviation of the wage employment share and the relative (log) worker earnings between wage and self-employed workers, as reported in Table 1. Under our parameterization of the ability distribution, with fixed $\boldsymbol{\Sigma}$ and $\hat{\mu}$, the wage employment share is a monotonic function of the relative wage $\hat{W}$, which depends on the elasticity parameter ρ and the preference shifter ζ. These two parameters also influence the mean (log) relative earnings.

Although most ability distribution parameters are estimated externally, we target moments of the relative average schooling between wage and self-employed workers—mapped to relative average ability in the model—focusing on the interquartile and 90–10 ratios. These moments help identify the mean absolute advantage parameters $\left(\mu_{\mu_S}, \sigma_{\mu_S}\right)$, which determine the dispersion in average ability across markets.

Finally, we target correlations between the employment-based HHI and several labor market outcomes, specifically the wage-employment share and (log) earnings in both sectors. The sensitivity of these variables to changes in employer concentration mainly depends on the across-sector elasticity (ρ) and the absolute advantage parameters $\left(\mu_{\mu_S}, \sigma_{\mu_S}\right)$.

Normalization.—To improve estimation precision, we apply the following normalizations. First, since the elasticity of substitution η is weakly separately identified from the productivity parameter θ, both being linked to the Pareto tail of the sales distribution across firms, we fix $\eta = 6$ and estimate θ in the MSM routine. Second, as the parameter f_1 shows minimal sensitivity to the targeted moments, we set it externally to 5×10^{-7}. This reduces the parameter vector to $\boldsymbol{\Phi} = \left(\mu_T, \sigma_T, \theta, f_0, \mu_{\mu_S}, \sigma_{\mu_S}, \rho, \zeta\right)$, thereby improving estimation precision.

Identification.—To support our identification strategy, we formally examine the connection between parameters and moments by computing the elasticity of each model-generated moment to each parameter, following standard practices in the literature (e.g., Kaboski and Townsend 2011). The full Jacobian matrix is provided in Supplemental Appendix Figure A.7. Below, we offer some insights based on the results of this analysis.

The parameters θ, ζ, and ρ are the most influential for most targeted moments. This is expected, as these parameters play key roles in determining the equilibrium relative wage $\hat{W}_k$ in each local labor market, as shown in equation (C.3) in Supplemental Appendix C.1. By targeting multiple moments directly linked to the relative wage, more than the number of unknown parameters, we ensure sufficient identifying variation for these parameters. Additionally, only the moments related to relative ability show sensitivity to changes in the dispersion parameter for workers' absolute advantages. This is reassuring, as the market equilibrium—which determines most (other) moments—depends solely on $\hat{\mu}$, not on the absolute advantage parameters.

The Jacobian matrix confirms the identification argument, demonstrating that the model provides enough variation to effectively identify the remaining parameters.

Table 3—Summary of Model Parameters

Parameter		Value
Panel A. Externally fixed		
η	Substitution elasticity within sector F	6
f_1	Fixed cost slope parameter	5×10^{-7}
Panel B. Externally estimated		
σ_F	SD of log ability as a wage worker	0.81
σ_S	SD of log ability as a self-employed	0.91
ϱ	Correlation of log abilities	0.89
$\hat{\mu}$	Mean comparative advantage	−0.12
Panel C. Estimated via MSM		
μ_T	Mean of market-level productivity	0.82
σ_T	SD of market-level productivity	0.96
f_0	Fixed cost intercept parameter	1.97×10^{-4}
θ	Firm-level productivity dispersion parameter	2.34
μ_μ	Mean of market-level mean absolute advantage	1.68
σ_μ	SD of market-level mean absolute advantage	0.10
ρ	Substitution elasticity across F and S	2.72
ζ	Sector F preference shifter	1.88

Notes: This table reports the parameter values for the quantitative model. See Section III for details on parameter estimation.

C. *Estimation Results*

We estimate the model in three steps. First, we calibrate the Cobb-Douglas expenditure shares $\{\alpha_k\}_{k\in[0,1]}$ and population shares $\{L_k\}_{k\in[0,1]}$ from the data, equating them to the income share and the share of the workforce in each local labor market.[24]

We then use our matched firm-worker level data to estimate the parameters of the variance-covariance matrix of the workers' ability distribution (Σ_k) as well as the mean comparative advantage $(\hat{\mu}_k)$ using the procedure described in Section IIIB. Lastly, we implement an MSM procedure to estimate all the remaining parameters using the procedure detailed in Section IIIB.

Table 3 summarizes the estimated parameter vector. Panel B provides the median estimates of the key Roy model parameters, based on the direct inference approach outlined in Section IIIB. Supplemental Appendix Figure A.6 displays the histograms of the estimated variance-covariance parameters and mean comparative advantage across markets.

The two abilities are highly correlated, with an estimated correlation coefficient of $\hat{\varrho} = 0.89$, and the ability for self-employment is more dispersed than the ability for wage work, that is, $\hat{\sigma}_S > \hat{\sigma}_F$. These parameters are precisely estimated, with bootstrap standard errors ranging from 0.02 to 0.07. The estimates suggest no correlation between workers' comparative and absolute advantage in wage employment but a positive correlation in self-employment advantages. This is consistent with the evidence in Figure 1, which shows that transitions into and out of wage employment

[24] For the model calibration, we use a merged sample comprising local labor markets where both firm-level and worker-level data across both sectors are available. Summary statistics for this sample are provided in Supplemental Appendix Table C.1. The sample includes 1,040 local labor market-year observations. For computational efficiency, we reduce the sample size to 234 for the baseline calibration. A histogram of the resulting vector (α_k, L_k) is shown in Supplemental Appendix Figure A.4.

Table 4—Targeted Moments and Model Fit

Moment	Model	Data	Moment	Model	Data
Panel A. Distribution moments					
log number of firms			Wage bill share of		
Mean	0.97	1.22	Markets with 1 firm	0.07	0.08
Standard deviation	0.95	1.17	Markets with $<$ 10 firms	0.89	0.84
			Markets with $<$ 50 firms	1.00	0.99
log of sales					
Ratio p75/p25	2.94	2.92	Share of wage employment		
Ratio p90/p10	5.29	5.30	Mean	0.66	0.71
CR_1, mean	0.66	0.69	Standard deviation	0.12	0.32
CR_1, standard deviation	0.29	0.29			
CR_4, mean	0.94	0.91	log of $Earnings_F/Earnings_S$		
CR_4, standard deviation	0.11	0.15	Mean	0.41	0.40
			Standard deviation	0.58	0.93
Employment HHI					
Mean, unweighted	0.57	0.59	log of $Schooling_F/Schooling_S$ ($Ability_F/Ability_S$)		
Standard deviation	0.34	0.35	Ratio p75/p25	1.42	1.28
Mean, weighted	0.30	0.33	Ratio p90/p10	1.18	1.04
Percent of markets with 1 firm	0.36	0.39			
Panel B. Regression coefficients					
Percent wage employment on (log) HHI^n			(log) $Earnings_F$ on (log) HHI^n		
Point estimate	−0.04	−0.07	Point estimate	−1.36	−0.14
Standard error	0.01	0.01	Standard error	0.13	0.02
(log) $Earnings_S$ on (log) HHI^n					
Point estimate	−1.17	−0.11			
Standard error	0.12	0.03			

Notes: This table reports the moments used in the estimation and compares them with those calculated from the estimated model. The data moments are computed in the sample of local labor markets where at least one formal firm is active and the share of self-employed workers and wage workers is strictly between 0 and 1. See Section III for more details on the moments' construction.

are more common among lower-earning self-employed workers, while transitions to self-employment are unrelated to wage earnings.[25] We also estimate $\hat{\mu} = -0.12$, indicating that the average worker in the population has a comparative advantage in self-employment. These findings align with experimental evidence suggesting that workers in low-income countries, given their current skill levels and wage rates, often choose self-employment over industrial jobs (Blattman and Dercon 2018).

Panel C presents the estimated parameter vector from the MSM procedure, with the corresponding model moments summarized in Table 4. The model demonstrates a strong fit to the data, which is noteworthy given that only 8 parameters were used to target 27 moments.

The model effectively captures various measures of concentration across local labor markets. It closely replicates the high share of monopsonistic labor markets, with 39 percent observed in the data and 36 percent predicted by the model, as well as the corresponding payroll share—8 percent in the data and 7 percent in the model.

[25] These transitions can be explained by shocks to relative unit earnings $\hat{W} = W_F/W_S$ combined with the estimates of the variance-covariance matrix of the joint ability distribution. Positive selection in self-employment implies that transitions are more frequent among lower-earning self-employed workers. Meanwhile, the lack of selection in wage work suggests that sector switchers earn wages comparable to those of inframarginal wage workers. Changes in $\hat{W}$ and their heterogeneity in terms of sign, size, and frequency across markets, combined with the estimated sign and strength of selection, are therefore sufficient to generate the patterns in Figure 1.

Additionally, the model predicts that approximately 66 percent of workers are wage employees, compared to 71 percent in the data. Wage workers in the model earn about 0.4 log points more than self-employed workers, in line with the empirical evidence.

The model also successfully replicates the negative cross-sectional correlations between earnings in both sectors and wage-employment rates with the employment-based HHI. All coefficients are both economically and statistically significant. However, the model falls short of accurately matching the correlations between concentration and mean log earnings in the two sectors. Although the signs of the coefficients are correct, their magnitudes deviate from the observed data. We find that this discrepancy is mostly driven by markets with one firm, to which the model assigns lower average earnings than in the data.

Overall, the model's ability to replicate the core patterns documented in Section I builds confidence in our estimated parameters, which are broadly consistent with findings from other studies in the literature. For instance, we estimate a Pareto shape parameter of $\theta = 2.34$, which is higher but close to the 1.5 in Huang et al. (2024) for Chilean importers. We also find limited variation in absolute advantage across markets ($\sigma_\mu = 0.10$), which aligns with our observation of remarkably stable estimates for the parameters of the ability distribution across markets. Lastly, we estimate a substitution elasticity between sector goods within a market of $\rho = 2.72$, lower than the substitution elasticity within sector F but higher than the substitution elasticity across product markets. The latter is implicitly set to 1 in our case due to the Cobb-Douglas assumption and estimated at 1.5 in Gutiérrez (2023). This is consistent with gradually decreasing substitution elasticity as we move to upper utility nests.

D. *Model Fit*

We begin by evaluating how effectively the model replicates the distributions of key variables across local labor markets. Supplemental Appendix Figure A.9 illustrates the distribution of normalized (log) sales, the (log) earnings gap between wage and self-employed workers, and the number of firms. The red bars represent the data, while the blue bars show the model's predicted distributions. Despite only targeting a few key moments in the estimation, the model's distributions closely match those observed in the data, indicating a good overall fit.

Model-Implied Reduced-Form Elasticities.—We now evaluate how well the model captures labor market power in the Peruvian economy. In Section IE, we provided evidence of significant labor market power across markets. However, those estimates derived from the data are reduced-form inverse labor supply elasticity estimates, which incorporate competitors' employment responses and do not directly map to the structural elasticity (Berger, Herkenhoff, and Mongey 2022). To assess the model's fit, we replicate Table 2 using model simulations by applying the same shock to firm productivity and labor demand used in Section IE. This is challenging for several reasons, including the model's static nature, the wage homogeneity within markets, and the absence of electricity as a production input for firms.

TABLE 5—REDUCED-FORM INVERSE SUPPLY ELASTICITY (*model estimates*)

			Self-empl. rate	
			Low	High
	(1)	(2)	(3)	(4)
All markets	0.364			
	(0.070)			
$HHI^{wn} \in (0, 0.18]$		0.242		
		(0.071)		
$HHI^{wn} \in (0.18, 0.25]$		0.319		
		(0.046)		
$HHI^{wn} \in (0, 0.25]$			0.214	0.284
			(0.033)	(0.134)
$HHI^{wn} \in (0.25, 1]$		0.560	0.621	0.479
		(0.160)	(0.177)	(0.294)

Notes: This table presents the estimates of the average inverse labor supply elasticity of treated firms, that is, $\hat{\epsilon}_{iF,k} \equiv \Delta \ln W_{F,k} / \Delta \ln n_{iF,k}$, across all markets with more than one firm (column 1) and within different market subsets (columns 2 to 4) in the estimated model. These estimates are compared to the reduced-form markdown estimates provided in Table 2. The procedure to obtain these estimates is detailed in Supplemental Appendix D.4. Low and high self-employment rates are defined as being below or above the average self-employment rate across local labor markets, respectively. Bootstrap standard errors are in parentheses. These are obtained by redrawing the i.i.d. shock associated with the assignment of τ values 1,000 times.

We overcome these challenges by following a three-step procedure, detailed in Supplemental Appendix D.4. First, we identify treated firms in the model by assigning each firm an electricity wedge τ. This assignment relies on the empirical relationship between τ and firm productivity, inferred from the data. A firm is classified as treated if its τ exceeds the economy-wide median, following the approach in Section IE. Second, we determine the magnitude of the productivity shock induced by electrification by estimating its effect on firm productivity in the data. Lastly, starting from the baseline model equilibrium, we simulate a 2.3 percent productivity shock to the treated firms, corresponding to the estimated average effect. The model's average reduced-form inverse labor supply elasticities are then calculated by taking the ratio of the (log) wage to (log) employment responses of treated firms in markets with more than one firm, consistent with the local average treatment effect within-market estimates reported in Table 2.

Table 5 presents the model-implied reduced-form estimates of labor market power across markets, along with bootstrap standard errors, averaged across all markets as well as within different subsamples. The results closely align with those in Table 2. The model estimates an average inverse elasticity of 0.36 across local labor markets, compared to 0.42 in the data. The model effectively replicates the relationship between average inverse elasticity and market concentration, capturing its gradient with precision. Additionally, it reflects the mitigating effect of self-employment, showing that labor market power is highest in markets with high employer concentration and low self-employment rates. In these markets, the model predicts an inverse elasticity of 0.62, compared to 0.75 in the data. Conversely, labor market power is lower in concentrated markets with a higher-than-average self-employment share, though the model underestimates the difference here, overshooting the inverse elasticity estimate in this latter group of markets. We attribute this discrepancy to the model's inability to fully capture the broad variation in self-employment rates across markets, with a standard deviation of 0.09 in the model compared to 0.32 in the data. However, the difference-in-differences between highly concentrated and less concentrated markets with varying self-employment rates is preserved.

The estimated model also allows for comparison between reduced-form inverse elasticities and their structural counterparts, reported in Supplemental Appendix Table A.7. The structural inverse elasticities are lower than the reduced-form estimates in Table 5, underscoring the importance of equilibrium responses from competitors. However, as discussed in Section IIC, the bias in reduced-form estimates does not account for the heterogeneity observed across markets in terms of concentration or self-employment prevalence. Supplemental Appendix Table A.7 supports this conclusion quantitatively. Additionally, Supplemental Appendix Figure A.8 illustrates that no discernible pattern emerges when comparing structural and reduced-form labor market power against employer concentration and self-employment rates.

E. *Robustness*

Our structural approach to identifying labor market power relies on parametric assumptions. To validate the robustness of our findings, we explore several alternative parameterizations and their effect on labor market power and its variation across markets.

Heterogeneity in Roy Parameters.—In our baseline specification, we assume a constant variance-covariance matrix and mean comparative advantage for workers' abilities across local labor markets. However, Supplemental Appendix Figure A.6 shows that markets vary in their relative skill endowments, raising concerns that overlooking this heterogeneity may lead to biases. In particular, inspection of equations (19) and (20) reveals that variation in labor supply elasticity may be partially driven by these additional sources of heterogeneity rather than self-employment shares alone.

To address this concern, we modify the model to allow for heterogeneity in both the variance-covariance matrix, Σ_k, and the mean comparative advantage, $\hat{\mu}_k$. Specifically, we group markets into I clusters based on population quantiles. For each cluster $i = 1, \ldots, I$, we obtain the group-specific parameters $\left(\sigma_{F,i}, \sigma_{S,i}, \varrho_i, \hat{\mu}_i\right)$ as the within-group median. Markets in the model are then assigned to groups according to their population quantile. In the baseline model, we implicitly set $I = 1$. In the robustness exercise, we set $I = 3$.

Supplemental Appendix Table A.8 presents the estimated Roy parameters at baseline and under group heterogeneity, showing minimal variation across groups. Column 2 of Supplemental Appendix Table A.9 reports the sensitivity of our labor market power estimates to this robustness check, demonstrating that the overall incidence of labor market power and its relationship with market concentration and self-employment remain essentially unchanged. These findings support our decision to use constant parameters for the baseline calibration.

Heterogeneity in Fixed Costs.—Firm entry costs into the wage sector represent barriers to starting a formal firm, including regulatory procedures, high licensing fees, limited access to credit, and inadequate infrastructure. These barriers are likely heterogeneous across local labor markets. In our baseline calibration, we assumed a constant cost structure across markets, implying that entry—and therefore market concentration—was fully proportional to variable profits and productivity. This assumption may influence labor market power estimates.

To address this, we recalibrate the model, allowing for an alternative parameterization of fixed costs, assuming each market draws f_k^e from a Weibull distribution with shape parameter f_κ and scale parameter f_λ. Column 3 of Supplemental Appendix Table A.9 shows that our labor market power estimates remain robust under this assumption. Supplemental Appendix Table A.10 demonstrates that this adjustment improves the model's ability to replicate the correlation between market concentration and earnings across local labor markets, particularly in highly concentrated markets where the baseline model underestimates earnings.

However, this adjustment has little impact on the model's ability to capture labor market power dynamics or its broader implications. While it resolves one specific issue, it also introduces additional assumptions about the relationship between fixed costs and productivity. Moreover, it worsens the model's fit in other dimensions—particularly in matching the number of firms across markets—making it a less appealing solution overall.

Full Entry Game.—In the baseline model, we simplify the entry process to avoid the computational complexity of solving for the exact equilibrium values of M_k, instead using an approximation where firms are treated as infinitesimally small at the entry stage. To assess robustness, we recalibrate the model under the full entry game. Column 4 of Supplemental Appendix Table A.9 shows that even with this more complex entry framework, our labor market power estimates—and their relationship with market concentration and self-employment—remain unchanged. This is reassuring but expected, as discussed in Section IIIA, since the entry assumption primarily affects equilibrium through the number of firms and market concentration directly targeted in calibration without altering the model's core outcomes.

Census Data.—In our baseline model estimation, we target moments derived from the EEA firm-level data. Supplemental Appendix B shows that the empirical facts presented in Section I are robust to using the 2007 Economic Census data to measure concentration and capture its variation across markets. We use those same data also to validate the model estimation. Specifically, we recalculate all moments using firm-level census data and the same local labor markets as in our baseline calibration. We exclude one-person firms from the census to omit self-employment. We then follow the procedure outlined in Section IIIB and show the results in column 5 of Supplemental Appendix Table A.9. Using census data reduces average concentration across markets, lowering the average markdown from 1.45 to 1.31. Most importantly, the relationship between labor market power, market concentration, and self-employment remains robust.

IV. Counterfactual Policy Analyses

Armed with the estimated model, we conduct two sets of counterfactual experiments to address our key research questions. First, we quantitatively assess the role of labor market power in shaping labor market outcomes in Peru. Second, we simulate three industrial policies aimed at promoting industrialization and increasing wage employment by targeting firms or workers. We measure their aggregate and distributional impacts and investigate how labor market power affects the success of these policies.

A. *Impact of Labor Market Power*

To investigate the impact of labor market power on labor market outcomes, we introduce a conduct parameter, $\iota \equiv dN_{F,k}/dn_{iF,k} \in \{0,1\}$, which captures the firm's perceived effect of its labor demand on aggregate market variables. When $\iota = 1$, firms are strategic and fully internalize the impact of their labor demand on aggregate labor demand and wages, as in our baseline model. Conversely, when $\iota = 0$, firms behave as wage takers, irrespective of market concentration.

Under this generalization of market conduct, the firm i's markdown in market k becomes

$$\psi_{iF,k} = 1 + \iota \frac{s_{iF,n}}{\epsilon\left(\hat{W}_k\right)}, \tag{25}$$

which highlights that the markdown equals one whenever firms act as wage takers.[26] We quantify the role of labor market power in the economy by comparing the baseline economy with one where $\iota = 0$, holding other things equal.

Figure 3 presents some key distributions of interest, while Supplemental Appendix Table A.11 shows the average outcomes in the two economies. Panel A of Figure 3 compares the distribution of wage employment across markets, showing that labor market power significantly limits wage employment in Peru. With perfectly competitive labor markets, the share of wage employment would increase by over 10 percentage points, from 66 to 77 percent.

Panel B shows that despite increased competition, concentration persists and even rises in the absence of labor market power due to market share reallocation. Without labor market power, the most productive firms gain market share, leading to higher concentration.[27]

Panel C shows that labor market power depresses average wages, while panel D reveals that it narrows the earnings gap between wage workers and the self-employed. Without labor market power, average earnings would rise by 31 percent in the wage employment sector and by 27 percent in the self-employment sector.

Drawing on insights from Section IIC, we can decompose the changes in average earnings in both sectors into their key components.[28] The increase in average wages in the no-labor-market-power economy is entirely driven by higher earnings

[26] The wage markdown of firm i in market k can be written as

$$\psi_{iF,k} = 1 + \frac{d\ln W_{F,k}}{d\ln n_{iF,k}} = 1 + \frac{d\ln W_{F,k}}{d\ln N_{F,k}} \cdot \frac{dN_{F,k}}{dn_{iF,k}} \cdot \frac{n_{iF,k}}{N_{F,k}} = 1 + \iota \frac{s_{iF,n}}{\epsilon\left(\hat{W}_k\right)}.$$

[27] See Eslava, Haltiwanger, and Urdaneta (2024) for empirical evidence of this channel.

[28] These results are detailed in Supplemental Appendix Table A.11.

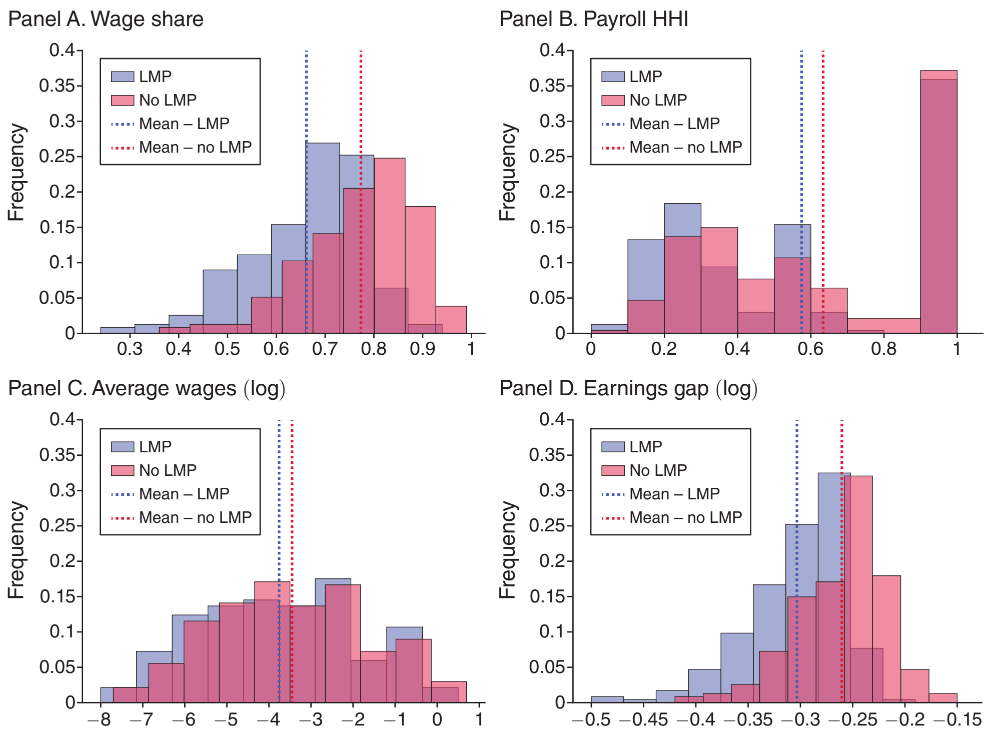

FIGURE 3. EFFECTS OF LABOR MARKET POWER

Notes: The four panels show the distribution of key labor market outcomes across markets in the baseline (blue) and in the counterfactual economy (red) with no labor market power. Supplemental Appendix Table A.11 complements these figures by reporting the average of selected outcomes across markets in the two economies together with the difference between the two.

per efficiency unit, with the elimination of markdowns accounting for a 35 percent wage increase. This is partially offset by a 4 percent reduction in labor revenue productivity (MRPL). As market share shifts toward more productive, high-markup firms, output prices fall, accounting for most of the decline in MRPL. The selection channel has no impact, as expected from our parameter estimates.

In the self-employment sector, average earnings also rise, and about two-thirds of the increase is driven by higher unit earnings, fully attributable to higher output prices. Unlike in the wage sector, the selection channel plays a crucial role here. In the counterfactual economy, the average ability of self-employed workers is 11 percent higher, as more workers transition to wage employment, leaving the remaining self-employed workers increasingly positively selected.

Overall, the results in this section demonstrate that labor market power has a strong hold on the Peruvian economy. It contributes to the scarcity of wage jobs, lowers firm size, and reduces wages and self-employment earnings through markdowns, selection, and revenue productivity effects. Our findings also show that worker self-selection is a key factor through which labor market power in wage employment reduces earnings in the self-employment sector, thereby influencing the earnings gap between wage workers and the self-employed.

B. *Industrial Policy*

Despite long-standing efforts to increase wage employment as a means of promoting inclusive growth, policy interventions have often had limited impact (McKenzie 2017; Bandiera et al. 2022). This section examines the extent to which the interaction between labor market power and self-employment contributes to this outcome. We simulate three industrial policy interventions—targeting firm productivity, worker productivity, and entry costs—and use our model to evaluate how labor market power affects their overall effectiveness, both qualitatively and quantitatively.

Firm Productivity.—Policy efforts to boost firm productivity have often focused on market integration, primarily through infrastructure improvements (Fiorini, Sanfilippo, and Sundaram 2021). The goal is to expand market access, enhance productivity, and reduce both information frictions and shipping costs for inputs and outputs. To assess such interventions, we examine a road infrastructure project in Peru. Between 2003 and 2010, the country added over 5,000 kilometers of new roads, expanding the network by more than 10 percent. Volpe Martincus, Carballo, and Cusolito (2017) evaluate this intervention and find that firm exports increased by an average of 3.7 percent as a result. Building on this evidence, we calibrate a shock in our model that shifts expected market-level productivity (T_k) to achieve a comparable increase in firm sales across markets.[29]

Although the shock is applied uniformly across markets, its effects vary significantly. Panel A of Figure 4 shows the estimated average impact across markets, segmented by quintiles of the baseline wage markdown distribution.[30] Wage employment shares and wages rise on average across all market groups, as intended by the policy. However, the rise in productivity does not fully translate into higher wages. The incomplete pass-through stems from an increase in wage markdowns, resulting from the policy's effects on its two key determinants: employer concentration and labor supply elasticity. As firm productivity rises, market entry increases, which reduces concentration. Yet the labor supply elasticity also decreases as more workers opt for wage employment. The latter effect dominates in most markets, as shown by Supplemental Appendix Figure A.10, leading to higher wage markdowns.[31]

Second, despite higher markdowns and stronger positive selection into self-employment, the earnings gap between wage and self-employed workers increases moderately. This occurs because the rising productivity of formal firms, combined with general equilibrium effects, more than offsets the opposing effects of markdowns and selection.

Third, and most importantly, the figure demonstrates that labor market power and its determinants strongly influence the policy's impact. Increasing firm productivity

[29] We estimate that T_k must increase by 8 percent to reach the targeted sales growth.

[30] Supplemental Appendix Table A.12 provides average changes in selected outcomes across all markets.

[31] We also compare the effects of this policy in general equilibrium (GE) versus a partial equilibrium (PE) setting, where aggregate income is fixed. The results shown in Supplemental Appendix Table A.13 reveal significant differences: In the PE model, a productivity shock leads to declining unit wages due to fixed demand and price reductions, causing lower wages in both sectors as workers reallocate. Conversely, the GE model shows that falling prices boost aggregate demand, increasing the marginal revenue product of labor and raising wages across all sectors. This underscores the importance of GE structure in accurately capturing wage responses, as the GE model significantly mitigates the negative wage impacts observed in the PE scenario.

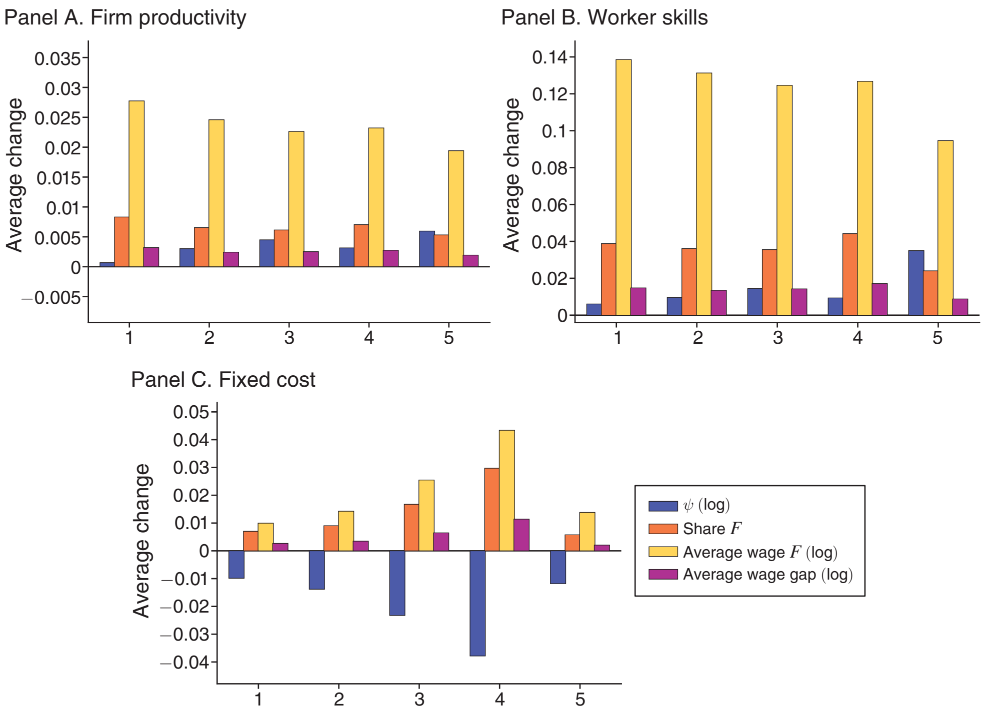

FIGURE 4. EFFECTS OF POLICY SHOCKS ACROSS MARKETS

Notes: The three panels illustrate the estimated change in wage markdown, wage employment share, average wage, and average earnings gap between wage workers and self-employed workers across local labor markets resulting from the three policy experiments. It does so for separate bins determined by the size of the wage markdown at baseline. Supplemental Appendix Figure A.10 complements these figures by showing the change in the wage markdown and its determinants, that is, employer concentration and wage labor supply elasticity.

is significantly more effective in markets with lower baseline wage markdowns. This is true despite the higher baseline levels of wage employment shares and wages in these markets, as discussed in Section IVA. The average increase in wage employment share and wages is 57 percent and 43 percent higher, respectively, in markets in the bottom quintile of the baseline wage markdown distribution compared to those in the top quintile.[32] Most notably, rising markdowns account for 98 percent of the variation in the policy's impact on wages and 85 percent of the variation in its effect on the wage employment share across markets.[33]

Worker Skills.—Next, we examine policies aimed at boosting the supply of wage labor by enhancing worker skills through targeted training programs. These initiatives operate on the belief that unemployment stems from a lack of specific technical skills, which can be addressed through short-term training (McKenzie 2017). Several such programs have been implemented across Latin America, including

[32] Wages, for instance, increase by 1.94 percent on average in the least competitive labor markets and by 2.77 percent in the most competitive ones, so $(2.77 - 1.94)/1.94 = 0.43$.

[33] These figures are derived from the R^2 of a simple regression implemented on simulated data, where the local labor market is the unit of observation. The dependent variable is the change in average wage or wage employment share following the policy shock, and the independent variable is the change in the wage markdown.

Peru's Job Youth Training Program, known as *Projoven*. Operating from 1996 to 2010, the program aimed to equip young people from low-income backgrounds with training and labor market experience aligned with the needs of the productive sector, catering directly to employer demands. An experimental evaluation of Projoven by Díaz and Rosas-Shady (2016) found that, 2 years after completing the program, participants had a 3.6 percentage point higher probability of securing wage employment compared to the control group, although the result was not statistically significant.[34] To simulate a similar training program in our model, we introduce a shock to workers' mean comparative advantage in wage employment, $\hat{\mu}$.[35]

Panel B of Figure 4 shows that, by improving worker skills, the program raises productivity in the formal sector, similar to a productivity shock to firms. This reduces concentration and increases wage employment. Additionally, as worker skills improve, the mean comparative advantage in wage employment increases, making self-employment less attractive and decreasing the supply elasticity of wage labor, as shown in Supplemental Appendix Figure A.10. This reduction in elasticity outweighs the decline in concentration, resulting in higher wage markdowns. Despite this, wages still increase as skills improve. Notably, the model closely replicates the 13.4 percent rise in monthly earnings reported by Díaz and Rosas-Shady (2016).

Labor market power and its changes are crucial in shaping the policy's impact. The average effects on wage employment and wages are 62 percent and 47 percent higher, respectively, in the most competitive labor markets compared to the least competitive ones. As with policies that boost firm productivity, rising markdowns account for 98 percent of the variation in the policy's effect on average wages and 85 percent of the variation in its impact on the wage employment share.

Firm Entry Cost.—Policies to reduce entry costs typically involve government programs that simplify entry regulations. A prime example is the Mexican Rapid Business Opening System (SARE), which aimed to streamline local business registration procedures across various municipalities starting in May 2002. Both Kaplan, Piedra, and Seira (2011) and Bruhn (2011) evaluate the impact of this reform on several economic outcomes at the municipality level.[36] For our policy experiment, we target the 2.2 percent increase in the fraction of wage earners documented in Bruhn (2011).[37]

Panel C of Figure 4 shows the policy impact across markets. The policy encourages firm entry and reduces concentration. Competition intensifies in the output and labor market, leading to lower markups and prices.[38] Wage employment increases, but the effect is modest compared to the large reduction in concentration. This is

[34] However, significant positive effects were found in the likelihood of obtaining formal employment, such as jobs with health insurance and pensions.

[35] To increase average wage employment by 3.6 percentage points, $\hat{\mu}$ must rise from -0.12 to 0.04 across all markets.

[36] The main difference between the two studies is that Bruhn (2011) uses household data from labor market surveys, whereas Kaplan, Piedra, and Seira (2011) uses social security data.

[37] We find that a 40 percent reduction in fixed costs across local labor markets is required to achieve an average 2.2 percent increase in wage employment in our model.

[38] Remarkably, the model replicates the 1 percent decrease in prices found by Bruhn (2011). Specifically, this refers to the average change across markets in the price index in the wage employment sector, $P_{F,k}$, as reported in Supplemental Appendix Table A.12.

because the drop in concentration stems from the entry of relatively unproductive firms, which have little impact on aggregate labor demand. As a result, the policy reduces concentration more than it affects labor supply elasticity, and wage markdowns decrease, as shown in Supplemental Appendix Figure A.10.

The policy's impact is highly heterogeneous across markets. However, unlike the firm productivity shock, reducing entry costs is the least effective in the most competitive labor markets. It is also relatively ineffective in the most concentrated and least competitive markets. In markets with moderately high markdowns, reducing entry costs is more effective because concentration is on the margin more responsive to the negative cost shift.

Yet, as in the previous two cases, changes in labor market power are crucial to understanding the effects of reducing fixed costs. Changes in markdowns explain 99 percent of the variation in the policy's impact on wages and 88 percent of the variation in its effect on the wage employment share.

Discussion.—These counterfactual exercises show that our framework provides a valuable perspective for understanding the impact of industrialization policies. The effectiveness of these policies is closely tied to labor market power and its key drivers—employer concentration and labor supply elasticity. While these policies help create more wage jobs, they also make self-employment less attractive, reducing labor supply elasticity. In some cases, this means that procompetitive policies can have the unintended effect of making the labor market less competitive. For productivity-enhancing policies, the drop in elasticity outweighs the reduction in concentration, leading to higher wage markdowns and weakening the policy's overall impact.

In contrast, policies that lower entry costs reduce both concentration and markdowns, making them more effective in markets with moderate labor market power. In all cases, markdown changes largely explain the variation in policy outcomes across markets. These insights are crucial for researchers and policymakers seeking to better understand labor market dynamics and develop effective strategies for industrialization and inclusive growth.

V. Conclusions

Addressing the scarcity of good jobs in developing countries remains a pressing challenge for policymakers. This paper draws on new evidence from Peru, a general equilibrium model, and counterfactual analyses to examine the crucial role of labor market power and its interaction with self-employment in shaping labor market outcomes, informing effective policy design.

Our findings show that self-employment in manufacturing plays a dual role in the presence of labor market power. On the one hand, it provides workers with an outside option when wage employment is scarce or unattractive, limiting employers' ability to suppress wages. On the other hand, policies aimed at expanding wage employment and reducing reliance on self-employment may inadvertently strengthen firms' wage-setting power, ultimately undermining their intended objectives.

More broadly, our results challenge the conventional view of self-employment as a perfectly elastic labor reservoir for industrialization (Lewis 1954; Rauch 1991). Instead, we demonstrate that labor market power can impede the efficient movement of workers into the modern industrial sector, leading to an overreliance on self-employment that may slow economic development. These findings highlight the need for industrial policies that explicitly account for labor market frictions to be effective (Donovan and Schoellman 2023).

An important caveat is that our analysis focuses on manufacturing, which accounts for a relatively small share of employment and value added in most economies. However, manufacturing has historically played a central role in economic development and remains a key target of industrial policy. In many low-income countries, manufacturing value added has grown without a corresponding increase in large-firm employment, while self-employment remains persistently high (Alfaro et al. 2023; Huneeus and Rogerson 2024). This divergence, despite targeted industrial policies (Juhász, Lane, and Rodrik 2023), underscores the need to better understand the barriers to manufacturing wage employment expansion.

At the same time, our findings—particularly on the dual role of self-employment under labor market power—are relevant beyond manufacturing and low-income countries. The digital economy has transformed labor markets in wealthier nations, increasing self-employment and flexible work arrangements, while reducing reliance on traditional jobs (Mas and Pallais 2017; Katz and Krueger 2019), yet firms continue to exert significant labor market power. Understanding how these trends interact is an important avenue for future research with meaningful policy implications. Additionally, extending our analysis to sectors such as agriculture and services, where self-employment is more prevalent, would provide further insights into labor markets in developing countries.

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