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Labor Market Power and Development†

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Imperfect competition in labor markets can lead to efficiency losses and lower aggregate output. This paper examines how variations in labor market competitiveness may account for differences in GDP per capita among countries. By structurally estimating an oligopsony model with free entry across different development stages, we find that labor market power decreases with GDP per capita. Wage markdowns vary from 54 percent in low-income countries to around 24 percent in the richest ones. If labor markets in poorer countries were as competitive as in more developed ones, their output per capita could rise by up to 44 percent. (*JEL* E23, J22, J31, J42, L13, L25, O47)

Productivity differences are crucial to understanding the vast differences in GDP per capita levels across countries. Since labor markets play an essential role in the efficient allocation of resources across firms, the extent of competition in these markets can have profound implications for wages and overall productivity.

In this paper, we study whether labor market competition differs across countries with different levels of economic development and whether such differences can help account for disparities in GDP per capita. We extend a standard model of monopsonistic competition (Card et al. 2018; Dustmann et al. 2022) to a general equilibrium setting with firm granularity and endogenous entry and structurally estimate the labor supply elasticity at various stages of development. In the model, firms maximize profits, taking into account the relationship between wages and labor supply. The model generates an equilibrium relation between wages offered by an individual firm and its number of employees and the implied wage-size premium maps directly to the underlying elasticity of labor supply. The tight relation between wage-size premium and labor supply elasticity allows us to implement an indirect inference approach to estimate the elasticity of the labor supply.

The labor supply elasticities we estimate are increasing with GDP per capita; labor markets are more competitive in richer countries. As we move from low- to high-GDP per capita countries in the sample, the elasticity increases from 0.85 to 3.06.

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This implies an average wage markdown of 54 percent among countries at the bottom of the development ladder, such as Zambia, Senegal, or India, and as low as 24 percent in countries at the top, such as Denmark, the Netherlands, or the United States.

Several factors might contribute to less competitive labor markets in poorer countries. Imperfect information, heterogeneous preferences, and mobility costs are among the key drivers of labor market power, as highlighted by previous research (Robinson 1933; Manning 2003). The labor markets in less developed countries often exhibit greater fragmentation, potentially due to the lack of adequate transportation and communication infrastructure (Brooks, Kaboski, Kondo, et al. 2021). Searching for formal jobs can be more time-consuming, and wage markdown can be explained by workers liking their job over and above the wage it pays (Berger et al. 2023). Moreover, workers in developing countries are less likely to be located in urban areas, where agglomeration forces make labor markets more competitive (Manning 2010; Luccioletti 2022). Governments in poorer countries might also lack the capacity to implement labor market regulations that curtail employers' market power. Lastly, a substantial pool of informal workers willing to move into formal employment can allow formal firms to offer wages below the marginal product of labor (Amodio, Medina, and Morlacco 2022).

The implications of a less competitive labor market extend beyond individual wages and have broader ramifications for the efficient allocation of workers across firms. By distorting the allocation of labor across firms, labor market power hinders overall productivity and lowers aggregate output. Through the lens of our model, countries at the bottom of the development ladder and with a GDP per capita similar to those of Zambia, Senegal, or India could experience a significant increase in output per capita. If their labor markets were as competitive as the countries at the top of the ladder, such as Denmark, the Netherlands, or the United States, their GDP per capita would increase up to 44 percent.

This paper builds on growing empirical and quantitative literature on labor market power (Manning 2013, 2021). Empirical studies often focus on specific labor markets; see, among others, Goolsbee and Syverson (2019); Falch (2010); and Staiger, Spetz, and Phibbs (2010). Azar, Berry, and Marinescu (2022) estimate the labor supply elasticity for the entire US labor market using an instrumental variable approach; their preferred empirical specification implies a labor supply elasticity of 4.8. Within this literature, Amodio and de Roux (2023) and Amodio, Medina, and Morlacco (2022) focus on market power in Colombia and Peru and estimate values for labor supply elasticities of 2.5 and 2.3, respectively. Brooks, Kaboski, Li, et al. (2021) study how labor market power affects wages and the labor share in India and estimate an elasticity of labor supply as low as 0.4. Consistent with our findings, Sokolova and Sorensen (2021) document a positive relationship between economic development and the extent of labor market competition. More recently, Amodio et al. (2024) document that the average wage markdown of manufacturing firms follows a hump shape over GDP per capita and show that employment regulation can account for cross-country differences. Our paper extends existing literature in two key ways. First, we use an indirect inference approach to estimate labor supply elasticity across countries at different development stages. Second, we demonstrate a negative correlation between a country's GDP per capita and oligopsony power.

Another strand of literature studies the implications of labor market power for inequality and welfare—for example, Card et al. (2018) and Dustmann et al. (2022). Lamadon, Mogstad, and Setzler (2022) estimate an equilibrium model of the monopsonistic labor market with two-sided heterogeneity and show that labor market power creates significant misallocation of workers to firms. Garcia-Louzao and Ruggieri (2023) use Lithuanian linked employer-employee data to show that higher labor market competition accounts for between 14 percent and 48 percent of the observed reduction in the dispersion of earnings. Berger, Herkenhoff, and Mongey (2022) build and estimate an oligopsony model of the labor market and quantify the welfare losses from labor market power relative to the efficient allocation as roughly 6 percent of lifetime consumption. Deb et al. (2022) show that one-quarter of the wage stagnation observed in the United States in the last 40 years can be attributed to monopsony in the labor market. Castro and Clementi (2023) introduce labor market power into a model of industry dynamics to study the link between pay compression and earnings inequality in Portugal. None of these papers, however, focus on the role of labor market power for cross-country income differences.

Finally, the paper is related to the extensive macrodevelopment literature that studies how frictions and distortions can account for cross-country income differences—for example, Guner, Ventura, and Xu (2008); Hsieh and Klenow (2009); Bento and Restuccia (2017); Poschke (2018); and Guner and Ruggieri (2022). We contribute to this literature by showing that differences in labor market power can be a crucial driver of differences in GDP per capita across countries.

I. The Model

We extend a streamlined model of monopsony, as presented, for example, in Card et al. (2018) and Dustmann et al. (2022), to account for endogenous entry and strategic interaction between firms. In contrast to models of competitive labor markets where firms take wages as given or to models with search frictions where firms and workers bargain over wages, firms post wages to maximize profits taking into account how posted wages affect labor supply.

The economy is static and populated by a continuum of workers of measure L, each endowed with identical efficiency units of labor. There is an endogenous number of active firms, J, that differ in their productivity z_j and workplace amenities a_j. Workers have idiosyncratic preferences over amenities provided by the firms. Each firm posts a wage w_j to maximize profits, taking the labor supply function of workers as given. Firms do not observe workers' preferences over firms and cannot perfectly discriminate among workers. Workers observe posted wages and choose which firms to work for. As a result, the number of workers a firm employs depends on wages posted by all firms. Job differentiation and strategic interactions endow firms with wage-setting power.

A. *The Problem of the Workers*

The utility of worker i working at firm j is given by

$$U_{ij} = \epsilon^L \ln(w_j) + a_j + v_{ij},$$

where w_j is the wage paid by firm j, ϵ^L denotes the labor supply elasticity, and v_{ij} is the idiosyncratic preference shock of worker i for working at firm j. Preference shocks v_{ij} are assumed to be independent and identically distributed random draws from a type I extreme value distribution with location and scale parameters equal to 0 and 1, respectively. Amenities and idiosyncratic preference shocks capture nonpecuniary match factors. A large literature documents the existence and the importance of nonwage job characteristics, such as commuting arrangements or schedule flexibility and their value to employees (Maestas et al. 2018; Mas and Pallais 2017; Sorkin 2018).

Given a vector $\mathbf{w} = (w_1, \dots, w_J)$ of posted wages, workers choose which firm to work for to maximize their utility. Following McFadden (1978), workers have logit probabilities of working for firm j, given by

$$(1) \qquad p_j = \Pr\left(\underset{k \in \{1, \dots, J\}}{\arg\max}\ U_{ik} = j\right) = \frac{\exp\left(\epsilon^L \ln(w_j) + a_j\right)}{\sum_{k=1}^{J} \exp\left(\epsilon^L \ln(w_k) + a_k\right)},$$

which can be written as

$$(2) \quad p_j = \frac{\exp\left(\epsilon^L \ln(w_j) + a_j\right)}{\lambda_j + \exp\left(\epsilon^L \ln(w_j) + a_j\right)}, \quad \text{where } \lambda_j = \sum_{k \neq j}^{J} \exp\left(\epsilon^L \ln(w_k) + a_k\right).$$

Let $\mathbf{p} = (p_1, \dots, p_J)$ be a vector of the resulting shares of workers supplying labor to each firm. Each firm faces an upward-sloping labor supply function given by

$$(3) \qquad L_j(w_j) = L \times p_j = L \frac{\exp\left(\epsilon^L \ln(w_j) + a_j\right)}{\lambda_j + \exp\left(\epsilon^L \ln(w_j) + a_j\right)}.$$

The firms that pay relatively higher wages or are endowed with higher amenities attract a larger share of workers.

B. *The Problem of the Firms*

We assume perfectly competitive product markets where firms are price takers. Let the production technology of a firm with productivity z_j that has L_j workers be given by

$$Y_j = z_j \ln(L_j).$$

The problem of the firm is to post a wage that maximizes profits given the labor supply function, $L_j(w_j)$. Since firms do not observe the preference shocks of individual workers, they cannot perfectly discriminate and will offer the same wage to all workers. The problem of the firm is then given by

$$\max_{w_j}\ \pi_j = z_j \ln\left(L_j(w_j)\right) - w_j L_j(w_j)$$

subject to

$$\ln\big(L_j(w_j)\big) = \ln(L) + \epsilon^L \ln(w_j) + a_j - \ln\Big(\lambda_j + \exp\big(\epsilon^L \ln(w_j) + a_j\big)\Big),$$

where, given equation (3), the number of workers, L_j, depends on the posted wage of every firm in the economy, **w**. Firms internalize this and how their wages affect the market-level wages and strategically interact with their competitors.

C. *Entry*

In equilibrium, the number of firms is determined by free entry. There is a fixed number of potential entrants, denoted by $\bar{E}$, that draw a value of productivity z_j and amenities a_j from two independent distributions, $\Phi(z_j)$ and $\Psi(a_j)$.[1] Following Eaton, Kortum, and Sotelo (2012) and Luttmer (2011), we assume that the underlying productivity distribution is Pareto with shape parameter α and scale parameter θ. We assume that firms' amenities follow a uniform distribution with bounds 0 and b. Upon learning their types, firms decide to enter if they can cover the entry cost, c_e—that is, if $\pi_j \geq c_e$.

D. *Equilibrium*

Given $\{L, \epsilon^L, \bar{E}, c_e\}$ and the distributions of firm productivities, $\Phi(z_j)$, and amenities, $\Psi(a_j)$, an equilibrium is a vector of labor supply decisions **p**, a vector of posted wages **w**, and a number of firms J, such that

- **p** is the solution to the workers' problem—that is, $\forall j = 1, \ldots, J$,

$$p_j = \frac{\exp\big(\epsilon^L \ln(w_j) + a_j\big)}{\lambda_j + \exp\big(\epsilon^L \ln(w_j) + a_j\big)}.$$

- **w** is the solution to the firms' problem—that is, $\forall j = 1, \ldots, J$,

$$w_j = \arg\max_{w_j}\left\{ z_j \ln\left(L \frac{\exp\big(\epsilon^L \ln(w_j) + a_j\big)}{\sum_k^J \exp\big(\epsilon^L \ln(w_k) + a_k\big)}\right) - w_j L \frac{\exp\big(\epsilon^L \ln(w_j) + a_j\big)}{\sum_k^J \exp\big(\epsilon^L \ln(w_k) + a_k\big)}\right\}.$$

- free entry condition holds—that is, given an entry cost c_e,

$$\pi_j(J) \geq c_e \quad \forall j \in J \quad \text{and} \quad \pi_j(J+1) \not\geq c_e \quad \forall j \in J+1$$

subject to $J \leq \bar{E}$.

A solution algorithm is presented in Supplemental Appendix A2.

[1] See Supplemental Appendix A1 for details.

E. *Discussion*

To highlight the key insights from the model, suppose, as in Card et al. (2018), that J is sufficiently large, so there are no strategic interactions. Then, the share of workers supplying labor to firm j can be written as

$$p_j \simeq \lambda \exp\left(\epsilon^L \ln(w_j) + a_j\right),$$

where

$$\lambda = \left[\sum_{k=1}^{J} \exp\left(\epsilon^L \ln(w_k) + a_k\right)\right]^{-1}$$

is now *common* to all firms. The labor supply function faced by a firm j becomes

$$L_j(w_j) = L\lambda \exp\left(\epsilon^L \ln(w_j) + a_j\right),$$

which implies the following relation between firm-level wages and firm size:

$$\ln(w_j) = \frac{1}{\epsilon^L}\ln(L_j) - \frac{1}{\epsilon^L}\left[\ln(L) + \ln(\lambda) + a_j\right]. \tag{4}$$

Everything else equal, equation (4) predicts a negative relation between the firm size wage premium, $\partial \ln(w_j)/\partial \ln(L_j)$, and the labor supply elasticity, which we summarize in the following proposition.

PROPOSITION 1: *Everything else equal, the firm size wage premium,* $\partial \ln(w_j)/\partial \ln(L_j)$, *declines when the elasticity of labor supply,* ϵ^L, *increases.*

Furthermore, profit maximization subject to equation (4) yields the following equilibrium employment choice by firm j:

$$\ln(L_j) = \frac{\epsilon^L}{1+\epsilon^L}\ln(z_j) + \frac{\epsilon^L}{1+\epsilon^L}\ln\left(\frac{\epsilon^L}{1+\epsilon^L}\right) + \frac{1}{1+\epsilon^L}\left[\ln(L) + \ln(\lambda) + a_j\right]. \tag{5}$$

We can then express the dispersion in log size across employers, $\mathrm{var}\left[\ln(L_j)\right]$, as

$$\mathrm{var}\left[\ln(L_j)\right] = \left(\frac{\epsilon^L}{1+\epsilon^L}\right)^2 \mathrm{var}\left[\ln(z_j)\right] + \left(\frac{1}{1+\epsilon^L}\right)^2 \mathrm{var}\left[a_j\right]. \tag{6}$$

Using equation (6), it can be shown that, when firm productivity is sufficiently dispersed, the dispersion in log size increases when the elasticity of labor supply increases.[2] The relation between firm productivity and employment steepens as the elasticity ϵ^L rises and labor markets become more competitive. A more competitive

[2] The proof is presented in Supplemental Appendix A3.

labor market allows more productive, higher-paying employers to become relatively larger, forcing low-productive, low-paying employers to shrink. Hence, a given dispersion in firm productivity results in greater employment dispersion. We summarize this result in the following proposition.

PROPOSITION 2: *When firm-level productivity is sufficiently dispersed*, *the size dispersion across firms*, $\text{var}\left[\ln\left(L_j\right)\right]$, *increases with the elasticity of labor supply* ϵ^L.

Finally, we look at how labor market competition affects wage dispersion. Substituting equation (5) into (4) and rearranging terms, we obtain

$$\ln\left(w_j\right) = \frac{1}{1+\epsilon^L}\ln\left(z_j\right) - \frac{1}{1+\epsilon^L}a_j + C,$$

where C is a market-level constant given by

$$C = \frac{1}{1+\epsilon^L}\ln\left(\frac{\epsilon^L}{1+\epsilon^L}\right) - \frac{1}{\left(1+\epsilon^L\right)}\left[\ln\left(L\right) + \ln\left(\lambda\right)\right].$$

Then, we can express wage dispersion, $\text{var}\left[\ln\left(w_j\right)\right]$, as

$$\text{(7)} \qquad \text{var}\left[\ln\left(w_j\right)\right] = \frac{1}{\left(1+\epsilon^L\right)^2}\text{var}\left[\ln\left(z_j\right)\right] + \frac{1}{\left(1+\epsilon^L\right)^2}\text{var}\left[a_j\right].$$

Equation (7) implies that everything else equal, the dispersion in log wages is lower when labor markets are more competitive. We summarize this result in the following proposition.

PROPOSITION 3: *The wage dispersion across firms*, $\text{var}\left[\ln\left(w_j\right)\right]$, *decreases with the elasticity of labor supply* ϵ^L.

An increase in the elasticity of the labor supply, caused by higher labor market competition, leads to a reduction in the wage markdown, $1/(1+\epsilon^L)$, at every firm. However, since wages paid by high-productivity firms are already close to the competitive equilibrium level, wages will increase more in low-productivity firms, generating a compression in the wage distribution.[3]

F. *Sources of Misallocation*

In the model, there are two sources of labor misallocation. The first source is amenities. Since high-amenity firms have market power, they can enter and survive in the economy even if their productivity is low. As the elasticity of labor supply increases, workers value amenities relatively less and care more about wages,

[3] See Autor, Dube, and McGrew (2023) for a similar argument to explain the compression in the distribution of wages observed in the United States in the aftermath of the COVID-19 pandemic.

and high-amenity firms with low productivity can't compete. As a result, labor gets reallocated from low- to high-productivity firms. Misallocation due to amenities is present even if the strategic interaction between firms is shut down, as illustrated in Propositions 1 to 3.

The second source of misallocation in the model comes from strategic interactions that generate dispersion in markdowns among firms. Suppose now that the number of active firms, J, is small enough such that firms strategically interact when posting their wages. Then, the solution to the firm problem satisfies the standard Lerner condition for the wage as a firm-specific markdown on the marginal product of labor:

$$w_j = \frac{1}{\left(1 + 1/\epsilon_j^L\right)} \frac{z_j}{L_j},$$

where $\epsilon_j^L = \left[\left.\frac{\partial \ln w_j}{\partial \ln L_j}\right|_{L_{-j}^*}\right]^{-1}$ and L_{-j}^* is the equilibrium employment in firms other than j. Taking the total differential of the labor supply function of firm j with respect to $\ln w_j$ and $\ln L_j$, we obtain

$$0 = -d\ln\left(L_j\right) + \epsilon^L d\ln\left(w_j\right) - \epsilon^L d\ln\left(w_j\right)\left[\frac{\exp\left(\epsilon^L \ln\left(w_j\right) + a_j\right)}{\lambda_j + \exp\left(\epsilon^L \ln\left(w_j\right) + a_j\right)}\right],$$

which implies the following inverse elasticity of labor supply:

$$\left.\frac{d\ln w_j}{d\ln L_j}\right|_{L_{-j}^*} = \frac{1}{\epsilon^L\left(1 - p_j\right)}.$$

When firms compete strategically, the elasticity of labor supply to their posted wages increases with their labor market share. Hence, strategic interaction introduces dispersion in markdown across firms, with larger firms setting higher markdowns.

II. Estimation

We estimate the model parameters separately for countries at different levels of economic development (as measured by GDP per capita). Each estimated model economy provides us with a set of outcomes (moments) to compare with the data, and we choose parameters to minimize the distance between model and data moments using the method of simulated moments.

We construct the data moments using World Bank Enterprise Surveys (WBES) (World Bank 2023a), which provide establishment-level data for over 130 countries between 2006 and 2022 and complement the WBES with additional data sources to overcome some of their limitations. We provide details on the data and the constructions of data moments in Supplemental Appendices B1 and B2. For any moment constructed using the WBES, we first divide a given country into local labor markets

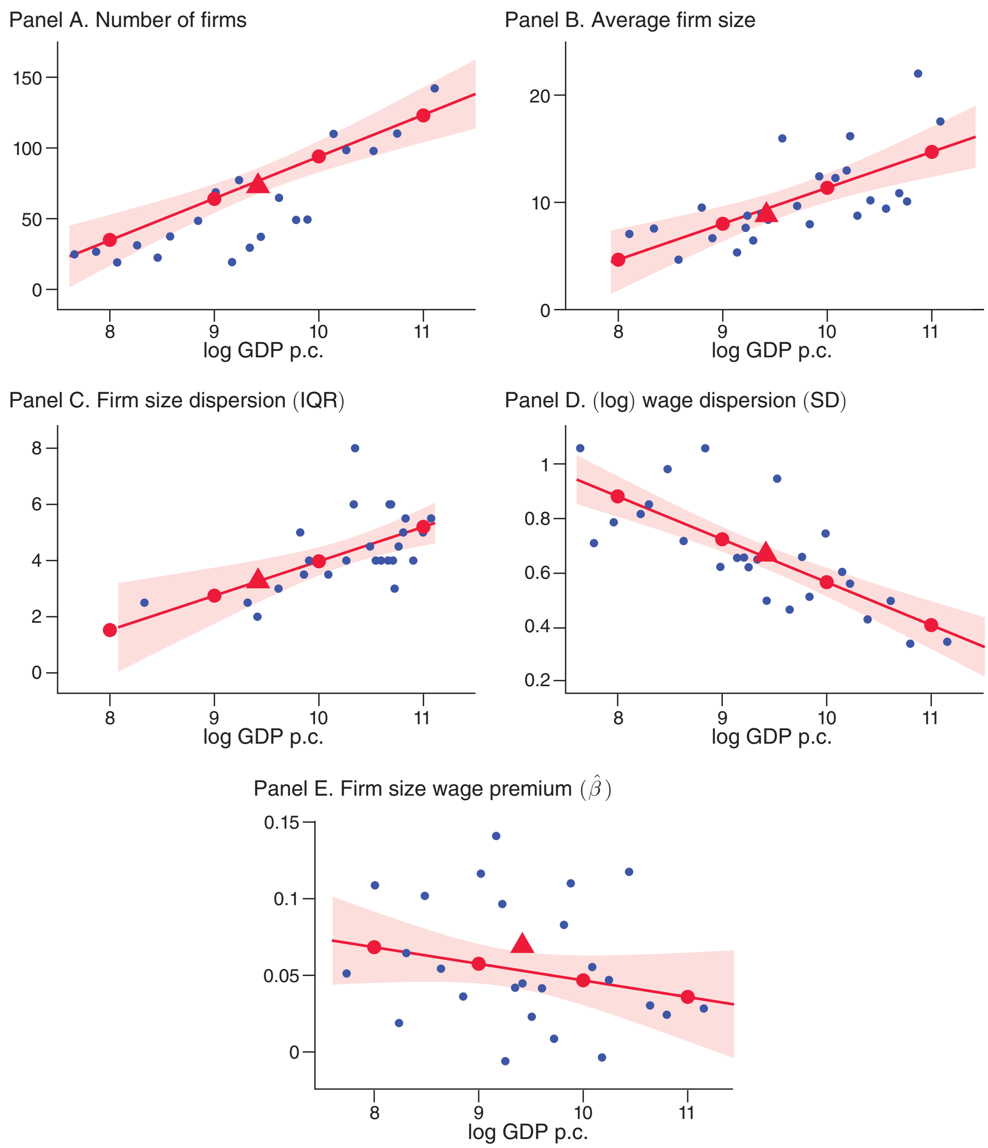

FIGURE 1. DATA AND CONSTRUCTED MOMENTS

Notes: Blue dots show bin scatters of the data (raw data in panel C). The fitted line is the result of auxiliary regressions (9), (10), (11), (12), and (13), in Supplemental Appendix B2, with 95 percent confidence intervals. The red dots represent the set of targeted moments for each stage of development. Triangles refer to Colombia.

defined by location and industry. Then, we calculate statistics, such as the number of firms or average firm size, for each of these markets and use their average across markets as a target for that particular country. Finally, for each data moment, we construct four synthetic countries along the development paths and use them as targets to estimate the model.

The first moment we use is the *number of firms*. Panel A of Figure 1 shows that the number of firms increases with development. There are only about 35 firms in an average labor market for countries with a GDP per capita of about \$3,000.[4] The number of firms increases sharply with development to about 120 firms per market in countries with a GDP per capita of about \$60,000. Figure C.1 in Supplemental Appendix C1 shows the distribution of the number of firms across local markets in Colombia. While the average labor market has 73 workers, there is a large dispersion, with many markets with one firm and a significant fraction with as many as 300 firms.

The second moment is the *average firm size*. Bento and Restuccia (2017) show that average firm size increases with development. Using their data, we reproduced this result for countries in our sample in panel B of Figure 1. Average firm size increases from about five workers per firm in countries with a GDP per capita of \$3,000 to about 15 workers in countries with a GDP per capita of \$60,000. The third moment is *firm size dispersion*. Poschke (2018) shows that size dispersion increases with development, reproduced using their data in panel C of Figure 1. The interquartile range is around 2 for the poorest countries in the sample and doubles for countries with the highest GDP per capita.[5]

The next moment is *wage dispersion across firms*, as measured by the standard deviation of log average wages. We calculate wage dispersion using the WBES, computed as an average across local markets defined by industry and location. Wage dispersion decreases with development, going from 0.88 for the poorest countries in the sample to 0.41 for the richest ones (panel D of Figure 1).

The final cross-country moment pertains to the relationship between economic development and the firm size wage premium. We first estimate, separately for each country in our sample, a relation between the log average wage paid firm by j in period t, w_{jt}, and its size L_{jt}, given by

$$\ln(w_{jt}) = \alpha + \beta \ln(L_{jt}) + \mathbf{X}_{jt}' \boldsymbol{\lambda} + \delta_t + \upsilon_{jt}, \tag{8}$$

where $\mathbf{X}_{jt}$ includes local market (sector and location) fixed effects, δ_t are time fixed effects, and υ_{jt} is the error term.

The *firm size wage premium*, as measured by the estimated β values from equation (8), is decreasing with development (panel E of Figure 1). This finding is robust to a wide set of specifications and controls, as shown in Table B1 in Supplemental Appendix B2.[6]

Although informative, we cannot use equation (4) from the model and back out the labor supply elasticity, ϵ^L, simply as the inverse of the estimated β values, as Proposition 1 would predict. This is because (i) firm-level amenities are unobserved and (ii) wages and employment are jointly determined in equilibrium with strategic

[4] The GDP per capita numbers are in PPP terms deflated to 2017 US dollars and taken from the World Bank Development Indicators (World Bank 2023b).

[5] It is possible to calculate the average firm size and size dispersion using the WBES data. Instead, we use data from Bento and Restuccia (2017) and Poschke (2018) because these data sources provide better coverage for high-income countries; the United States, for example, is not in the WBES. However, we conduct a robustness check where all targeted moments are constructed using the WBES and obtain very similar results, which are reported in Supplemental Appendix C7.

[6] The estimated firm size wage premium refers to a representative sample of formal firms since the WBES dataset does not include informal firms. On the other hand, the firm size wage premium among informal firms is positive and steeper than that of formal firms (Balkan and Tumen 2016). Moreover, accounting for informality does not change the correlation between the firm size wage premium and GDP per capita across countries, as documented by Reed and Tran (2019).

interaction among firms, both causing endogeneity, hence making the OLS estimates of β biased. To deal with endogeneity, we estimate the labor supply elasticity at different development stages by indirect inference, forcing the model to replicate the estimated β values across countries.

The model economy implies a positive relation between firm size dispersion and the labor supply elasticity, ϵ^L, (Proposition 2), and a negative relation between wage dispersion across firms and the labor supply elasticity, ϵ^L, (Proposition 3). As a result, if the estimated labor supply elasticities increase with the level of development, then the model will imply a positive relation between firm size dispersion and the level of development and a negative relation between wage dispersion and development, as we observe in the data.

There are seven parameters to be determined in the model: the number of potential entrant firms $\bar{E}$, the labor supply elasticity ϵ^L, the mass of workers L, the shape and the scale of the Pareto distribution of underlying firm productivity levels, α and θ, the upper bound of the uniform distribution of firm amenities b, and the cost of entry c_e. Following Amodio, Medina, and Morlacco (2022), we fix the number of potential entrant firms, $\bar{E}$, to 374. This value corresponds to the ninetieth percentile of the distribution of the number of firms across all the local markets in the WBES sample (all industry location pairs in all countries).[7]

The six remaining parameters are then estimated with the method of simulated moments using six data targets. To this end, we first construct targets for four levels of development as measured by log GDP per capita levels of 8, 9, 10, and 11, corresponding to 3,000, 8,000, 22,000, and 60,000 international US dollars, respectively. Figure 1 shows the OLS fitted lines for the cross-country data, where larger circles represent the point estimates at four stages of development. We estimate the model for each artificial country by matching the moments shown in Figure 1.[8] We complement these four artificial countries with targets for Colombia. Amodio and de Roux (2023) provide estimates of the labor supply elasticity in Colombia by estimating equation (8) using an IV approach. We view the model's ability to generate an estimate close to theirs as a validation check since labor supply elasticities are obtained using very different methodologies.

Model Fit and Estimated Parameters.—Figure 2 shows the model fit. Despite its parsimonious structure, the model does a remarkable job of matching the data, and for all targets, the model and data overlap almost perfectly. This is achieved despite having a model with a discrete number of firms and endogenous entry, which makes matching the observed number of firms quite challenging.[9]

Various model parameters simultaneously affect multiple targets, but each moment primarily depends on a specific parameter. Labor supply elasticity is disciplined by targeting the OLS estimates of size-wage premium (equation (4)). The scale of the Pareto distribution, determining average firm productivity, is disciplined by log GDP per capita. The shape of the Pareto distribution, contributing to variance in firm productivity, is controlled by observed dispersion in firm (log) size (equation (6)).

[7] See Figure C.2 in Supplemental Appendix C1.
[8] Table C1 in Supplemental Appendix C2 reports the data targets.
[9] Figure C.3 in Supplemental Appendix C3 shows that the minimum is achieved.

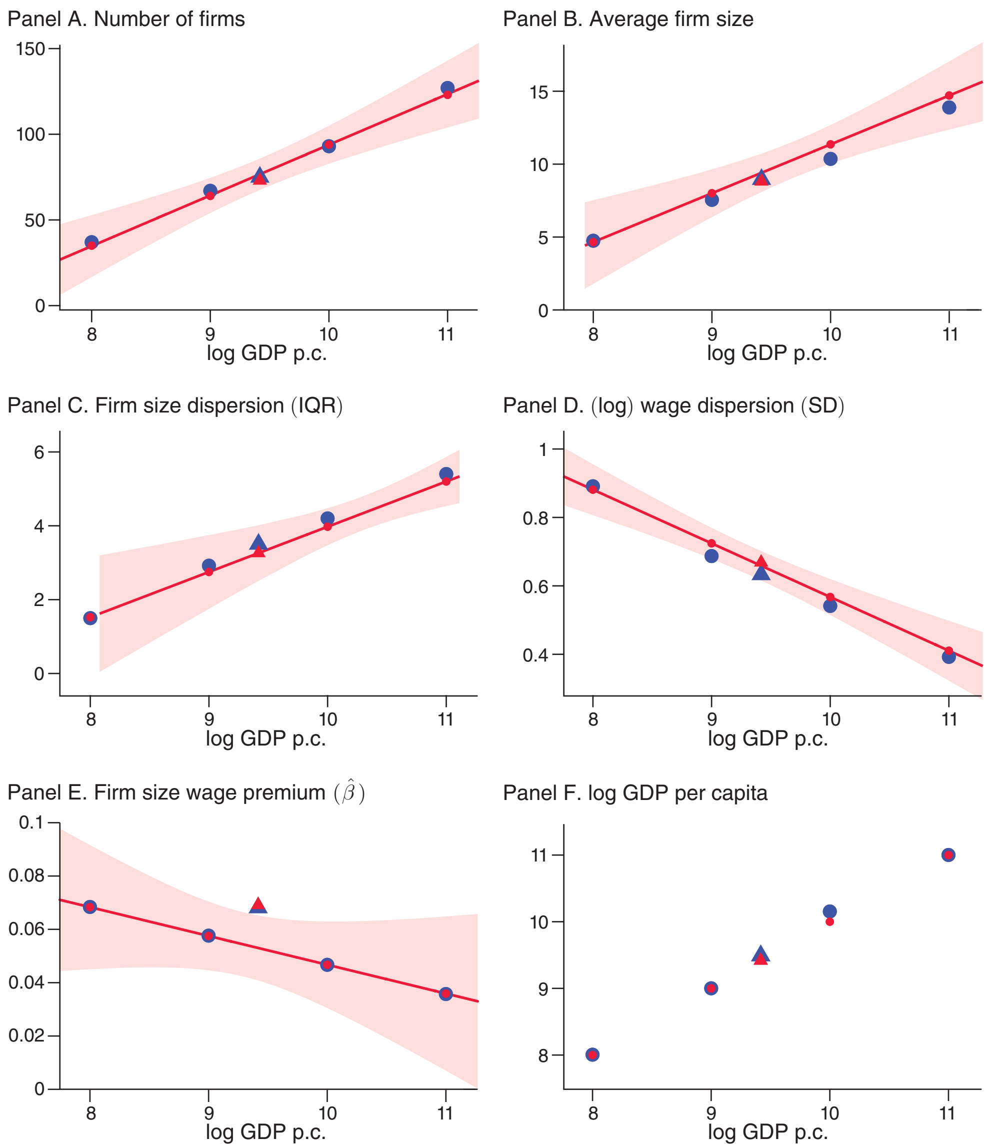

Figure 2. Model Fit: Targeted Moments

Notes: Blue dots show the six simulated moments at the estimated parameters, and red dots show the six targeted empirical moments. Blue and red triangles refer to Colombia.

Workforce size directly impacts overall employment levels and is determined by average firm size. Entry costs influence the number of firms by affecting entry. The upper bound of the uniform distribution of amenities is disciplined by residual wage dispersion across firms (equation (7)) since as amenities gain importance, the link between firm productivity and wages offered gets weaker.[10]

[10] In Supplemental Appendix C6, we show that the estimates are robust to a more flexible function form, gamma, for the distribution of amenities. Since the gamma distribution has two parameters, we use two moments of wage distribution as targets: dispersion (interquartile range) and skewness of the residual wage distribution.

TABLE 1—ESTIMATED MODEL PARAMETERS

log GDP per capita	LS elasticity (ϵ^L)	Mass of workers (L)	Pareto shape (α)	Pareto scale (θ)	Uniform dispersion (b)	Entry cost (c_e)
8 (\$2,980)	0.85	175.74	1.58	1,591.64	9.05	0.82
	(0.65)	(72.095)	(0.006)	(0.254)	(1.908)	(0.0)
9 (\$8,100)	1.74	505.84	1.68	5,386.55	6.69	1.16
	(0.417)	(27.559)	(0.002)	(0.195)	(1.334)	(0.0)
10 (\$22,000)	2.58	970.37	1.68	18,522.16	6.02	1.52
	(0.337)	(17.936)	(0.001)	(0.168)	(0.287)	(0.0)
11 (\$59,900)	3.06	1,763.65	1.91	97,162.06	4.77	1.87
	(0.307)	(13.767)	(0.001)	(0.11)	(0.694)	(0.0)
Colombia (\$12,300)	2.3	675.1	1.69	8,669.78	6.49	1.25
	(0.353)	(16.871)	(0.001)	(0.182)	(0.466)	(0.0)

Notes: This table reports the estimate of the labor supply elasticity, ϵ^L; measure of workers, L; Pareto shape, α; Pareto scale, θ; dispersion of amenities, b; and entry cost, c_e, for four synthetic targeted countries plus Colombia. The entry cost is reported as a fraction of the Pareto scale, θ. Standard errors in parentheses are computed using the delta method.

Table 1 reports country-specific estimated parameters and standard errors (in parentheses). The estimated labor supply elasticity increases steeply with development; that is, labor markets are much more competitive in countries with higher GDP per capita. The estimated elasticity is 0.85 for the poorest countries in the sample and increases up to 3.06 for the richest ones. These values imply an average wage markdown of around 54 percent among the poorest countries. The estimated wage markdowns fall within the range of estimates reported for India by Brooks, Kaboski, Li, et al. (2021), which are between 29 percent and 71 percent and correspond to values of the firm-level labor supply elasticity of 0.4 to 2.5. For the richest countries, our estimates imply an average wage markdown of 24 percent. This is within the range of estimates of 24 percent and 17 percent provided by Berger, Herkenhoff, and Mongey (2022) and Azar, Berry, and Marinescu (2022) for the United States. It also lies between 16 percent and 25 percent, the estimates obtained by Datta (2022) for the United Kingdom.

The estimated elasticity for Colombia is 2.3, almost equal to the IV estimate of 2.5 reported by Amodio and de Roux (2023). The match is remarkable, given the methodological differences in obtaining these estimates. Furthermore, this result illustrates the ability of our identification strategy to overcome the bias that would arise from using the OLS estimate from equation (4) to recover the labor supply elasticity. Using the WBES data, we estimate a wage-size premium for Colombia, as implied by equation (8), of 0.075. If we were to use this estimate naïvely, we would assign a value to ϵ^L of $1/0.075 = 13.3$, a much higher value than our estimated labor supply elasticity for Colombia.

In the model, labor demand hinges on a firm's wage and those of other firms (equation (3)). As a result, endogenous firm entry and the equilibrium number of firms play an essential role in the model. To assess the importance of endogenous entry, we reestimate the model for Colombia with zero entry costs without targeting the number of firms. Results (Table C3 in Supplemental Appendix C5) show that the number of firms nearly doubles, from 73 to 125, and the elasticity of labor supply, ϵ^L, rises to 8.7, over three times higher than the baseline estimate. More competitive markets with more firms yield higher elasticity estimates. Thus, accurately targeting firms in data is crucial; otherwise, arbitrarily high firm numbers bias elasticity estimates.

Finally, we find that the entry costs increase significantly with development. They are equal to 225 percent of the average wage in countries with a GDP per capita of $3,000. For the richest countries, they are ten times the average wage. This finding is consistent with Bollard, Klenow, and Li (2016), who document that in China, the United States, and India, average discounted profits rise systematically with average labor productivity at the time of entry, which, in models with a zero profit condition for entrants, implies that the cost of creating a new business increases with development.

III. Does Labor Market Power Matter for Development?

How much of the observed cross-country differences in GDP per capita can be accounted for by differences in labor market competition? To answer this question, we conduct the following exercise: We set the labor supply elasticity in each artificial country to the highest estimate obtained (3.06 for the richest countries in the sample; see Table 1), keeping all other parameters unchanged. We then simulate the model to obtain a set of counterfactual outcomes and compare them to the benchmark.

Panel A of Figure 3 shows the baseline and counterfactual GDP per capita levels (in logs) along different stages of development. We find that countries at the bottom of the development ladder, like Zambia, Senegal, or India in our sample, would have a 44 percent higher GDP per capita if they had the same labor supply elasticity as countries at the top of the ladder, such as the Netherlands, Denmark, or the United States. The increase in GDP per capita for more developed countries, such as Indonesia or Peru, would be approximately 16.5 percent. The same exercise predicts that Colombia could increase its GDP per capita by roughly 6 percent. If every country had the highest estimated degree of labor market competition, the difference in (log) GDP per capita would shrink by 15 percent.[11] These are large effects, which suggest that imperfect labor market competition can account for a significant share of the output loss attributed to resource misallocation in poorer countries.[12] They are, for example, aligned to the magnitudes in Hsieh and Klenow (2009), who also conduct a model-based assessment of the misallocation of resources across productive units in China, India, and the United States.

Panel B and C of Figure 3 compare baseline and counterfactual model-based wage and firm-size dispersion across countries, respectively. Panel D reports the model-based conditional firm size wage premia across countries, estimated using baseline and counterfactual simulated data and controlling for firm-level amenities. Labor market power affects each of these outcomes, as predicted by Propositions 1, 2, and 3: Higher labor market competition implies lower conditional firm size wage premia, higher firm size dispersion, and lower wage dispersion at any stage of development. If every country had the lowest estimated degree of firms' labor market power, the difference in firm-level wage dispersion would reduce by 72 percent, the

[11] This value is computed as 100 times 1 minus the ratio between the slopes from regressing each outcome against log GDP per capita in the counterfactual (red dashed line) in the baseline model (blue dashed line).

[12] The estimated labor supply elasticities are very similar if all targeted moments are constructed using the WBES data, including average firm size and firm size distribution; see Table C9 in Supplemental Appendix C7. The increases in GDP per capita associated with more competitive labor markets are also similar to results in this section; see Figure C.4 in Supplemental Appendix C7.

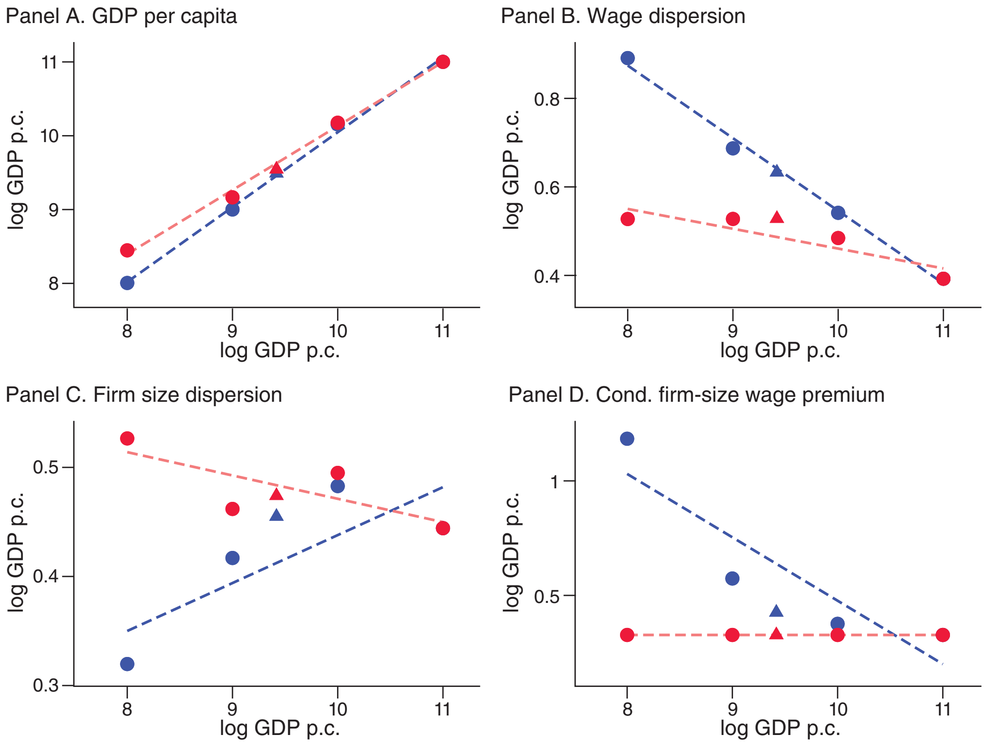

Figure 3. Counterfactual Results

Notes: Blue dots show simulated moments at the baseline; red dots show simulated moments under the counterfactual. Baseline and counterfactual moments for Colombia are represented by triangles.

firm size dispersion would become negatively sloped over development, and the difference in the conditional firm size wage premia across countries would disappear. Finally, higher labor supply elasticities lead to higher welfare, particularly in countries with lower GDP per capita. The welfare of the poorest countries, as a fraction of the richest ones, increases from around 44 percent in the baseline economy to 82 percent in the counterfactual.[13]

Higher labor supply elasticity reduces the significance of amenities for labor decisions, making labor supply functions more elastic. This aligns posted wages better with labor's marginal revenue product, leading to increased selection at entry and shifting workers from low- to high-productivity firms, ultimately boosting output per capita. We show this mechanism in Figure 4. Panels on the left-hand side report the distribution of active firms by bins of log productivity (as computed in the baseline economy). Panels on the right-hand side report the cumulative employment shares across firms ranked by their productivity values. Each panel refers to a targeted artificial country, while the last two panels refer to Colombia. Blue and red lines in each panel indicate baseline and counterfactual scenarios.

[13] See Figure D.1 in Supplemental Appendix D.

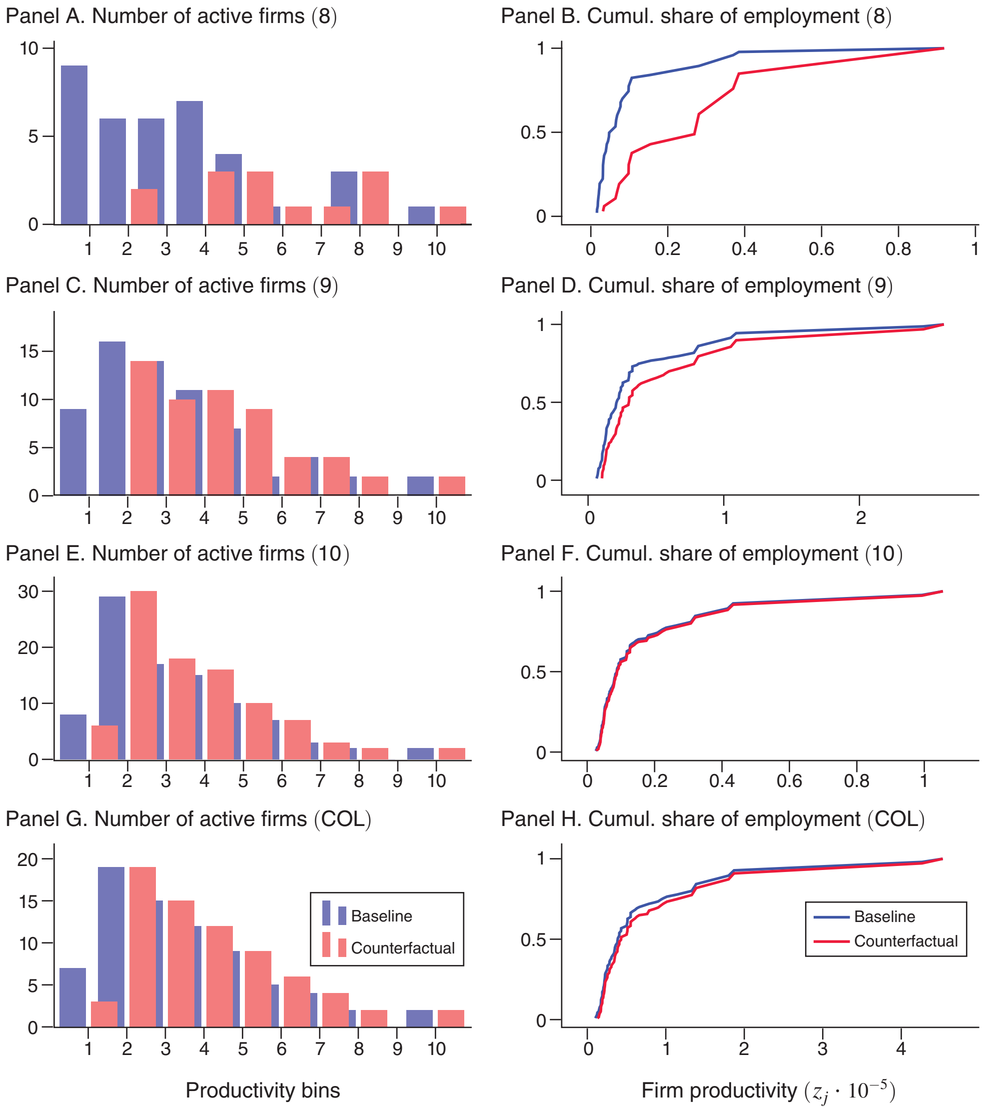

FIGURE 4. REALLOCATION EFFECTS OF HIGHER LABOR MARKET COMPETITION

Notes: Panels A, C, E, and G show the number of active firms by log-productivity equal-width bin. Panels B, D, F, and H show the cumulative share of employment across firms ranked by productivity (z_j). Blue (red) lines and bars refer to the baseline (counterfactual) scenario.

For the poorest artificial country, panels A and B of Figure 4 show that higher labor market competition makes the economy more selective and more concentrated: The number of active firms in the economy reduces from 37 to 13, and the distribution of firms shifts toward the more productive ones (panel A).[14] Equilibrium

[14] As we show in Table D1 in Supplemental Appendix D, in the benchmark, Herfindahl–Hirschman Index (HHI) on firm-level employment is higher in poorer countries with less competitive labor markets. However, in the counterfactuals, the HHI index increases. In the benchmark, oligopsony rents attract entry, while a more competitive labor market results in a reallocation of labor to more productive firms—a mechanism emphasized by Syverson (2019).

changes in the number of firms amplify the gains in GDP per capita. Tables D1 and D2 in Supplemental Appendix D1 highlight the role of endogenous firm entry. If the number of firms is fixed at their baseline values, the gains in GDP per capita from higher labor market competition would be 23 percent lower in the poorest artificial country.[15] Figure D.2 in Supplemental Appendix D2 shows how the dispersion of markdowns changes by the number of firms for the poorest artificial economy. The dispersion increases sharply as the number of firms approaches zero. However, around the number of firms we observe in the data (35 for this group of countries), changes in the number of firms generated by differences in labor market power are likely to have a small effect on markdown dispersion.

With a more competitive labor market, the distribution of employment also shifts toward high-productivity firms: The cumulative share of employment in the counterfactual scenario lies significantly below the one in the baseline economy (panel B). In the benchmark of the poorest country, 84 percent of workers are employed in firms whose productivity values are at most 20 percent the highest in the economy. In the counterfactual, 43 percent of workers are employed in such low-productivity firms. Similar changes apply to other targeted countries, although with different magnitudes.

IV. Conclusions

This paper examines how firms' labor market power influences GDP per capita differences across countries. By structurally estimating an oligopsonistic competition model, we find that labor market supply elasticity, which governs labor market competition, rises with GDP per capita. The average wage markdown is approximately 24 percent in the richest countries and 54 percent in the poorest. These disparities result in inefficient labor allocation across firms, reducing GDP per capita. If firms in the poorest countries had the labor market power of the richest, GDP could surge by up to 44 percent. These findings bridge the gap between the literature on the role of misallocation of resources for cross-country income differences and more recent studies on the importance of the labor market for inequality, welfare, and productivity.

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[15] See column 4 of panel A in Table D1 in Supplemental Appendix D1.

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