I Z A Institute of Labor Economics
Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 16529

Labor Market Power and Development

Tristany Armangué-Jubert
Nezih Guner
Alessandro Ruggieri

OCTOBER 2023

DISCUSSION PAPER SERIES

IZA DP No. 16529

Labor Market Power and Development

Tristany Armangué-Jubert
IDEA, UAB and BSE

Nezih Guner
CEMFI and IZA

Alessandro Ruggieri
CUNEF Universidad

OCTOBER 2023

ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Labor Market Power and Development*

Imperfect competition in labor markets can lead to efficiency losses and lower aggregate output. In this paper, we study whether differences in competitiveness of labor markets can help explain differences in GDP per capita across countries. We structurally estimate a model of oligopsony with free entry for countries at different stages of development and show that the labor supply elasticity, which determines the extent of firms' labor market power, is increasing with GDP per capita. Wage mark-downs range from 55 percent among low-income countries to around 23 percent among the richest. Output per capita in poorer countries would increase by up to 69 percent if their labor markets were as competitive as in countries at the top of the development ladder.

JEL Classification: J42, L13, O11, E24
Keywords: labor market power, oligopsony, development, inequality

Corresponding author:
Nezih Guner
CEMFI
Calle Casado del Alisal, 5
28014 Madrid
Spain
E-mail: nezih.guner@cemfi.es

* We thank Francesco Amodio, Andre Groeger, Claudio Luccioletti, and Alan Manning for their helpful comments. All errors are ours.

1 Introduction

Productivity differences are crucial to understanding the vast differences in GDP per capita levels across countries. Labor markets play a crucial role in the efficient allocation of resources across firms, and 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 explain disparities in GDP per capita worldwide. We extend a standard model of monopsonistic competition (Card et al., 2018; Dustmann et al., 2022) to a general equilibrium setting with endogenous firms' 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. As a result, 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 model parameters.

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 labor supply elasticity increases from 0.82 to 3.24. This implies an average wage mark down equal to 55 percent among countries at the bottom of the development ladder, such as Zambia, Senegal, or India, and as low as 23 percent in countries at the top, such as Denmark, 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 et al., 2021a). Searching for formal jobs can be more time-consuming, and wages might be set by non-competitive bargaining (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 et al., 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 impedes economic growth. 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 — up to 69 percent, if their labor markets were as competitive as the countries at the top of the ladder, such as Denmark, Netherlands, or the United States.

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 et al. (2010). Azar et al. (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 et al. (2022) focus on market power in developing countries, i.e. Colombia and Peru, and estimate values for labor supply elasticities of 2.5 and 2.3, respectively. Brooks et al. (2021b) 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. In their meta-study, Sokolova and Sorensen (2021) document a positive relationship between economic development and the extent of labor market competition. Our paper builds upon and extends the existing literature in two significant ways. We employ an indirect inference approach to generate comparable estimates of labor supply elasticity for countries at varying stages of development and show a negative relation 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, e.g., Card et al. (2018), Dustmann et al. (2022). Lamadon et al. (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% and 48% of the observed reduction in the dispersion of earnings. Berger et al. (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 observed wage stagnation in the US 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 how pay compression across firms during recent decades affected 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 macro-development literature that studies how frictions and distortions can account for cross-country income differences, e.g., 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.

2 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 the relationship between wages and 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 each worker's preference 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 some wage-setting power.

2.1 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 over working at firm j, 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. Both the amenities a_j, which are common across workers, and the idiosyncratic preference shocks capture non-pecuniary match factors such as, for example, commuting time or relationship with other employees. A large literature documents the existence and the importance of non-wage 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 $\vec{\mathbf{w}} = \{w_1, \ldots, w_J\}$ of posted wages, workers choose which firm to work to maximize their utility. As a result, following McFadden (1978), workers have "logit" probabilities of working for firm j that are given by

$$p_j = Prob\left(\arg\max_{k\in\{1,\ldots,J\}}\{U_{ik}\} = j\right) = \frac{\exp\left(\epsilon^L \ln(w_j) + a_j\right)}{\sum_{k=1}^{J} \exp\left(\epsilon^L \ln(w_k) + a_k\right)}, \tag{1}$$

which we can rewrite as

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

Let $\vec{\mathbf{p}} = \{p_1, \ldots, p_J\}$ be a vector of the resulting shares of workers supplying labor to each firm. Therefore, firms face an upward-sloping labor supply function given by

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

2.2 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 knowledge of the labor supply function, $L_j(w_j)$. Since firms do not observe the preference shocks of individual workers, they cannot perfectly discriminate. The problem of the firm is then given by

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

subject to,

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

where, given equation (3), the number of workers, L_j, depends on the posted wage of every firm in the economy, $\vec{\mathbf{w}}$. Firms internalize this effect and how their wages affect the market-level wage index, λ_j, and strategically interact with their competitors.

2.3 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 the literature, e.g., Eaton et al. (2012) and Luttmer (2011), we assume that the underlying productivity distribution follows a Pareto distribution with shape parameter α and scale parameter θ, while 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, i.e., if $\pi_j \geq c_e$.

2.4 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 $\vec{\mathbf{p}}$, a vector of posted wages $\vec{\mathbf{w}}$ and a number of firms J such that:

1. $\vec{\mathbf{p}}$ is the solution to the workers' problem, i.e., $\forall j = 1, \ldots, J$,

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

2. $\vec{\mathbf{w}}$ is the solution to the firms' problem, i.e., $\forall j = 1, \ldots, J$,

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

[1] See Appendix A1 for details.

3. Free entry condition holds, i.e., given an entry cost c_e,

$$\pi_j(J) \geq c_e \quad \forall j \in J \quad \text{and} \quad \pi_j(J+1) \ngeq c_e \quad \forall j \in J+1.$$

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

A solution algorithm is presented in Appendix A2.

2.5 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

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

where

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

is common to all firms and taken as given by firm j. The labor supply function faced by a firm j becomes

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

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

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

Everything else equal, equation (4) predicts a negative correlation 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:

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

We can then express the dispersion in log size across employers, $\text{var}[\ln L_j]$, as

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

Equation (6) implies that everything else equal, the dispersion in log size is higher when the elasticity of labor supply increases. The relation between firm productivity and employment steepens as the elasticity ϵ^L rises, and labor markets become more competitive. A more competitive 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 *The size dispersion across firms, var$[\ln(L_j)]$, 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 re-arranging terms, we obtain:

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

where C is a market-level constant given by

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

Then, we can express wage dispersion, $\text{var}[\ln(w_j)]$, as a function of model primitives

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

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

Proposition 3 *The wage dispersion across firms, var*$[\ln(w_j)]$*, 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 mark-down, $\frac{1}{1+\epsilon^L}$, at every firm. However, because 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.[2]

Propositions 1 to 3 illustrate how the model economy works without strategic interactions among firms. As a result, we do not bring equation (4) directly to the data and estimate the elasticity of labor supply using OLS, given the bias generated by strategic interaction among firms. In what follows, we structurally estimate the model parameters, including the elasticity of labor supply, accounting for firm granularity.

3 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 (MSM).

We construct the data moments using World Bank Enterprise Surveys (WBES), 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 its limitations. We provide details on the data and the constructions of data moments in Appendices B1 and B2.

The first moment we use is the *Number of Firms*. We calculate the number of

[2]See Autor et al. (2023) for a similar argument to explain the compression in the distribution of wages observed in the U.S. in the aftermath of the COVID-19 pandemic.

firms in an average location-industry pair in each country, which we consider as representing a labor market. Panel A in Figure 1 shows that the number of firms increases with development. There are only about 37 firms in an average labor market for countries with a GDP per capita of about 3,000\$.[3] 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\$.

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 in 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 in 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.

The next moment is *Wage Dispersion Across Firms*, as measured by the standard deviation of log average wages. Wage dispersion decreases with development, going from 0.8 for the poorest countries in the sample to 0.4 for the richest ones (Panel D in Figure 1).

The final cross-country fact 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

$$\ln(w_{jt}) = \alpha + \beta \ln(L_{jt}) + X_{jt}\lambda + \delta_t + v_{jt}, \tag{8}$$

where X_{jt} includes sector and location fixed effects, δ_t are time fixed effects, and v_{jt} is the error term.

The Firm-Size Wage Premium, as measured by the estimated β values from equa-

[3] The GDP per capita numbers are in PPP terms deflated to 2017 US Dollars.

tion 8, is decreasing with development (Panel E in Figure 1). This finding is robust to a wide set of specifications and controls, as shown in Table 2 in Appendix B2.

Given estimates of β, we cannot use equation (4) from the model and back out the labor supply elasticity, ϵ^L, for each country, 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 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). It also implies 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.

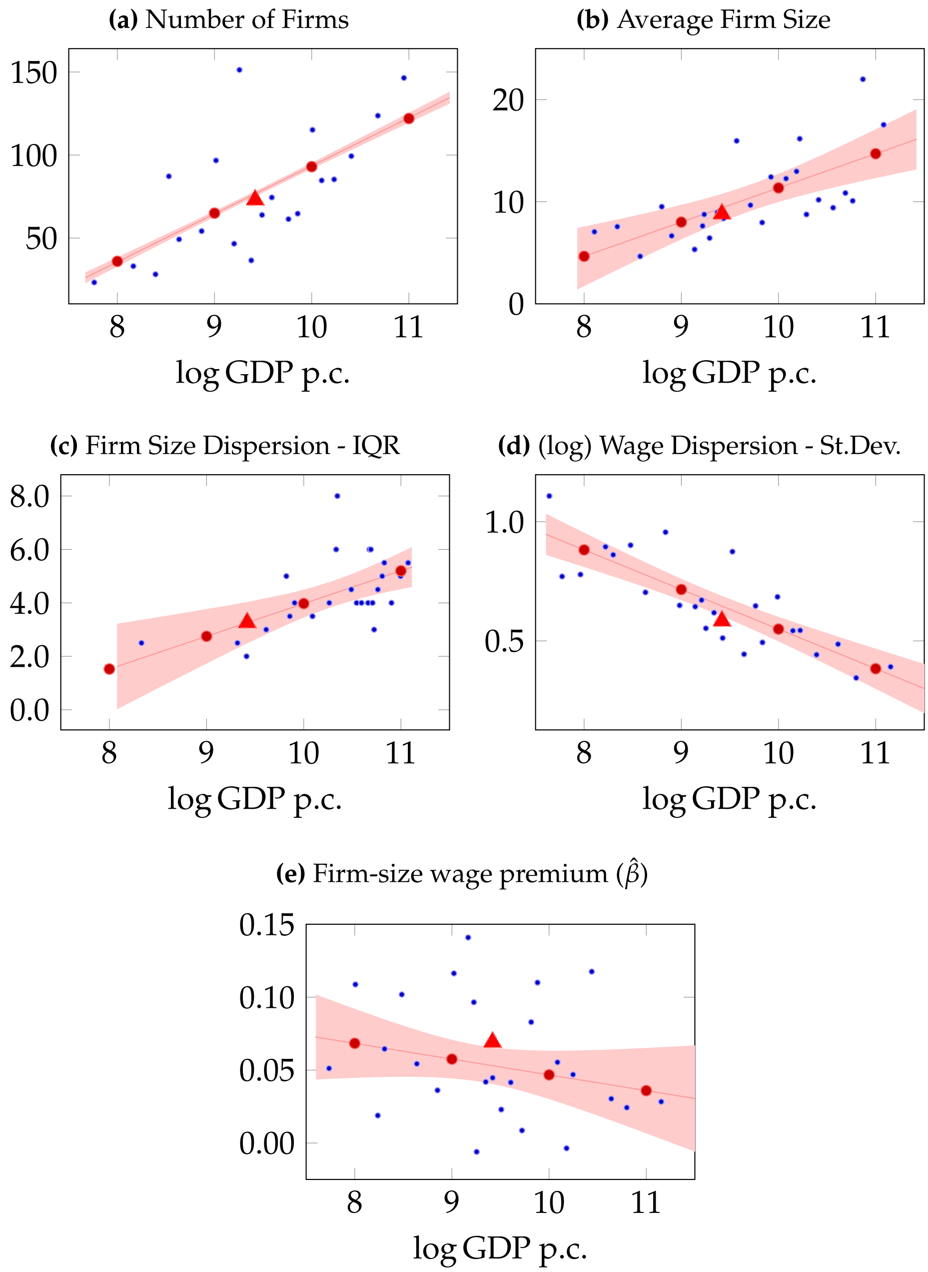
There are seven parameters to be determined in the model: the number of potential entrant firms $\bar{E}$, the labor supply elasticity ϵ^L, the mass of workers L, the shape and the scale of the Pareto distribution of underlying firm productivity levels, α and θ, the upper bound of the Uniform distribution of firm amenities b, and the cost of entry c_e.

Following Amodio et al. (2022), we fix the number of potential entrant firms, $\bar{E}$, to a value of 374 such that it covers over 95 percent of all observed country-region-industry labor markets in the WBES dataset.[4] The six remaining parameters are then estimated via the method of simulated moments using six data targets.

To this end, we first construct targets for four levels of development as mea-

[4]See Figure 5 in Appendix C1.

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 auxilliary regressions (9), (10), (11), (12), and (13) with 95% confidence intervals. The red dots represent the set of targeted moments for each stage of development. Triangles refer to Colombia.

sured by log GDP per capita levels of 8, 9, 10, and 11, corresponding to 3, 8, 22, and 60 thousand international US dollars, respectively. Figure 1 shows a fitted OLS line for the cross-country data, where larger circles along the fitted line 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.[5]

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.

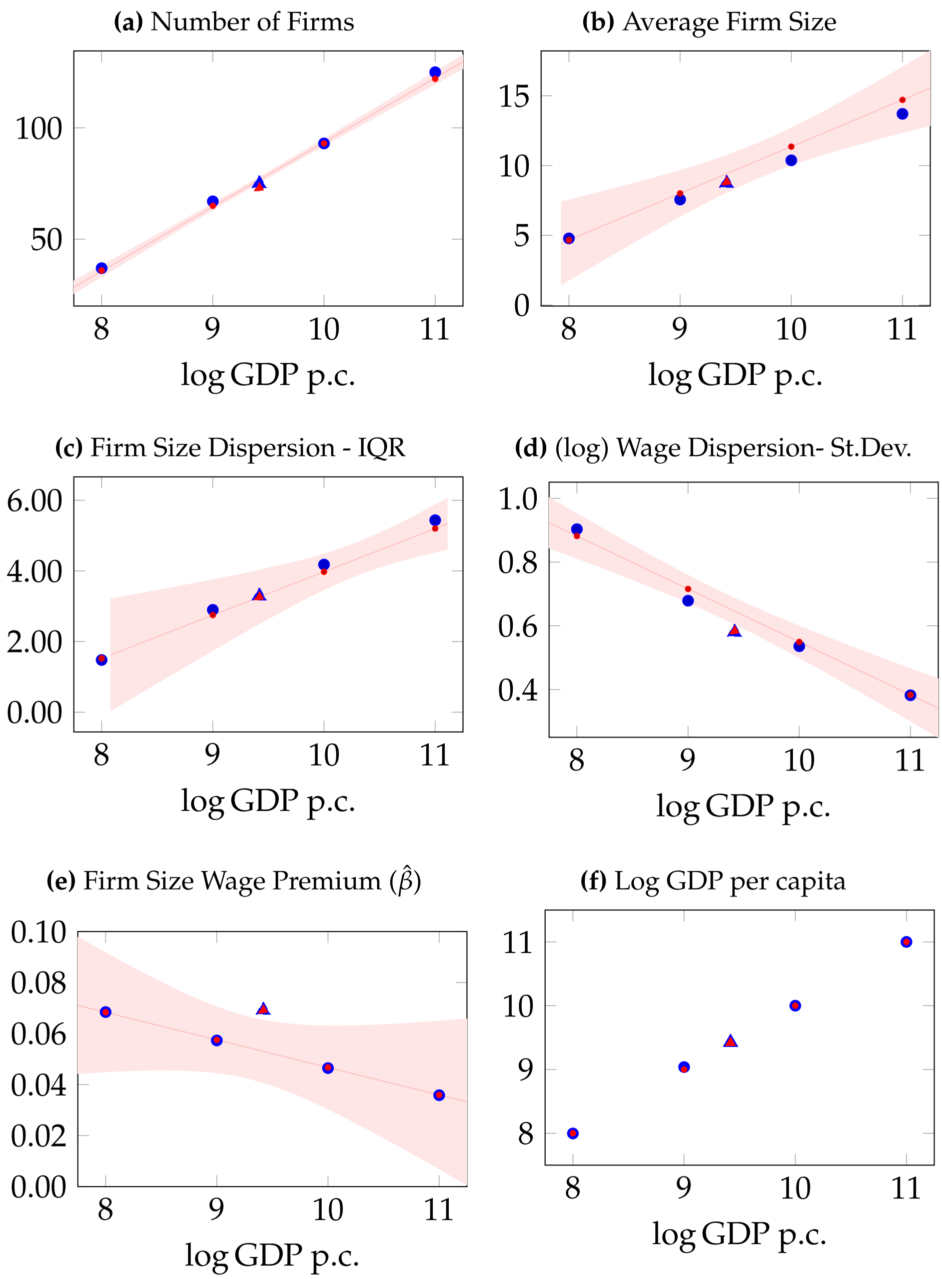
3.1 Model Fit and Estimated Parameters

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. Figure 6 in Appendix C3 shows the minimum is achieved.

While changes in various model parameters can simultaneously affect multiple targets, each specific model moment is primarily influenced by a specific parameter. In particular, the labor supply elasticity is disciplined by targeting the OLS estimate from regressing the log of wages on the log of firm size (equation 4). The scale of the Pareto distribution plays a pivotal role in shaping the average productivity of firms in the economy and is disciplined through our target of log GDP per capita. Meanwhile, the shape of the Pareto distribution contributes to the variance in firm productivity and is controlled by aiming for the observed dispersion in firm (log) size, as indicated in equation (6). The size of the workforce directly impacts overall employment levels and is guided by the average firm size. The cost of entry influences the number of firms by affecting their entry decisions. Lastly, the upper bound of the Uniform distribution of

[5]Table 8 in Appendix C2 reports the exact data targets.

Figure 2: Model Fit: Targeted Moments



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

amenities determines the residual wage dispersion across firms, as defined in equation (7).

Table 1 reports country-specific estimates and standard errors (in parenthesis). The estimated labor supply elasticity increases steeply with development, i.e., labor markets are much more competitive in countries with higher GDP per capita. The estimated elasticity is 0.82 for the poorest countries in the sample and increases up to 3.24 for the richest ones. These values imply an average wage mark-down of around 55% among the poorest countries. The estimated wage mark-downs fall within the range of estimates reported for India by Brooks et al. (2021b), which are between 29% and 71% 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 mark-down of 23%. This is very close to the point estimates of 24% and 17% by Berger et al. (2022) and Azar et al. (2022) for the United States. It also lies between 16% and 25%, the estimates obtained by Datta (2022) for the United Kingdom.[6]

The estimated elasticity for Colombia is 2.42, identical 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 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 naively, 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, a firm's labor demand depends on the wage it posts and wages posted by all other firms in the economy, as illustrated in equation (3). As a result, the estimates of the labor supply elasticity we obtain account for granularity and strategic interaction among employers. When there is a large number of firms, the strategic interactions become negligible, and the estimated param-

[6] Azar et al. (2022) define wage mark-down as $1/\epsilon^L$. Given their estimate of ϵ^L, they obtain a mark-down of 21%. If mark-downs were defined as in Manning (2013), i.e., $1/(1+\epsilon^L)$, the estimate of labor supply elasticity would imply a mark-down of 17%. In this paper, we follow the latter for comparability.

Table 1: Estimated model parameters.

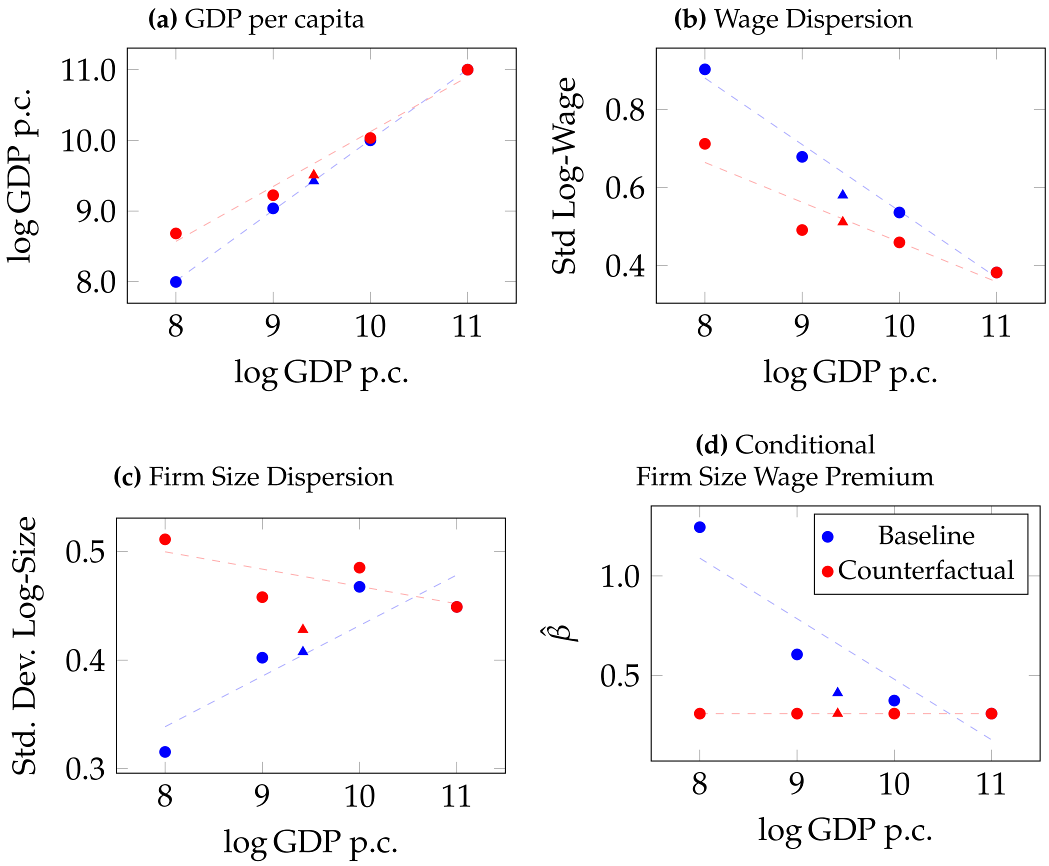
log GDP per capita	Pareto Shape (α)	Uniform Dispersion (b)	LS Elasticity (ϵ^L)	Mass of Workers (L)	Entry Cost (c_e)	Pareto Scale (θ)
8 ($ 2,980)	1.56	8.76	0.8	176.75	0.83	1513.95
	(0.006)	(2.914)	(0.000)	(120.386)	(0.000)	(0.249)
9 ($ 8,100)	1.72	6.28	1.65	506.57	1.16	5906.99
	(0.002)	(2.997)	(0.000)	(51.099)	(0.000)	(0.175)
10 ($ 22,000)	1.71	6.08	2.67	964.64	1.5	19146.58
	(0.001)	(0.129)	(0.000)	(30.687)	(0.000)	(0.154)
11 ($ 59,900)	1.91	4.91	3.24	1713.09	1.86	95108.08
	(0.001)	(2.234)	(0.050)	(31.072)	(0.000)	(0.118)
Colombia ($ 12,300)	1.89	4.91	2.42	1713.09	1.14	95108.08
	(0.002)	(0.523)	(0.0)	(30.844)	(0.0)	(0.132)

Notes: This table reports the estimate of the Pareto shape, α, dispersion of amenities, b, labor supply elasticity ϵ^L, measure of workers, L, entry cost c_e, and Pareto scale θ, for 4 synthetic targeted countries plus Colombia. The entry cost is presented as a fraction of the Pareto scale, θ. Standard errors in parenthesis are computed using the Delta method.

eters reflect that. To assess the importance of strategic interactions on our estimates, we re-estimate the model for Colombia with zero entry cost without targeting the number of active firms in the economy. We report the estimates in Table 10 in Appendix C5. Under this alternative estimation strategy, the equilibrium number of firms is 127, almost twice as much as those observed in the data. The estimate of ϵ^L is now 8.62, three times higher than the labor supply elasticity estimated with strategic interactions. Hence, ignoring granularity, or the fact that lower wages in other firms reduce labor demand for any given firm, results in significantly higher estimates of labor supply elasticity.

Finally, we find that the estimated entry costs increase significantly with development. They are equal to 140% of the average wage in countries with a GDP per capita of 3,000$. For the richest countries, they are 9.07 times the average wage. This finding is consistent with Bollard et al. (2016), who document that in China, the US, 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.

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.

4 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 equal to the highest estimate obtained (3.24 for the richest countries in the sample, see Table 1) while leaving all other parameters unchanged. We then simulate the model to obtain a set of counterfactual outcomes and compare them to the benchmark.

Panel A in 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 69 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 19 percent. The same exercise predicts that Colombia could increase its GDP per capita by approximately 8.4 percent if the degree of firms' labor market power were reduced to the one observed in the richest countries in the sample. If every country had the highest estimated degree of labor market competition, the difference in (log) GDP per capita would shrink by 22 percent.[7] These are large effects, which suggest that imperfect labor market competition might explain a significant share of the output loss attributed to resource misallocation in poorer countries. They are, for example, aligned to the magnitudes obtained 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 US.

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 40 percent, the firm-size dispersion would decline over development, and the difference in the conditional firm-size wage premia across countries would disappear.

Higher labor supply elasticity reduces the relative importance of amenities for labor supply decisions, makes the labor supply function more elastic, and pushes

[7] 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).

posted wages toward the marginal revenue product of labor. These two effects lead to a re-ordering of the competitive ranking of firms, hence higher selection at entry, and a reallocation of workers from low- to high-productivity firms. Both effects make output per capita higher. 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, ordered by GDP per capita in ascending order, while the last two panels refer to Colombia. Blue and red lines in each panel refer to baseline and counterfactual scenarios, respectively.

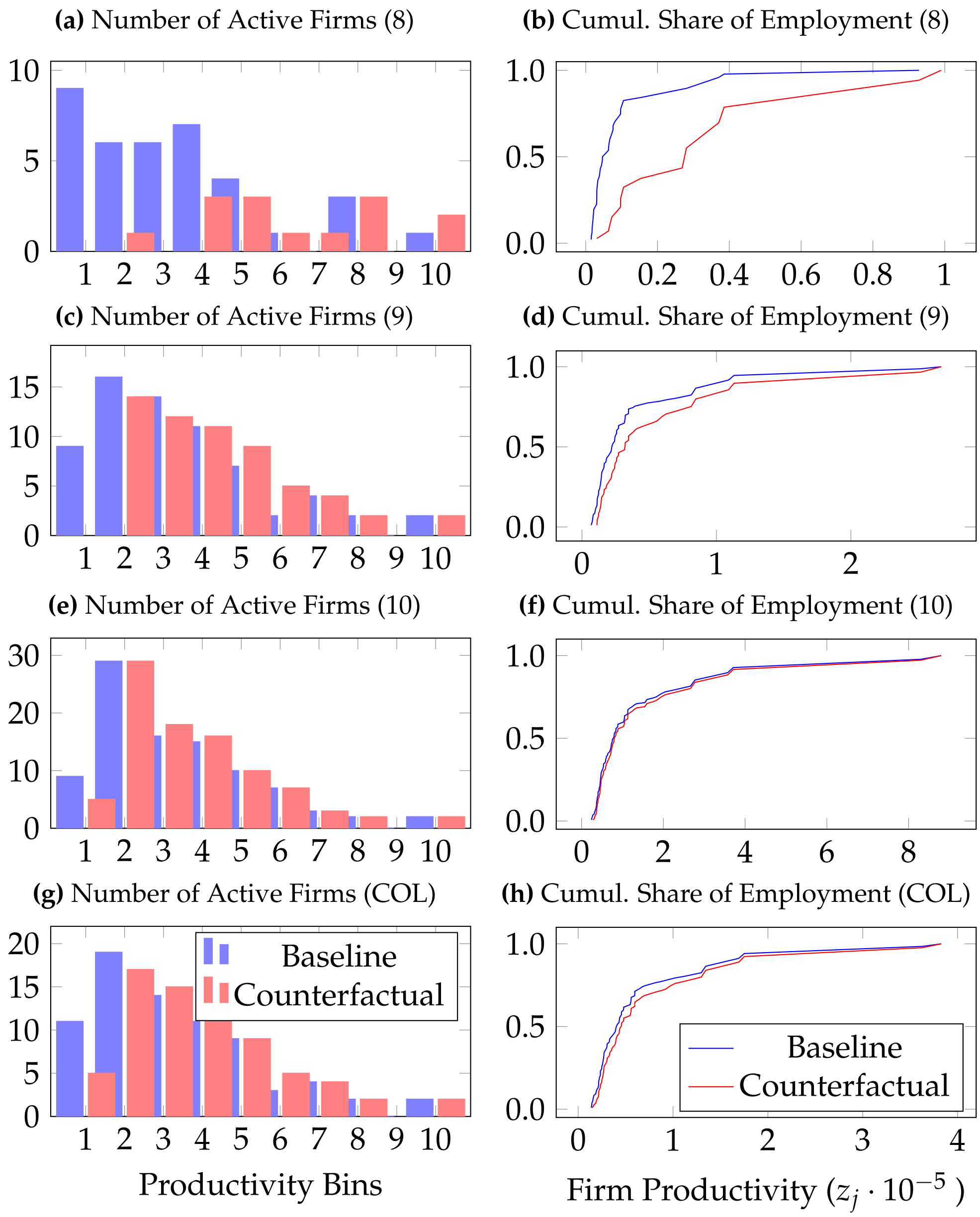
Focusing on the poorest artificial country, Panels A and B Figure 4 show that higher labor market competition makes the economy more selective and more concentrated:[8] the number of active firms in the economy reduces from 37 to 14, and the distribution of firms shifts towards the more productive firms (Panel A). Equilibrium changes in the number of firms amplify the gains in GDP per capita. Tables 11 and 12 in Appendix report a quantification of the role of endogenous firm entry on GDP per capita and several other outcomes. If the number of firms is fixed at their baseline values, the gains in GDP per capita from higher labor market competition would be 16.5 percent lower in the poorest artificial country.[9]

With a more competitive labor market, the distribution of employment also shifts towards high-productivity firms: the cumulative share of employment in the counterfactual scenario lies significantly below the analogous curve in the baseline economy (Panel B). In the benchmark, about 85% of workers are employed in firms whose productivity values are at most 20% the highest in the economy. In the counterfactual, only 40% of workers are employed in such low-

[8]As we show in Table 7 in Appendix , in the benchmark, Herfindahl-Hirschman Index on firm-level employment is higher in poorer countries with less competitive labor markets. However, in the counterfactuals, the HHI index increase, not decrease, when we make the labor market more competitive. In the benchmark, oligopsony rents attract entry in poor countries, while a more competitive labor market results in the reallocation of labor to more productive firms - a mechanism emphasized by Syverson (2019).

[9]See Column 4 of Block A in Table 11.

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.

productivity firms. Similar changes apply to other targeted countries, although with different magnitudes.

5 Conclusions

In this paper, we study whether the labor market power of firms over workers contributes to the large observed differences in GDP per capita across countries. We structurally estimate a model of oligopsonistic competition for different countries with different levels of development and show that labor market supply elasticity, which governs the degree of competition in the labor market, increases with GDP per capita. The average wage mark-down is about 55 percent in the richest countries in our sample and about 23 percent in the poorest ones.

These differences translate into inefficient labor allocation across firms and lower GDP per capita. If firms in the poorest countries had the labor market power we observe in the richest ones, GDP in those countries would increase by up to 69 percent. These results connect extensive literature on the role of misallocation of resources for cross-country income differences with recent empirical and quantitative papers on the importance of the labor market for inequality, welfare, and productivity.

References

Amodio, Francesco and Nicolas De Roux, "Labor Market Power in Developing Countries: Evidence from Colombian Plants," *Journal of Labor Economics (Forthcoming)*, 2023.

_ , Pamela Medina, and Monica Morlacco, "Labor Market Power, Self-employment, and Development," *IZA Discussion Paper*, 2022.

Autor, David, Arindrajit Dube, and Annie McGrew, "The unexpected compression: Competition at work in the low wage labor market," Technical Report, National Bureau of Economic Research 2023.

Azar, José A, Steven T Berry, and Ioana Marinescu, "Estimating Labor Market Power," Technical Report, National Bureau of Economic Research 2022.

Bento, Pedro and Diego Restuccia, "Misallocation, Establishment Size, and Productivity," *American Economic Journal: Macroeconomics*, July 2017, *9* (3), 267–303.

Berger, David, Kyle Herkenhoff, and Simon Mongey, "Labor Market Power," *American Economic Review*, 2022, *112* (4), 1147–93.

Berger, David W, Kyle F Herkenhoff, Andreas R Kostøl, and Simon Mongey, "An Anatomy of Monopsony: Search Frictions, Amenities and Bargaining in Concentrated Markets," Technical Report, National Bureau of Economic Research 2023.

Bollard, Albert, Peter J. Klenow, and Huiyu Li, "Entry Costs Rise with Development," *Unpublished Manuscript*, 2016.

Brooks, Wyatt J, Joseph P Kaboski, Illenin O Kondo, Yao Amber Li, and Wei Qian, "Infrastructure Investment and Labor Monopsony Power," *IMF Economic Review*, 2021, *69*, 470–504.

_ , _ , Yao Amber Li, and Wei Qian, "Exploitation of Labor? Classical Monopsony Power and Labor's Share," *Journal of Development Economics*, 2021, *150*, 102627.

Card, David, Ana Rute Cardoso, Joerg Heining, and Patrick Kline, "Firms and Labor Market Inequality: Evidence and Some Theory," *Journal of Labor Economics*, 2018, *36* (S1), S13–S70.

Castro, Rui and Gian Luca Clementi, "The Dynamics of Firm-level Pay: Theory and Evidence from Portugal," *Unpublished manuscript*, 2023.

Datta, Nikhil, "Local Monopsony Power," *Unpublished Manuscript*, 2022.

Deb, Shubhdeep, Jan Eeckhout, Aseem Patel, and Lawrence Warren, "What Drives Wage Stagnation: Monopsony or Monopoly?," *Journal of the European Economic Association*, 2022, *20* (6), 2181–2225.

Dustmann, Christian, Attila Lindner, Uta Schönberg, Matthias Umkehrer, and Philipp Vom Berge, "Reallocation Effects of the Minimum Wage," *The Quarterly Journal of Economics*, 2022, *137* (1), 267–328.

Eaton, Jonathan, Samuel Kortum, and Sebastian Sotelo, "International Trade: Linking Micro and Macro," Technical Report, National Bureau of Economic Research 2012.

Falch, Torberg, "The Elasticity of Labor Supply at the Establishment Level," *Journal of Labor Economics*, 2010, *28* (2), 237–266.

Garcia-Louzao, Jose and Alessandro Ruggieri, "Labor Market Competition and Inequality," *Unpublished manuscript*, 2023.

Goolsbee, Austan and Chad Syverson, "Monopsony Power in Higher Education: A Tale of Two Tracks," Technical Report, National Bureau of Economic Research 2019.

Guner, Nezih and Alessandro Ruggieri, "Misallocation and Inequality," *CEPR Discussion Paper*, 2022, (DP17113).

Hsieh, Chang-Tai and Peter J Klenow, "Misallocation and Manufacturing TFP in China and India," *The Quarterly Journal of Economics*, 2009, *124* (4), 1403–1448.

Lamadon, Thibaut, Magne Mogstad, and Bradley Setzler, "Imperfect Competition, Compensating Differentials, and Rent Sharing in the US Labor Market," *American Economic Review*, 2022, *112* (1), 169–212.

Luccioletti, Claudio, "Labor Market Power Across Cities," Technical Report, CEMFI Working Paper 2214. 2022.

Luttmer, Erzo G. J., "On the Mechanics of Firm Growth," *The Review of Economic Studies*, 02 2011, *78* (3), 1042–1068.

Maestas, Nicole, Kathleen J Mullen, David Powell, Till Von Wachter, and Jeffrey B Wenger, "The Value of Working Conditions in the United States and Implications for the Structure of Wages," Technical Report, National Bureau of Economic Research 2018.

Manning, Alan, "The Real Thin Theory: Monopsony in Modern Labour Markets," *Labour Economics*, 2003, *10* (2), 105–131.

— , "The plant size-place effect: agglomeration and monopsony in labour markets," *Journal of economic geography*, 2010, *10* (5), 717–744.

— , *Monopsony in Motion: Imperfect Competition in Labor Markets*, Princeton University Press, 2013.

— , "Monopsony in Labor Markets: A Review," *ILR Review*, 2021, *74* (1), 3–26.

Mas, Alexandre and Amanda Pallais, "Valuing Alternative Work Arrangements," *American Economic Review*, December 2017, *107* (12), 3722–59.

McFadden, Daniel, "Modelling the Choice of Residential Location," in "Spatial Interaction Theory and Planning Models" 1978, pp. 530–552.

Poschke, Markus, "The Firm Size Distribution Across Countries and Skill-Biased Change in Entrepreneurial Technology," *American Economic Journal: Macroeconomics*, 2018, *10* (3), 1–41.

Robinson, J, "The Economics of Imperfect Competition. Palgrave Macmillan," 1933.

Sokolova, Anna and Todd Sorensen, "Monopsony in Labor Markets: A Meta-analysis," *ILR Review*, 2021, *74* (1), 27–55.

Sorkin, Isaac, "Ranking Firms Using Revealed Preference*," *The Quarterly Journal of Economics*, 01 2018, *133* (3), 1331–1393.

Staiger, Douglas O, Joanne Spetz, and Ciaran S Phibbs, "Is there Monopsony in the Labor Market? Evidence from a Natural Experiment," *Journal of Labor Economics*, 2010, *28* (2), 211–236.

Syverson, Chad, "Macroeconomics and Market Power: Context, Implications, and Open Questions," *Journal of Economic Perspectives*, August 2019, *33* (3), 23–43.

Model Appendix

A1: Discrete Distributions of Potential Entrants

Let the primitive, or underlying, distribution of firm productivities be a Pareto with shape parameter α and scale parameter θ:

$$f(x;\alpha) = \frac{\alpha}{x^{\alpha+1}}$$

Then, given some number of potential entrants $\bar{E}$, we draw the productivity of all potential entrants following Eaton et al. (2012) and Amodio et al. (2022). We first draw the productivity of the most productive firm denoted A^1, which by the Fisher–Tippett Theorem (Fisher and Tippett, 1928) follows a scaled Fréchet distribution with shape α and scale $\bar{E}^{1/\alpha}$:

$$f(x;\alpha,\theta) = \frac{\alpha}{\theta}\left(\frac{x}{\theta}\right)^{-\alpha-1}\exp(-(x/\theta)^{-\alpha})$$

It follows that if we define:

$$U^k = \frac{1}{\bar{E}^{1/\alpha}}\left(A^k\right)^{-\alpha}$$

U^1 is distributed with an exponential:

$$F(u) = 1 - \exp(-u)$$

Given U^1, U^k for $k > 1$ are obtained by exploiting the fact that:

$$\Pr[U^{k+1} - U^k \leq u] = 1 - \exp(-u)$$

as shown by Eaton and Kortum (2010).[10]

Given the full vector $\mathbf{U}$, the vector of productivities $\mathbf{A}$ is obtained by reversing the transformation from A^k to U^k.

[10] This can be found here: `https://www.blogs.uni-mainz.de/fb03-economics-macro/files/2018/11/EatonKortum030410.pdf`

A2: Solution Algorithm

Given a set of parameters $\{\alpha, \theta, a, b, L, \epsilon^L, \bar{E}, c_e\}$, a distribution of firm productivities $\Phi(z_j; \alpha, \theta)$ and distribution of firm amenities $\Psi(a_j; a, b)$, an algorithm to solve for the equilibrium works as follows:

1. Given the number of potential entrants $\bar{E}$ and the distributions $\Phi(z_j)$ and $\Psi(a_j)$, draw the vectors of productivities $\vec{\mathbf{A}}$ and amenities $\vec{\mathbf{a}}$ of potential entrants.

2. Set the initial number of firms equal to the number of potential entrants $J^{x=-1} = \bar{E}$.

3. Solve the fixed point of wage schedules and rank firms by profitability, use the positive profit threshold to guess the starting value $J^{x=0}$.

4. With the current value of J^x, solve the fixed point of wage schedules:

   (a) Guess the vector of wages $\vec{\mathbf{w}}^{i=0} = [w_1^{i=0}, w_2^{i=0}, ..., w_J^{i=0}]$.

   (b) For each firm $j \in J$:

      i. Compute λ_j using equation 2.

      ii. Solve the profit maximization problem using the current vector $\vec{\mathbf{w}}$ and associated value of λ_j to obtain an updated wage w_j^{i+1}.

      iii. Adjust the updated wage for smooth convergence using: $w_j^{i+1} = \delta w_j^{i+1} + (1-\delta) w_j^i$ and some $\delta \in (0, 1)$.

   (c) If $\vec{\mathbf{w}}^i$ and $\vec{\mathbf{w}}^{i+1}$ are sufficiently close, the Nash Equilibrium has been found. If not, return to step (b).

5. Given the fixed point of wage schedules $\vec{\mathbf{w}}^*$, compute the vector of firm profits $\vec{\boldsymbol{\pi}}$ and:

   - If $\pi_j \geq 0 \; \forall j$ and $J^{x-1} \neq J^x + 1$ set $J^{x+1} = J^x + 1$ and return to step 4.
   - If $\pi_j \geq 0 \; \forall j$ and $J^{x-1} = J^x + 1$ stop with J^x.

- If $\pi_j \ngeq 0 \, \forall j$ and $J^{x-1} \neq J^x - 1$ set $J^{x+1} = J^x - 1$ and return to step 4. The firm removed is the firm with the lowest competitiveness.[11]
- If $\pi_j \ngeq 0 \, \forall j$ and $J^{x-1} = J^x - 1$ stop with J^{x-1}.

[11] This ranking comes from step 3.

Data Appendix

B1: Data Sources

We use data from four different sources: the World Bank World Development Indicators, the World Bank Enterprise Surveys, Poschke (2018) and Bento and Restuccia (2017).

World Bank World Development Indicators are a collection of internationally comparable statistics about countries' development. Details can be found in `https://datatopics.worldbank.org/world-development-indicators/`. The only variable we use is GDP per capita, PPP, in 2017 international dollars (NY-GDP-PCAP-PP-KD).

World Bank Enterprise Surveys are a series of establishment-level surveys conducted in over 130 countries that are representative of countries' private formal sector. Details are provided in `https://www.enterprisesurveys.org/en/enterprisesurveys`. We use standardized data provided in two different datasets: "Firm-Level-TFP-Estimates-and-Factor-Ratios-Data-and-Documentation.zip" (WBES-1) and "StandardizedNew-2006-2023-core4.zip" (WBES-2).

From WBES-1 we use the following variables:

- *idstd*: unique firm identifier.
- *wt*: weight according to median eligibility.
- *country_official*: the official country name.
- *year*: year of the survey wave.
- *d2_gdp09* - deflated total sales in 2009 USD.
- *n2a_gdp09* - deflated total labor cost in 2009 USD.

From WBES-2 we use the following variables:

- *idstd*: unique firm identifier.
- *wt*: sampling weight.

- *stra_sector*: stratification sector.
- *d1a2*: 4-digit ISIC code of main product/service sold by the firm.
- *a2x*: stratification region.[12]
- *a14y*: year.
- *a17*: perception about the truthfulness regarding provided figures.
- *b1*: legal firm status.
- *b5*: year of firms' start of operations.
- *d3a*: percentage of national sales.
- *size_num*: number of employees.
- *e30*: obstacles from informal competition (4 categories).

From the WBES-2 data we construct the following controls:

- exporter: binary variable that equals one if more than 5% of the firm's sales are abroad.
- foreign: binary variable that equals one if more than 50% of the firm is owned by foreign entities.
- public: binary variable that equals one if the firm is a publicly traded company.
- firm age group: categorical variable that groups firms into 1) 5 or fewer years since beginning of operations, 2) between 6 and 15 years since the beginning of operations, and 3) over 15 years since the beginning of operations.

The WBES has some limitations. First, the number of observations is limited and ranges from around 150 for small economies such as those of island states in the Caribbean, to around 600 for medium economies such as Sweden, and up

[12]See the WBES sampling note for details on stratification `https://www.enterprisesurveys.org/en/methodology`.

to around 2000 for large economies such as Germany. Table 7 in Appendix B3 shows the number of observations in each country in the sample, as well as the years of each survey wave and the level of GDP per capita. Second, the WBES does not cover the informal sector, which is much more prevalent in low and middle-income countries, and it only surveys establishments with more than 5 employees. This omission makes the WBES data not suitable for the derivation of mean firm size and firm size dispersion.

Poschke (2018). We use the inter-quartile range of the firm size distribution provided in Poschke (2018) for 44 countries.

Bento and Restuccia (2017). We use the mean firm size data provided in Bento and Restuccia (2017) for 134 countries.

B2: Sample and Construction of Moments

For each target, we merge the source data for the moment of interest with the GDP per capita data. We exclude countries with a GDP per capita under $2000.

B2.1: Firm Size Wage Premium

We use WBES data for the construction of the firm-size wage premium targets. We use establishments' total cost of labor and the number of employees to compute the average wage in each establishment. Interviewers are asked to evaluate the truthfulness of the figures provided on a scale of 1) taken directly from establishment records, 2) estimates computed with some precision, 3) are arbitrary and unreliable numbers, and 4) are a mixture of estimates and records. We keep responses rated as either 1, 2, or 4 to exclude unreliable data. Finally, the data are winsorized at the country level by establishment wages, we drop the top and bottom 2.5% of values, to exclude possible outliers.

We first estimate equation (8) separately for each country via OLS including year, region, and sector fixed effects to obtain a set of possibly biased estimates of the firm-size wage premium. Due to limited sample sizes, we use the World

Bank's strata regions and sectors as controls, which ensures that each country-region-sector has sufficient observations.

We then merge the resulting estimates for each country with its GDP per capita level and run the following auxiliary regression to obtain predicted levels of the firm-size wage premium along the development path:

$$\hat{\beta}_i = \alpha_1 + \alpha_2 \ln(GDPpc_i) + v_i. \tag{9}$$

Figure 1 (Panel E) shows the country-level estimates from the first set of regressions as well as the fitted line from the auxiliary regression and the points used as targets at each of the 4 stages of development. The Figure also shows our first suggestive finding: the firm size wage premium is decreasing in development. This finding is robust to a wide set of specifications and controls, as shown in Table 2.

B2.2: Mean Firm Size

As discussed, the WBES data is not a good source for cross-country comparisons of the firm-size distribution, due to the non-inclusion of firms with fewer than 5 employees. To get estimates of the mean firm size at each of the 4 stages of development, we use the data from Bento and Restuccia (2017). Bento and Restuccia (2017) harmonize census and representative survey data from 134 countries to construct comparable firm-size statistics across countries. We winsorize the data to exclude possible outliers by dropping the top and bottom 2.5% of values. We merge their data, winsorized to exclude possible outliers, with our GDP per capita data from the World Bank's World Development Indicators and run the following regression to obtain an OLS line of best fit and point estimates of mean firm size at the 4 stages of development:

$$\bar{\ell}_i = \alpha_1 + \alpha_2 \ln(GDPpc_i) + v_i. \tag{10}$$

We replicate their finding that average firm size is increasing in development, as shown in Figure 1 (Panel B) together with the fitted line and the point estimates that will be used as targets in the model estimation. Table 3 shows the result

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
log(GDPpc)	-0.0256	-0.0222	-0.0152	-0.0255	-0.0274	-0.0256	-0.0251	-0.0158	-0.0108	-0.0218	-0.0228	-0.0111	-0.015	-0.005
	(0.009)	(0.008)	(0.008)	(0.009)	(0.008)	(0.009)	(0.008)	(0.009)	(0.008)	(0.008)	(0.008)	(0.007)	(0.009)	(0.008)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	No	Yes	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	No	No	Yes	No	No	No	No	No	Yes	No	No	Yes	No	Yes
Exporter FE	No	No	No	Yes	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Foreign-Owned FE	No	No	No	No	Yes	No	No	No	No	No	Yes	Yes	Yes	Yes
Informal Competition FE	No	No	No	No	No	Yes	No	No	No	No	No	No	Yes	Yes
Publicly-Traded FE	No	No	No	No	No	No	Yes	No	No	No	No	No	Yes	Yes
Firm Age Group FE	No	No	No	No	No	No	No	Yes	No	No	No	No	Yes	Yes
Constant	0.3068	0.2734	0.1978	0.2992	0.3161	0.3019	0.2999	0.2023	0.1548	0.2627	0.2661	0.1455	0.1772	0.0742
	(0.081)	(0.075)	(0.078)	(0.079)	(0.079)	(0.082)	(0.079)	(0.083)	(0.073)	(0.073)	(0.071)	(0.069)	(0.08)	(0.077)

Standard errors in parentheses

Table 2: Estimated coefficients of the auxiliary regression specified by equation (8) with different sets of controls in the country-specific regression specified by equation (9).

of estimating equation (10) used to plot the line of best fit and to compute the targets.

Table 3: Results of OLS Estimation of equation (10)

R-squared	0.227				N	68
Average Firm Size	Coefficient	Std. err.	t	P> $\|t\|$	[0.025	0.975]
Intercept	-22.1524	7.41	-2.989	0.004	-36.947	-7.358
ln GDPpc	3.3508	0.761	4.402	0.0	1.831	4.871

B2.3: Firm Size Dispersion

As for the case of average firm size, the WBES data is unsuitable for the construction of targeted firm size dispersion moments due to the omission of small firms and their relatively higher prevalence in low and middle-income countries. Poschke (2018) merges data from the Global Entrepreneurship Monitor and the Amadeus database to compute several moments to describe the firm size distribution in over 35 countries. We use that data, winsorized to exclude possible outliers by dropping the top and bottom 2.5% of values, which we merge with our data on GDP per capita, to run the following regression to obtain an OLS line of best fit and point estimates of interquartile range of the firm size distribution at the 4 stages of development:

$$iqr_i = \alpha_1 + \alpha_2 \ln(GDPpc_i) + v_i. \tag{11}$$

We replicate the finding in Poschke (2018), who shows that firm size dispersion is increasing with development. Figure 1 (Panel C) shows the country-level data from Poschke (2018) as well as the fitted line obtained by estimating equation (11) via OLS and the point estimates at the 4 stages of development. Table 4 shows results.

Because of no coverage in Poschke (2018), the value for the IQR of firm size in Colombia is imputed using the cross-country regression (11).

Table 4: Results of OLS Estimation of equation (11)

R-squared	0.264				N	39
IQR	Coefficient	Std. err.	t	P> $\|t\|$	[0.025	0.975]
Intercept	-8.2774	3.473	-2.383	0.022	-15.315	-1.24
ln GDPpc	1.2252	0.337	3.638	0.001	0.543	1.907

B2.4: Wage Dispersion

For this, we use the WBES data. As before, the data are winsorized at the country level by establishment wages to exclude possible outliers. At each country-year pair, we compute the weighted standard deviation of the average wages paid in each establishment. We then merge the resulting dataset with the GDP per capita data and estimate the following regression via OLS:

$$std(\ln(w))_i = \alpha_1 + \alpha_2 \ln(GDPpc_i) + v_i. \tag{12}$$

We find a strong negative relationship between GDP per capita and the dispersion of wages across firms. Figure 1 (Panel D) shows the country-level data, the fitted values from the cross-country regression, and the point estimates at each of the 4 stages of development to be used as targets in the SMM estimation of the model. Table 5 shows results.

Table 5: Results of OLS Estimation of Equation (12)

R-squared	0.325				N	125
Std of Log-Wage	Coefficient	Std. err.	t	P> $\|t\|$	[0.025	0.975]
Intercept	2.2111	0.202	10.928	0.0	1.811	2.612
ln GDPpc	-0.1662	0.022	-7.701	0.0	-0.209	-0.123

B2.5: Number of Firms

Finally, to construct the targeted number of firms, we use the WBES data merged with the GDP per capita data and estimate the following regression via OLS:

$$J_i = \alpha_1 + \alpha_2 \ln(GDPpc_i) + v_i. \tag{13}$$

Figure 1 (Panel A) shows the country-level data, the fitted values from the cross-country regression, and the point estimates at each of the 4 stages of development to be used as targets in the SMM estimation of the model. Table 6 shows results.

Table 6: Results of OLS Estimation of equation (13)

R-squared	0.037				N	37889
Number of Firms	Coefficient	Std. err.	t	P> $\lvert t\rvert$	[0.025	0.975]
Intercept	-195.644	7.208	-27.142	0.0	-209.772	-181.516
ln GDPpc	28.9131	0.762	37.957	0.0	27.42	30.406

B3: WBES Sample Summary

Country	Total Number of Observations	Survey Waves	GDP per capita (PPP 2017 USD)
Gambia, The	325	2006 2018	2000
Mali	1035	2007 2010 2016	2019
Zimbabwe	600	2016	2287
Solomon Islands	151	2015	2535
Lesotho	150	2016	2688
Nepal	850	2009 2013	2777
Tajikistan	1071	2008 2013 2019	2845
Senegal	1107	2007 2014	2847
Benin	150	2016	2859
Zambia	1805	2007 2013 2019	3115
Cameroon	724	2009 2016	3483

Djibouti	266	2013	3664
Cambodia	373	2016	3762
Papua New Guinea	65	2015	3813
Myanmar	1239	2014 2016	3884
Ghana	1214	2007 2013	3925
Bangladesh	2440	2013 2022	3933
Kenya	2439	2007 2013 2018	4020
Timor-Leste	364	2021 2015	4131
Pakistan	1247	2013	4267
Kyrgyz Republic	865	2009 2013 2019	4700
Sudan	662	2014	4777
Nigeria	4567	2007 2014	4828
Honduras	1128	2006 2010 2016	4914
Nicaragua	1147	2006 2010 2016	4916
India	18657	2022 2014	5071
Mauritania	387	2006 2014	5149
Uzbekistan	1995	2008 2013 2019	5862
Lao PDR	1330	2009 2012 2016 2018	6079
West Bank and Gaza	799	2013 2019	6182
Philippines	2661	2009 2015	6405
Bolivia	1339	2006 2010 2017	6858
Vietnam	2049	2009 2015	7049
Angola	785	2006 2010	7170
Morocco	1503	2013 2019	7285
Eswatini	457	2006 2016	7376
Guatemala	1457	2006 2010 2017	7544
El Salvador	1772	2006 2010 2016	7695
Iraq	1775	2011 2022	8493
Indonesia	2764	2009 2015	8975
Belize	150	2010	8989
Kosovo	743	2013 2009 2019	9044
Namibia	909	2006 2014	9464
Jamaica	376	2010	9700

Guyana	165	2010	9832
Bhutan	253	2015	9877
Mongolia	1082	2009 2013 2019	10042
Peru	2635	2006 2010 2017	10126
Sri Lanka	610	2011	10190
Moldova	1083	2009 2013 2019	10272
Tunisia	1207	2013 2020	10306
China	2700	2012	10371
Egypt, Arab Rep.	7786	2013 2016 2020	10447
Jordan	1174	2013 2019	10547
Ecuador	1385	2006 2010 2017	10609
Armenia	1280	2009 2013 2020	10952
Albania	1041	2013 2007 2019	11388
Paraguay	1338	2006 2010 2017	11446
St. Vincent and the Grenadines	154	2010	11606
Georgia	1314	2008 2013 2019	12029
Bosnia and Herzegovina	1083	2009 2013 2019	12159
Colombia	2935	2006 2010 2017	12306
Dominica	150	2010	12335
Grenada	153	2010	12494
Botswana	610	2006 2010	12970
South Africa	2034	2007 2020	13071
Ukraine	3190	2008 2013 2019	13182
Brazil	1802	2009	13917
Azerbaijan	995	2009 2013 2019	14220
Dominican Republic	719	2010 2016	14322
St. Lucia	150	2010	14448
North Macedonia	1086	2009 2013 2019	14662
Serbia	1109	2009 2013 2019	16018
Barbados	150	2010	16020
Thailand	1000	2016	16393
Mauritius	398	2009	16625

Costa Rica	538	2010	16667
Lebanon	1093	2013 2019	17676
Belarus	1233	2008 2013 2018	17908
Mexico	2960	2006 2010	18236
Suriname	385	2018 2010	18347
Montenegro	416	2009 2019 2013	18421
Antigua and Barbuda	151	2010	18702
Uruguay	1575	2006 2010 2017	19214
Bulgaria	2368	2007 2009 2013 2019	19259
Panama	969	2006 2010	19483
Chile	2050	2006 2010	20282
Argentina	3108	2006 2010 2017	22599
Kazakhstan	2590	2009 2013 2019	23229
Romania	1895	2009 2013 2019	24405
St. Kitts and Nevis	150	2010	24573
Russian Federation	6547	2012 2009 2019	25376
Latvia	966	2009 2013 2019	25819
Malaysia	2221	2015 2019	25913
Croatia	1397	2007 2013 2019	26557
Poland	2366	2009 2013 2019	27201
Trinidad and Tobago	370	2010	27329
Hungary	1406	2013 2009 2019	27383
Slovak Republic	972	2009 2013 2019	27533
Greece	600	2018	29141
Lithuania	904	2009 2013 2019	29613
Estonia	906	2009 2013 2019	30339
Bahamas, The	150	2010	34688
Slovenia	955	2009 2013 2019	34773
Portugal	1062	2019	34946
Israel	483	2013	36436
Spain	1051	2021	37913
Cyprus	240	2019	41739
Italy	760	2019	42739

France	1566	2021	44993
Malta	242	2019	45426
Finland	759	2020	47444
Belgium	614	2020	48979
Sweden	1191	2014 2020	50295
Germany	1694	2021	53180
Austria	600	2021	54121
Netherlands	808	2020	54275
Denmark	995	2020	55519
Ireland	606	2020	91100
Luxembourg	170	2020	111751

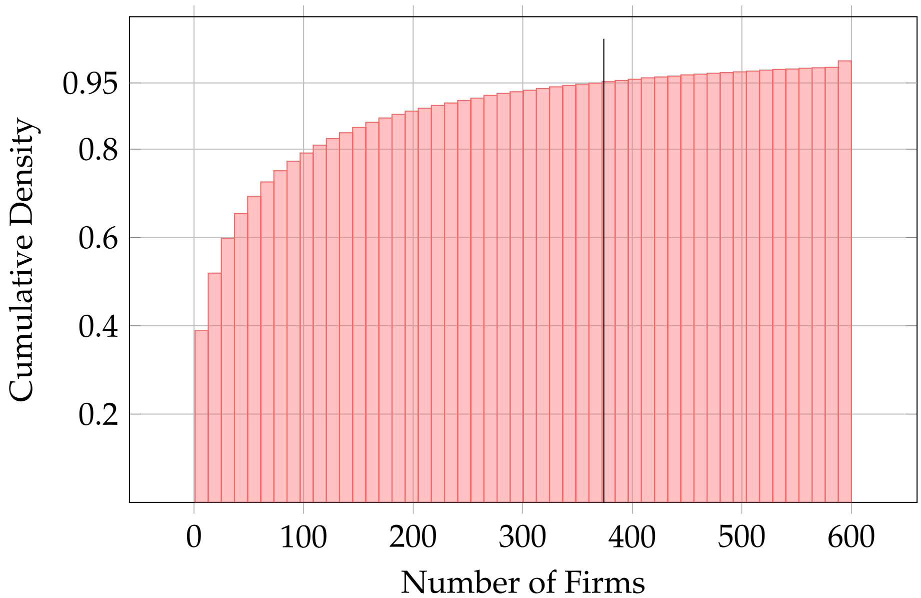
Table 7: Summary statistics for the harmonized WBES sample merged with GDP per capita in 2017 USD in PPP terms. In countries with multiple WBES waves, the reported GDP per capita is an average over the years of each wave.

Estimation Appendix

C1: Distribution of Number of Firms

We fix the number of potential entrants ex-ante, letting it be large enough to cover 95% of the observed distribution of number of firms in a given country-year-region-industry cell in the WBES dataset. Figure 5 shows the histogram of the number of firms at each cell.

Figure 5: Number of Firms by Labor Market



Notes: Cumulative distribution of the number of firms in country-region-sector triplets in the WBES data. The vertical black line represents the fixed number of potential entrant firms in the model, $\bar{E}$, which covers over 95% of observed markets.

C2: Targeted Moments

Table 8 reports the targeted moments for each synthetic country we construct plus Colombia.

Table 8: Targeted moments

log GDP per capita	Mean Firm Size	Firm Size Dispersion	Wage Dispersion	Firm Size Wage Premium	Number of Firms
8 ($ 2,980)	4.654	1.524	0.882	0.068	36
9 ($ 8,100)	8.005	2.749	0.716	0.058	65
10 ($ 22,000)	11.356	3.975	0.549	0.047	93
11 ($ 59,900)	14.707	5.200	0.383	0.036	122
Colombia ($ 12,300)	8.814	3.261	0.584	0.069	73

Notes: The table shows the targeted moments for each country in the estimation.

The loss function used in the estimation is the sum of squared percentage deviations

$$l = g(\omega)'\mathbb{I}g(\omega), \tag{14}$$

where

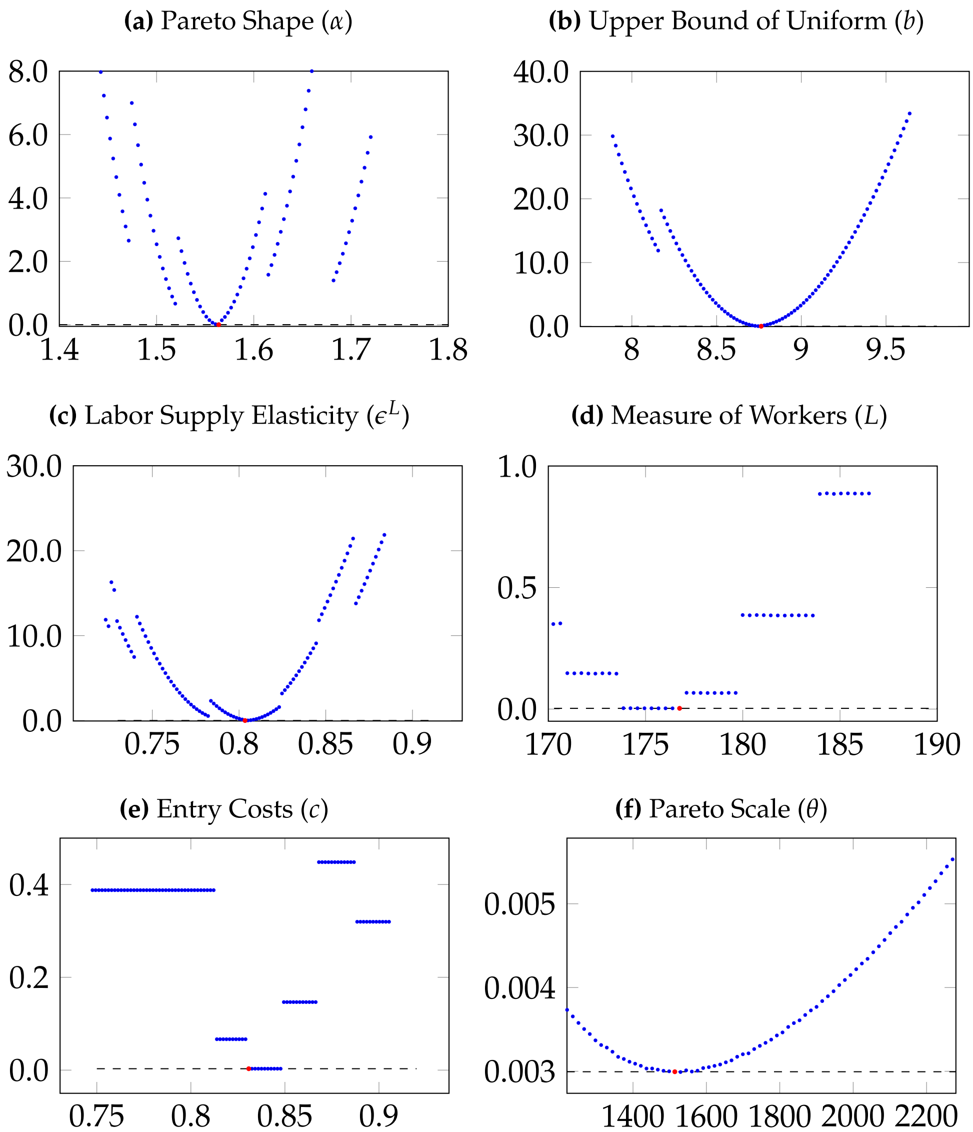
$$g(\omega) = \left[1 - \frac{\gamma^s(\omega)}{\gamma^d}\right],$$

is a vector of percentage deviations of the simulated moments, $\gamma^s(\omega)$ from the observed (targeted) ones, γ^d. The standard errors are calculated using the Delta method.

C3: Global Minima in Estimation

To check the identification of our estimates we conduct the following validation exercise. For each of these parameters $(\alpha, b, \epsilon^L, L, c, \theta)$ we plot the loss function around the estimate for a country with log GDP per capita of 9. Figure 6 shows the results. Despite the discontinuous nature of the objective function that we minimize, our estimates appear to be on a well-defined global minimum.

Figure 6: Global Minima in Estimation



Notes: Each of the 6 panels shows the loss function evaluated at the estimated parameter vector, changing only the parameter in each subtitle. The red dot shows the estimated parameter value. The dashed line goes through the minimum value of the loss function found.

C4: Model Fit

In Table 9, we report the estimated parameters from estimating equations (9), (10), (11), (12) and (13) on the data and on the model's simulated moments. As in Figure 2, the table shows a very close fit for the firm size wage premium, the average firm size, firm size dispersion, the wage dispersion, and number of firms.

Table 9: Auxiliary regressions with observed and simulated data

	Data		Model	
Regression	Intercept	Slope	Intercept	Slope
Firm Size Wage Premium	0.155	-0.011	0.155	-0.011
Average Firm Size	-22.152	3.351	-19.011	2.959
Firm Size Dispersion	-8.277	1.225	-9.000	1.315
Wage Dispersion	2.211	-0.166	2.246	-0.171
Number of Firms	-195.644	28.913	-195.000	29.000

Notes: This table reports data and model-based estimates of equations (9), (10), (11), (12) and (13) using both the data and model.

C5: Strategic interaction

Table 10 reports the estimated parameters for Colombia obtained by targeting the number of firms in the economy and in the alternative scenario of zero entry cost limited firm granularity, and no strategic interaction.

Table 10: Estimated model parameters: Colombia.

Pareto Shape (α)	Uniform Dispersion (b)	LS Elasticity (ϵ^L)	Mass of Workers (L)	Entry Cost (c_e)	Pareto Scale (θ)
		Baseline			
1.88	7.12	2.42	655.12	1.14	11953.16
		No strategic interaction			
1.50	24.07	8.62	956.06	0	7030.39

Notes: This table reports the estimate of the Pareto shape, α, dispersion of amenities, b, labor supply elasticity ϵ^L, measure of workers, L, entry cost c_e, and Pareto scale θ, for Colombia, for the cases with and without strategic interaction. The entry cost (for the benchmark estimatin) is presented as a fraction of the Pareto scale, θ.

Counterfactual Appendix

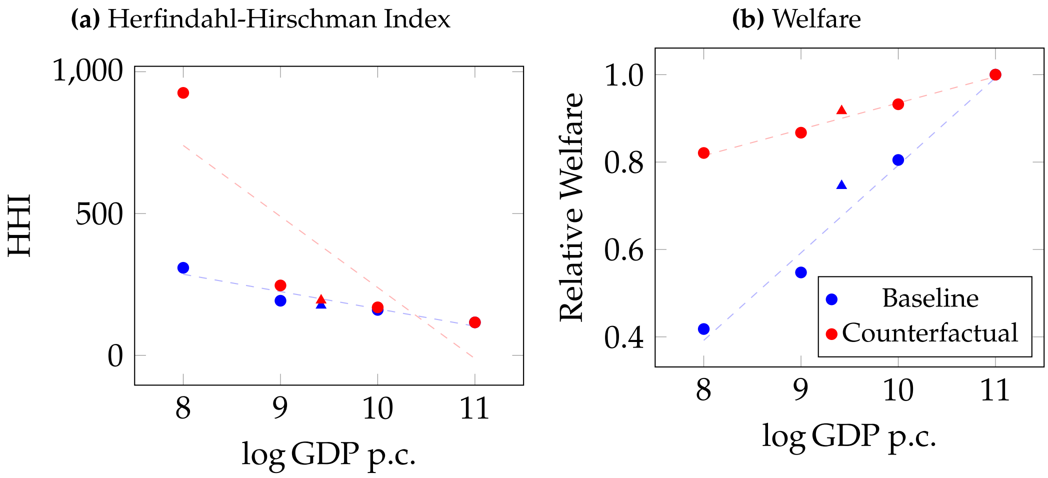
Figure 7 reports the dynamics of concentration, measured by the Herfindahl-Hirschman index (Panel A) and a measure of model-based welfare (Panel B) across countries over development for baseline and counterfactual equilibria. Welfare is computed as the expected worker-level utility, i.e.

$$W = \ln\left(\sum_{j=1}^{J} \exp(\epsilon^L \ln(w_j) + a_j)\right)$$

and it is expressed relative to the value of the richest country.

Concentration declines over development, while model-based welfare is steeply increasing. A counterfactual increase in labor supply elasticity leads to a higher concentration and to higher welfare, particularly in the poorest targeted countries.

Figure 7: Further 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.

Tables 11 and 12 report a series of outcomes for each targeted country under the baseline equilibrium (column 1), a counterfactual equilibrium obtained by replacing the country-specific labor supply elasticity to the highest estimated value (column 2), and the same counterfactual equilibrium imposing the number of firms to be fixed to the baseline values (column 3).

Table 11: Counterfactual outcomes

Countries	Baseline	Counterfactual General Equilibrium	Counterfactual Fixed Number of Firms	Explained, %
	(1)	(2)	(3)	(4)
		A. GDP per capita		
8 ($2,980)	1	1.686	1.573	16.47 %
9 ($8,100)	1	1,187	1,169	9.40 %
10 ($22,000)	1	1,033	1,032	5.46 %
11 ($59,900)	1	1	1	-
Colombia ($12,300)	1	1.084	1.075	10.13 %
		B. Wage Dispersion		
8 ($2,980)	0.903	0.712	0.586	-66.13%
9 ($8,100)	0.679	0.491	0.493	1.33%
10 ($22,000)	0.536	0.459	0.461	2.81%
11 ($59,900)	0.382	0.382	0.382	-
Colombia ($12,300)	0.580	0.511	0.513	2.75%
		C. Firm Size Dispersion		
8 ($2,980)	0.315	0.511	0.698	-95.35%
9 ($8,100)	0.402	0.458	0.465	-11.70%
10 ($22,000)	0.468	0.485	0.484	6.20%
11 ($59,900)	0.449	0.449	0.449	-
Colombia ($12,300)	0.408	0.428	0.427	4.75%
		D. Conditional Firm Size Wage Premium		
8 ($2,980)	1.245	0.309	0.309	-
9 ($8,100)	0.606	0.309	0.309	-
10 ($22,000)	0.374	0.309	0.309	-
11 ($59,900)	0.309	0.309	0.309	-
Colombia ($12,300)	0.413	0.309	0.309	-

Notes: This table reports selected outcomes in the baseline equilibrium (column 1), in a full counterfactual equilibrium (column 2), and in a counterfactual equilibrium with fixed number of firms (column 3). Column (4) reports the percent change in each outcome explained by changes in the equilibrium number of firms.

Column 4 in both tables reports the percentage change of each outcome explained by counterfactual changes in the number of firms.

Table 12: Counterfactual outcomes

Countries	Baseline (1)	Counterfactual: General Equilibrium (2)	Counterfactual: Fixed Number of Firms (3)	Explained, % (4)
		A. Number of firms		
8 ($2,980)	37	14	37	-
9 ($8,100)	67	59	67	-
10 ($22,000)	93	92	93	-
11 ($59,900)	125	125	125	-
Colombia ($12,300)	75	71	75	-
		B. HH Index		
8 ($2,980)	308.7	925.6	468.1	74.14%
9 ($8,100)	192.6	246.5	220.9	47.50%
10 ($22,000)	160.2	169.3	167.6	19.24%
11 ($59,900)	116.2	116.2	116.2	-
Colombia ($12,300)	176.1	194.2	184.5	53.48%
		C. Average Wage		
8 ($2,980)	1	1.852	2.165	-36.67%
9 ($8,100)	1	1.295	1.331	-12.24%
10 ($22,000)	1	1.065	1.061	5.85%
11 ($59,900)	1	1	1	-
Colombia ($12,300)	1	1.116	1.125	-7.97%
		D. Welfare		
8 ($2,980)	0.418	0.821	0.864	-10.70%
9 ($8,100)	0.547	0.867	0.874	-2.13%
10 ($22,000)	0.805	0.932	0.933	-0.40%
11 ($59,900)	1	1	1	-
Colombia ($12,300)	0.746	0.917	0.920	-1.64%

Notes: This table reports selected outcomes in the baseline equilibrium (column 1), in a full counterfactual equilibrium (column 2), and in a counterfactual equilibrium with a fixed number of firms (column 3). Column (4) reports the percent change in each outcome explained by changes in the equilibrium number of firms.

References

Amodio, Francesco, Pamela Medina, and Monica Morlacco, "Labor Market Power, Self-employment, and Development," *IZA Discussion Paper*, 2022.

Bento, Pedro and Diego Restuccia, "Misallocation, Establishment Size, and Productivity," *American Economic Journal: Macroeconomics*, July 2017, *9* (3), 267–303.

Eaton, Jonathan and Samuel Kortum, "Technology in the Global Economy: A Framework for Quantitative Analysis," *Unpublished Manuscript*, 2010.

_ , _ , and Sebastian Sotelo, "International Trade: Linking Micro and Macro," Technical Report, National Bureau of Economic Research 2012.

Fisher, Ronald Aylmer and Leonard Henry Caleb Tippett, "Limiting Forms of the Frequency Distribution of the Largest or Smallest Member of a Sample," in "Mathematical proceedings of the Cambridge philosophical society," Vol. 24 Cambridge University Press 1928, pp. 180–190.

Poschke, Markus, "The Firm Size Distribution Across Countries and Skill-Biased Change in Entrepreneurial Technology," *American Economic Journal: Macroeconomics*, 2018, *10* (3), 1–41.