Labor Market Power and Development*

Tristany Armangué-Jubert
IDEA, UAB, BSE

Nezih Guner
CEMFI

Alessandro Ruggieri
CUNEF Universidad

July 2, 2024

Abstract

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 increases with GDP per capita. Wage mark-downs vary from 54% in low-income countries to around 24% in the richest ones. If labor markets in poorer countries were as competitive as in more developed ones, their output per capita could rise by up to 45%.

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

*Armangué-Jubert: tristany.armangue@barcelonagse.eu, Guner: nezih.guner@cemfi.es, Ruggieri: alessandro.ruggieri@cunef.edu. We thank Francesco Amodio, Andre Groeger, Claudio Luccioletti, Alan Manning, and participants at the World Bank DECIG Seminar Series 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. 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 0.84 to 3.14. 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, 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 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 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 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, Netherlands, or the United States, their GDP per capita would increase up to 45 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 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 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. 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. Firstly, we use an indirect inference approach to estimate labor supply elasticity across countries at different development stages. Secondly, 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, 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 wage stagnation observed in the US 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 macro-development literature that studies how frictions and distortions can account for cross-country income differences, e.g., Guner et al. (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.

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 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.

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 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 non-pecuniary match factors. 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. Following McFadden (1978), workers have "logit" probabilities of working for firm j, 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 can be written 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. Each firm faces an upward-sloping labor supply function given by

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

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

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 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

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

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 and how their wages affect the market-level wages 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 Eaton et al. (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, 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 now *common* to all firms. 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 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:

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

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

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

Using equation (6) it can be shown that, when firm productivity is sufficiently dispersed, the dispersion in log size increases with 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 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, 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:

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

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

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

[2]See the proof in Appendix A3.

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, 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 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]

2.6 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, 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:

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

[3]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.

where $\epsilon_j^L = \left[\frac{\partial \ln w_j}{\partial \ln L_j} \Big|_{L^*_{-j}} \right]^{-1}$ 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

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

which implies the following inverse elasticity of labor supply:

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

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.

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, 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 its limitations. We provide details on the data and the constructions of data moments in Appendices B1 and B2. For any moment constructed using the WBES, we first divide a given country into local labor markets 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 in 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 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 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.[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 0.88 for the poorest countries in the sample to 0.41 for the richest ones (Panel D in Figure 1).

The final cross-country moment pertains to the relationship between economic

[4]The GDP per capita numbers are in PPP terms deflated to 2017 US Dollars and taken the World Bank Development Indicators (WDI, 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 US, 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 Appendix C7.

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 local market (sector and location) fixed effects, δ_t are time fixed effects, and v_{jt} is the error term.

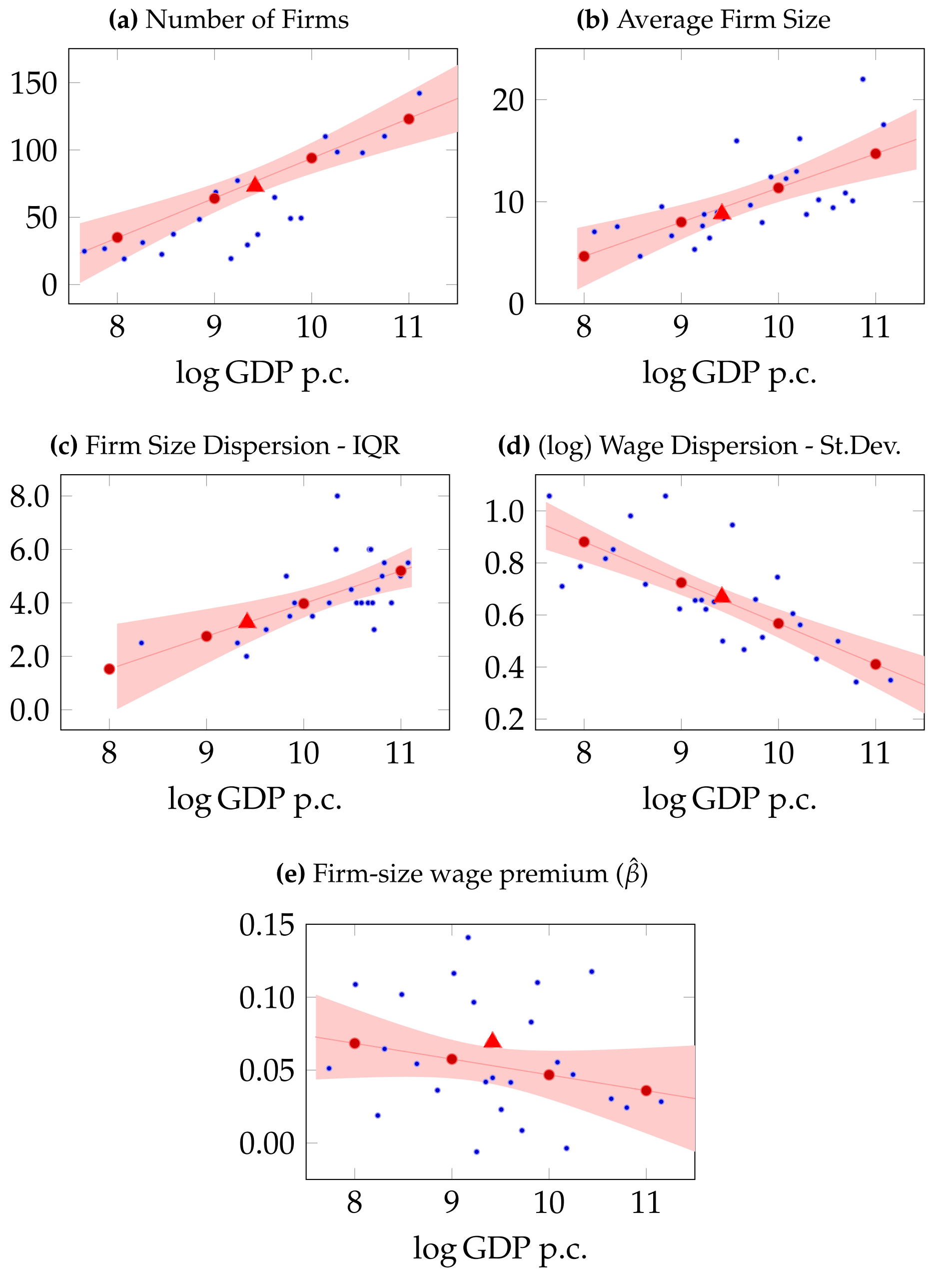
The Firm-Size Wage Premium, as measured by the estimated β values from equation 8, is decreasing with development (Panel E in Figure 1). This finding is robust to a wide set of specifications and controls, as shown in Table B1 in Appendix B2.[6]

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 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.

[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).

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) with 95% confidence intervals. The red dots represent the set of targeted moments for each stage of development. Triangles refer to Colombia.

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 374. This value corresponds to the 95th 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, 8, 22, and 60 thousand 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.

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.[9]

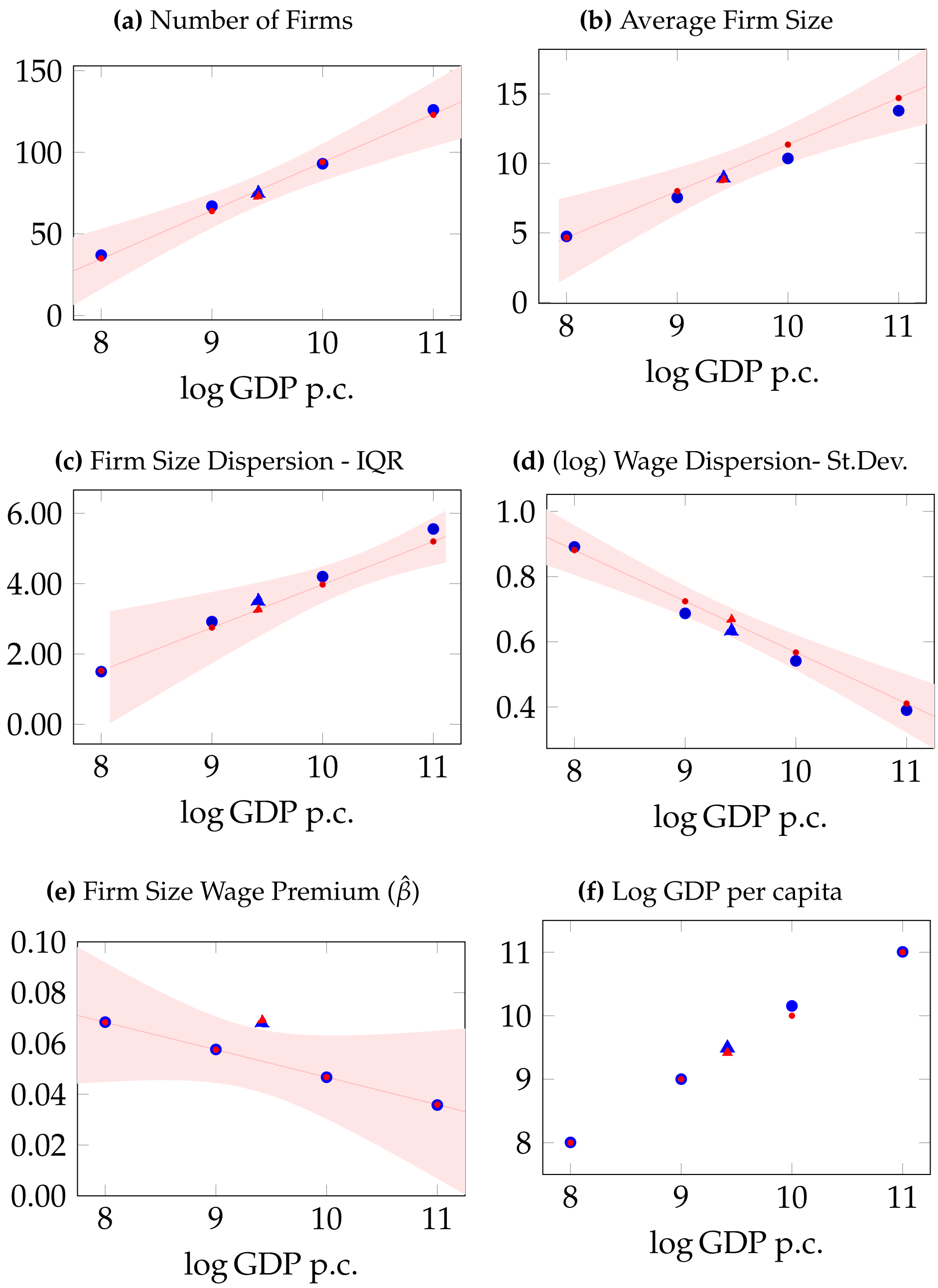
Various model parameters simultaneously affect multiple targets, but each moment primarily depends on a specific parameter. Labor supply elasticity is dis-

[7] See Figure C.2 in Appendix C1.

[8] Table C1 in Appendix C2 reports the data targets.

[9] Figure C.3 in Appendix C3 shows 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.

ciplined 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). 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]

Table 1 reports country-specific estimated parameters 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 0.84 for the poorest countries in the sample and increases up to 3.14 for the richest ones. These values imply an average wage mark-down of around 54% 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 24%. This is within the range of estimates of 24% and 17% provided 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.

The estimated elasticity for Colombia is 2.35, 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

[10]In 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)	0.84	175.65	1.58	1561.63	9.05	0.82
	(0.658)	(71.724)	(0.006)	(0.255)	(1.703)	(0.0)
9 ($8,100)	1.74	505.84	1.68	5386.55	6.69	1.16
	(0.417)	(27.207)	(0.002)	(0.195)	(1.301)	(0.0)
10 ($22,000)	2.66	963.42	1.66	20315.69	6.08	1.47
	(0.328)	(17.051)	(0.001)	(0.173)	(0.314)	(0.0)
11 ($59,900)	3.14	1738.44	1.88	93740.78	4.9	1.89
	(0.301)	(13.206)	(0.001)	(0.114)	(0.387)	(0.0)
Colombia ($12,300)	2.35	671.92	1.67	8951.16	6.62	1.23
	(0.346)	(16.664)	(0.002)	(0.186)	(0.224)	(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 4 synthetic targeted countries plus Colombia. The entry cost is reported as a fraction of the Pareto scale, θ. Standard errors in parenthesis are computed using the Delta method.

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, 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 re-estimate the model for Colombia with zero entry costs without targeting the number of firms. Results (Table C3 in 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% of the average wage in countries with a GDP per capita of 3,000$. For the richest countries, they are 10 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.

4 Does Labor Market Power Matter for Development?

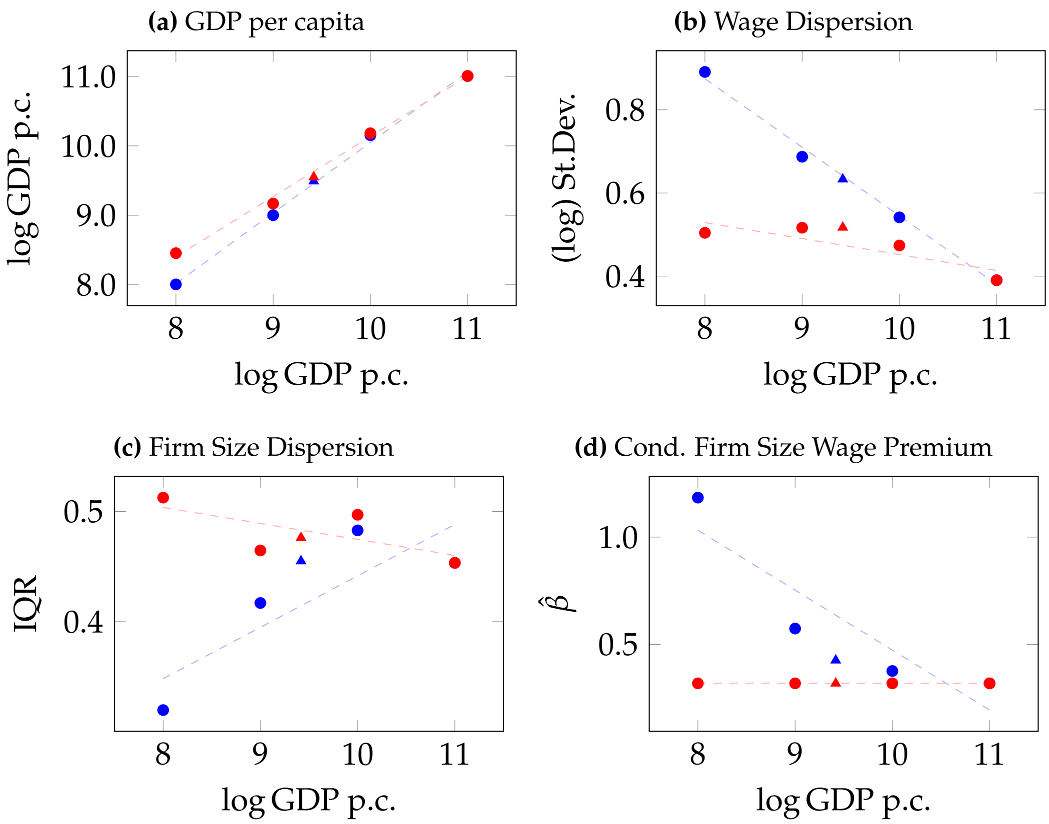
How much of the observed cross-country differences in GDP per capita can be accounted for by differences in labor market competition? To answer this question, we conduct the following exercise: We set the labor supply elasticity in each artificial country to the highest estimate obtained (3.14 for the 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 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 45 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 17 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 US.

[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 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 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.

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 77 percent, the 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.

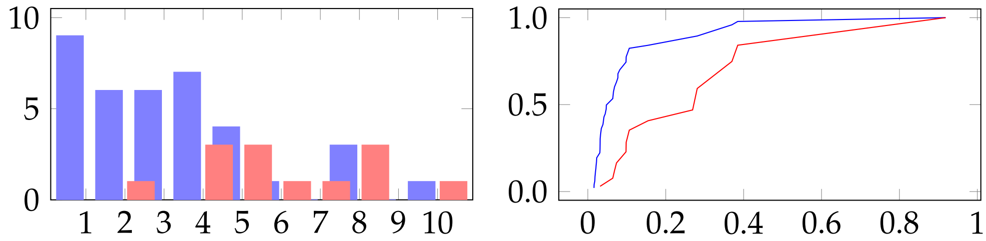
For the poorest artificial country, Panels A and B in Figure 4 show that higher labor market competition makes the economy more selective and more concentrated: the number of active firms in the economy reduces from 37 to 13, and the distribution of firms shifts towards the more productive ones (Panel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

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

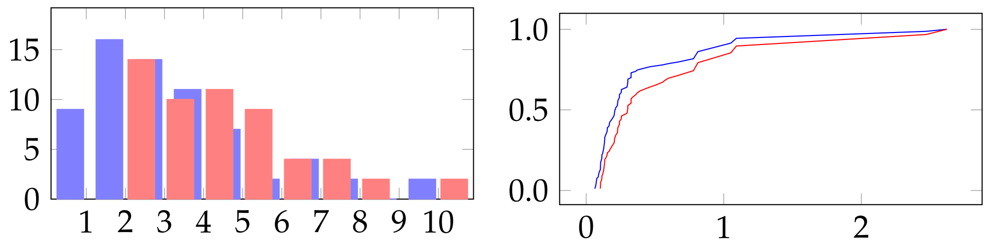
[14] As we show in Table D.1 in Appendix D, in the benchmark, Herfindahl-Hirschman Index

Figure 4: Reallocation Effects of Higher Labor Market Competition

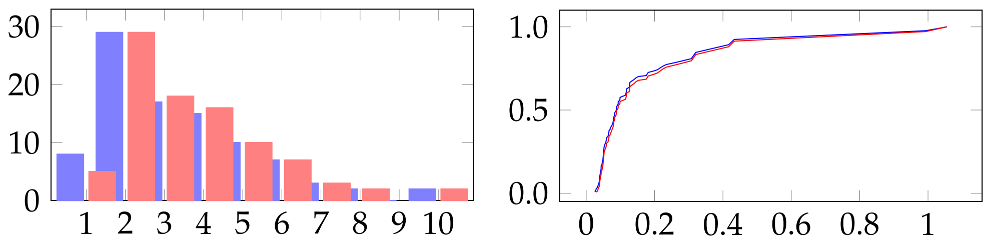
(a) Number of Active Firms (GDPpc = 3000$) **(b)** Cumul. Share of Employment (GDPpc = 3000$)



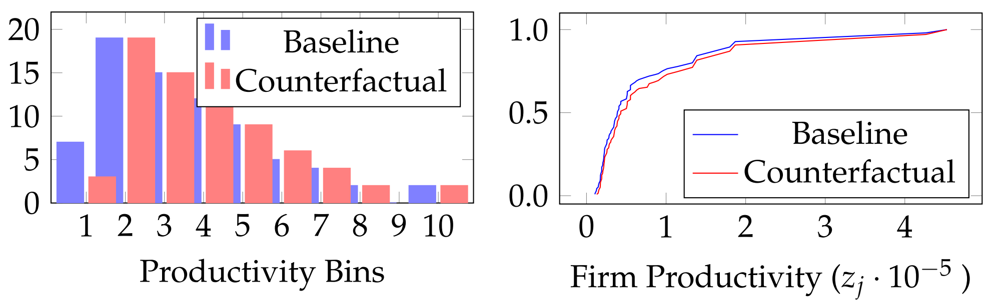
(c) Number of Active Firms (GDPpc = 8000$) **(d)** Cumul. Share of Employment (GDPpc = 8000$)



(e) Number of Active Firms (GDPpc = 22000$) **(f)** Cumul. Share of Employment (GDPpc = 22000$)



(g) Number of Active Firms (COL) **(h)** Cumul. Share of Employment (COL)



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.

librium changes in the number of firms amplify the gains in GDP per capita. Tables D1 and D2 in Appendix D 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 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 towards 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% of workers are employed in firms whose productivity values are at most 20% the highest in the economy. In the counterfactual, 41% of workers are employed in such low-productivity firms. Similar changes apply to other targeted countries, although with different magnitudes.

5 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 mark-down is approximately 24% in the richest countries and 54% 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 45%. These findings bridge the gap between

(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).

[15]See Column 4 of Block A in Table D1.

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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Online Appendix (not intended for publication)

Model Appendix

A1: Discrete Distributions of Potential Entrants

Following Eaton et al. (2012) and Amodio et al. (2022), let the primitive, or underlying, distribution of firm productivities be a Pareto with shape parameter α and scale parameter θ:

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

Given some number of potential entrants $\bar{E}$, 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).[16]

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

[16] 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 $\pi_j \neq 0 \, \forall j$ 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.[17]

- If $\pi_j \neq 0 \, \forall j$ and $J^{x-1} = J^x - 1$ stop with J^{x-1}.

A3: Proofs to Proposition 2

Equation (6) in the main text shows that the dispersion of log employment across firms can be written as:

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

Taking the first derivative with respect to ϵ^L we get:

$$\frac{\partial \text{var}[\ln L_j]}{\partial \epsilon^L} = \frac{[2\epsilon^L(1+\epsilon^L)^2 - 2(\epsilon^L)^2(1+\epsilon^L)]}{(1+\epsilon^L)^4} \text{var}[\ln(z_j)] - \frac{2(1+\epsilon^L)}{(1+\epsilon^L)^4} \text{var}[a_j].$$

The variance of log employment $\text{var}[\ln L_j]$ increases with the labor supply elasticity ϵ^L as long as $\frac{\partial \text{var}[\ln L_j]}{\partial \epsilon^L} > 0$, meaning:

$$\begin{aligned}
[2\epsilon^L(1+\epsilon^L)^2 - 2(\epsilon^L)^2(1+\epsilon^L)]\text{var}[\ln(z_j)] - 2(1+\epsilon^L)\text{var}[a_j] &> 0 \\
[\epsilon^L(1+\epsilon^L) - (\epsilon^L)^2]\text{var}[\ln(z_j)] - \text{var}[a_j] &> 0 \\
[\epsilon^L + (\epsilon^L)^2 - (\epsilon^L)^2]\text{var}[\ln(z_j)] - \text{var}[a_j] &> 0 \\
\epsilon^L \text{var}[\ln(z_j)] - \text{var}[a_j] &> 0 \\
\text{var}[\ln(z_j)] &> \frac{\text{var}[a_j]}{\epsilon^L}
\end{aligned}$$

The last condition implies that the variance of log employment $\text{var}[\ln L_j]$ increases with the labor supply elasticity ϵ^L as long as log productivity is sufficiently dispersed across firms. This completes the proof.

[17] 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 from these indicators 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 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.[18]
- *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 the 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

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

up to around 2000 for large economies, such as Germany. Table B6 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 more prevalent in low and middle-income countries, and it only surveys establishments with more than 5 employees. Finally, the number of high-income countries in the WBES is small (the US, for example, is not in the WBES).

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

Poschke (2018). We use the inter-quartile range of the firm size distribution provided in Poschke (2018) for 44 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, controlling for 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 B1.

B2.2: Mean Firm Size

While it is possible to calculate the average firm size using the WBES data, we use data from Bento and Restuccia (2017) as it provides better coverage for high-income countries. Furthermore, the samples in the WBES are restricted to firms with more than 5 workers. 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 B2 shows the result of estimating equation (10) used to plot the line of best fit and to compute the targets.

	(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)

Table B1: Estimated coefficients of the auxiliary regression specified by equation (8) with different sets of controls in the country-specific regression specified by equation (9).

Table B2: Results of OLS Estimation of equation (10)

R-squared	0.227				N	68
Mean 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	0.76	4.402	0.0	1.831	4.871

B2.3: Firm Size Dispersion

As was the case for calculating the average firm size, We used a different data source to calculate firm size dispersion. 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 B3 shows results.

The value for the IQR of firm size in Colombia is imputed using the cross-country regression (11), since it is not available in Poschke (2018),

Table B3: 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	3.47	-2.383	0.022	-15.315	-1.24
ln GDPpc	1.2252	0.34	3.638	0.001	0.543	1.907

B2.4: Wage Dispersion

For this target, we use the WBES data. The data are again 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 B4 shows results.

Table B4: Results of OLS Estimation of Equation (12)

R-squared	0.273				N	125
Std of Log-Wage	Coefficient	Std. err.	t	P> $\|t\|$	[0.025	0.975]
Intercept	2.1364	0.22	9.866	0.0	1.708	2.565
ln GDPpc	-0.1569	0.02	-6.795	0.0	-0.203	-0.111

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 B5 shows results.

Table B5: Results of OLS Estimation of equation (13)

R-squared	0.207				N	112
Number of Firms	Coefficient	Std. err.	t	P> $\|t\|$	[0.025	0.975]
Intercept	-201.8617	52.21	-3.866	0.0	-305.339	-98.385
ln GDPpc	29.5728	5.52	5.359	0.0	18.637	40.509

B3: WBES Sample Summary

Table B6: 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.

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

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Table B6: 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.

Country	Total Number of Observations	Survey Waves	GDP per capita (PPP 2017 USD)
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

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Table B6: 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.

Country	Total Number of Observations	Survey Waves	GDP per capita (PPP 2017 USD)
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

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Table B6: 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.

Country	Total Number of Observations	Survey Waves	GDP per capita (PPP 2017 USD)
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

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Table B6: 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.

Country	Total Number of Observations	Survey Waves	GDP per capita (PPP 2017 USD)
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

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Table B6: 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.

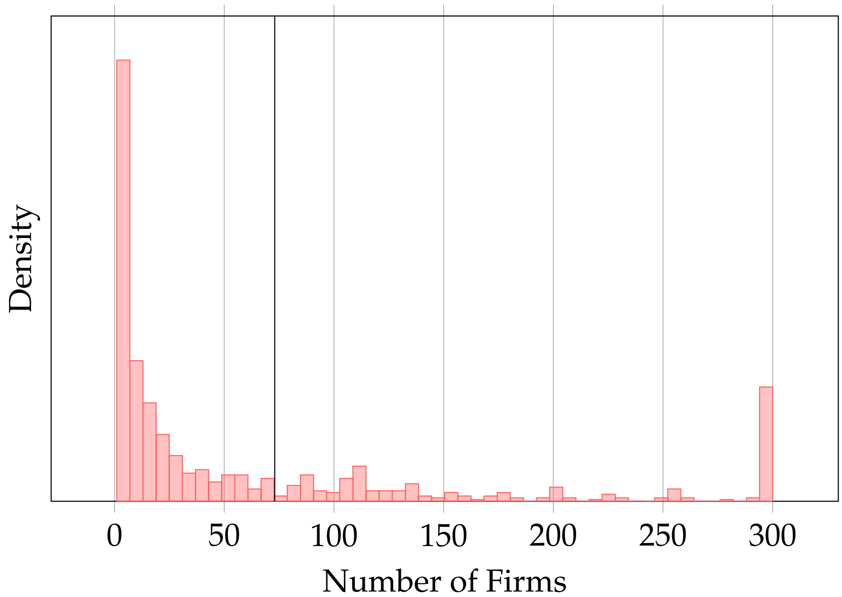
Country	Total Number of Observations	Survey Waves	GDP per capita (PPP 2017 USD)
Netherlands	808	2020	54275
Denmark	995	2020	55519
Ireland	606	2020	91100
Luxembourg	170	2020	111751

Estimation Appendix

C1: Distribution of Number of Firms

Figure C.1 reports the distribution of firms across different local labor markets in Colombia. While the average number of firms is 73, there is significant variation: while many local labor markets feature only a handful of firms, a substantial fraction of them is populated by more than 300 companies. In the estimation, we use the average number of firms across local labor markets as a target to identify the entry cost.

Figure C.1: Number of Firms by Local Labor Market in Colombia

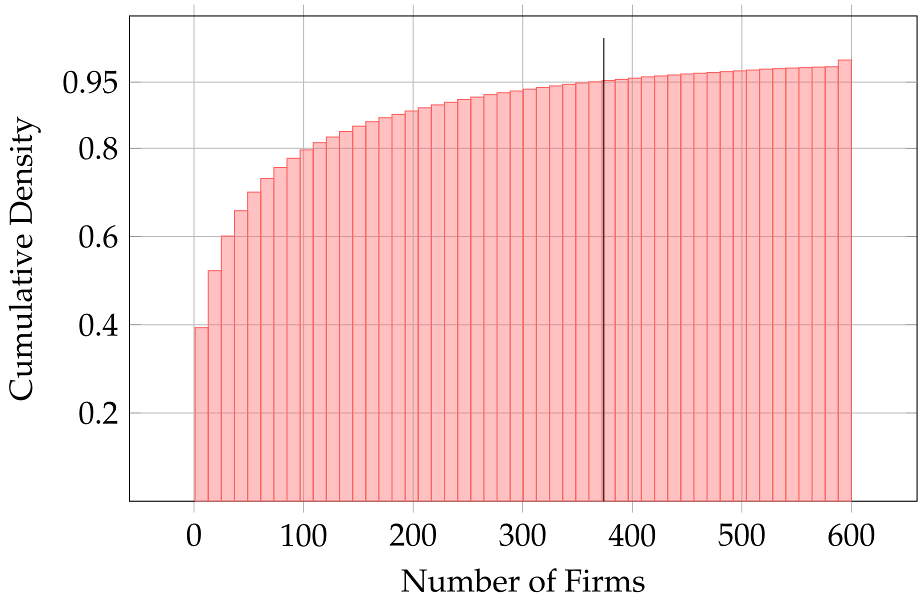


Notes: Distribution of the number of firms in region-sector tuples in Colombia. The vertical black line represents the average, used as a target.

While the average number of firms is lower, the distribution looks very similar to the one documented for the US by Berger et al. (2022).

We fix the number of potential entrants, $\bar{E}$, ex-ante, letting it be large enough to cover 95% of the observed distribution of the number of firms in a given country-year-region-industry cell in the WBES dataset. Figure C.2 shows the histogram of the number of firms at each cell.

Figure C.2: 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 C1 reports the targeted moments for each synthetic country and Colombia.

Table C1: 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	0.881	0.068	35
9 ($8,100)	8.005	2.749	0.724	0.058	64
10 ($22,000)	11.356	3.975	0.567	0.047	94
11 ($59,900)	14.707	5.2	0.411	0.036	123
Colombia ($12,300)	8.814	3.261	0.669	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

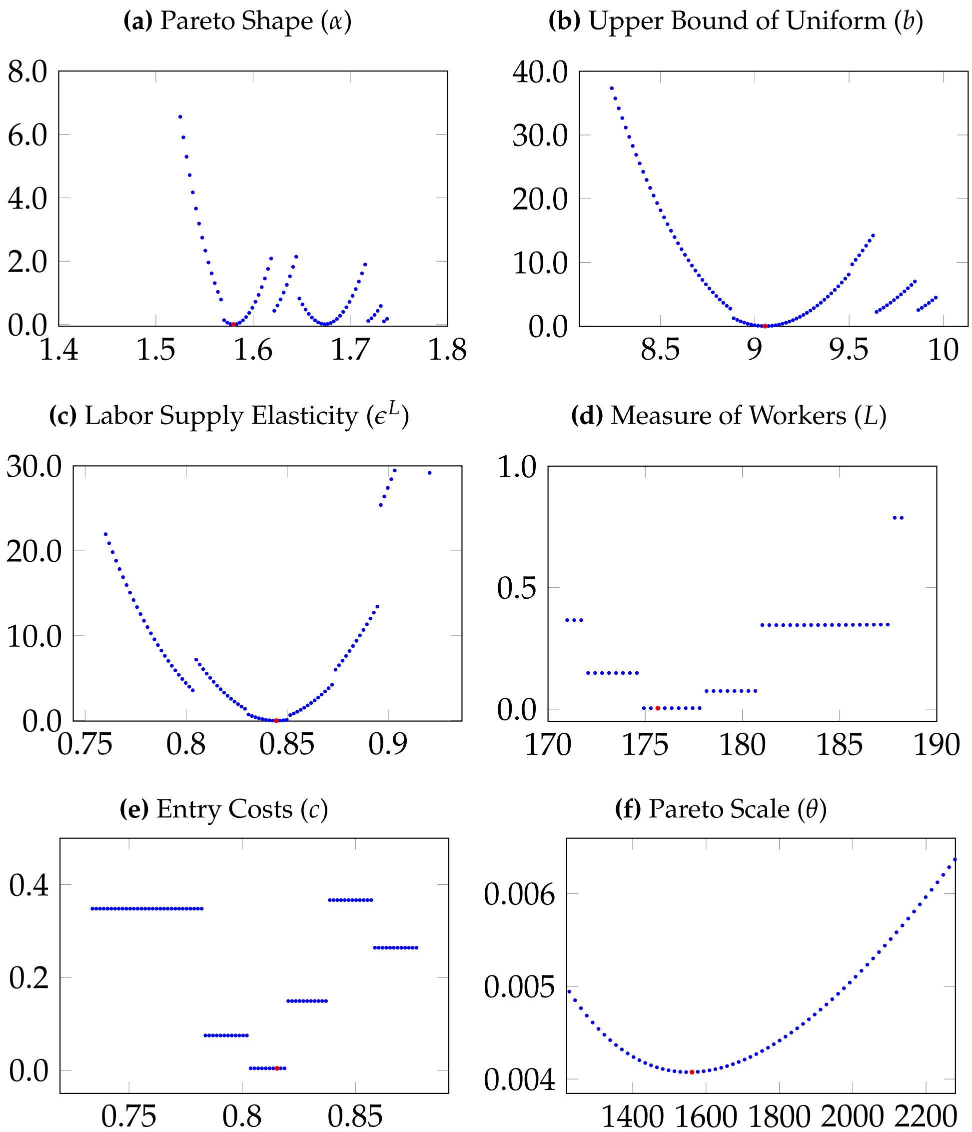
$$g(\omega) = \left[1 - \frac{\gamma^s(\omega)}{\gamma^d}\right],$$

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 illustrate the identification of the model parameters, we conduct the following exercise. For each parameter $(\alpha, b, \epsilon^L, L, c, \theta)$, we plot the loss function around the estimate for a country with log GDP per capita of 9. Figure C.3 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 C.3: 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 C2, 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 C2: Auxiliary regressions with observed and simulated data

	Data		Model	
	Intercept	Slope	Intercept	Slope
Regression				
Firm Size Wage Premium	0.155	-0.011	0.154	-0.011
Average Firm Size	-22.152	3.351	-18.887	2.935
Firm Size Dispersion	-8.277	1.225	-9.052	1.320
Wage Dispersion	2.136	-0.157	2.173	-0.162
Number of Firms	-201.862	29.573	-193.093	28.700

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

C5: Endogenous Entry

Table C3 reports the estimated parameters for Colombia obtained without targeting the number of firms in the economy and setting the entry cost to zero.

Table C3: Estimates with zero entry cost: Colombia.

LS Elasticity (ϵ^L)	Mass of Workers (L)	Pareto Shape (α)	Pareto Scale (θ)	Uniform Dispersion (b)	Entry Cost (c_e)
8.70	962.85	1.50	7046.08	24.66	0.00
(0.117)	(7.679)	(0.001)	(0.217)	(0.821)	(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 Colombia, for the case without entry costs and without targeting of the number of firms.

Table C4 shows data targets (row A) and simulated moments obtained by estimating the model with a zero entry cost (row B).

Table C4: Model fit with zero entry cost: Colombia

Scenario	log GDPpc	Mean Firm Size	Firm Size Dispersion	Wage Dispersion	Firm Size Wage Premium	Number of Firms
A. Data	9.418	8.814	3.261	0.669	0.069	73
B. Zero Entry Cost	9.419	7.703	3.751	0.596	0.070	125

Notes: The table shows the simulated moments for Colombia in the baseline estimation and the estimation without entry costs. Row A refers to the empirical targets. Row B refers to the simulated statistic obtained with a model with zero entry cost.

C6: Distribution of Amenities

In the main estimation, we assume that firms' amenities follow a uniform distribution with bounds 0 and b. In this section of the Appendix, we show that our estimates are robust to different functional form assumptions. As 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. In particular, we re-estimate the model for Colombia, assuming that the amenities of firms follow a Gamma with scale and shape parameters a and b. Table C5 reports the estimated parameters with the Gamma distribution, which is quite flexible and can take different forms depending on a and b, together with the baseline estimates where amenities are distributed uniformly.

Table C5: Estimates with Gamma distribution for amenities: Colombia.

	LS Elasticity (ϵ^L)	Mass of Workers (L)	Pareto Shape (α)	Pareto Scale (θ)	Upper Bound Uniform (b)	Gamma Shape (a)	Gamma Scale (b)	Entry Cost (c_e)
A. Uniform	2.349	671.918	1.666	8951.155	6.623	-	-	1.229
	(0.346)	(16.664)	(0.002)	(0.186)	(0.224)	-	-	(0.0)
B. Gamma	2.410	601.698	1.391	4197.858	-	2.265	1.036	0.413
	(0.938)	(28.463)	(0.001)	(0.286)	-	(1.488)	(1.433)	(0.0)

Notes: This table reports robustness estimates of the labor supply elasticity ϵ^L, measure of workers, L, Pareto shape, α, Pareto scale, θ, upper bound of the uniform distirbution of amenities, b, shape and scale of the Gamma distribution of amenities, a and b, and entry cost c_e, for Colombia. The entry cost is reported as a fraction of the Pareto scale, θ.

In the robustness estimation, we estimate the shape and scale of the Gamma distribution to be 2.04 and 0.97, respectively. Compared to the baseline, this implies a lower average value for amenities (0.91 against 3.56) and a lower dispersion (1.97 against 2.06). Nevertheless, moving from a uniform to a Gamma distribution does not alter our estimate of the labor supply elasticity (2.35 against 2.43). Table C6 shows empirical targets (row A) and the simulated moments obtained using a model with Gamma distribution for amenities (row B).

Table C6: Model fit with Gamma distribution for amenities: Colombia

	log GDPpc	Mean Size	Firm	Firm Size Dispersion	Log-Wage Skewness	Wage Dispersion	Firm Size Wage Premium	Number of Firms
A. Data	9.418	8.814		3.261	-0.270	0.669	0.069	73
B. Uniform	9.491	8.959		3.504	-	0.633	0.068	75
C. Gamma	9.453	7.163		3.639	-0.288	0.811	0.069	84

Notes: The table shows the simulated moments for Colombia with a Gamma distribution of amenities. Row A refers to the empirical targets. Row B refers to the simulated statistic obtained with a model with Gamma distribution for amenities.

C7: Estimation Using WBES Firm Size Distributions

In the baseline estimation, we use data from Bento and Restuccia (2017) and Poschke (2018) because these data sources provide better coverage for high-income countries. In this Appendix, we show the parameter estimates when all targeted moments are constructed using the WBES.

Table C7: Targeted Moments from WBES

log GDP per capita	Mean Firm Size	Firm Size Dispersion	Wage Dispersion	Firm Size Wage Premium	Number of Firms
8 ($2,980)	7.804	1.938	0.881	0.068	35
9 ($8,100)	8.354	2.002	0.724	0.058	64
10 ($22,000)	8.904	2.066	0.567	0.047	94
11 ($59,900)	9.453	2.13	0.411	0.036	123
Colombia ($12,300)	10.927	2.205	0.669	0.069	73

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

Table C8: Simulated Moments

log GDPpc	Mean Firm Size	Firm Size Dispersion	Wage Dispersion	Firm Size Wage Premium	Number of Firms
8 ($2,980)	6.513	1.960	0.839	0.069	35
9 ($8,100)	7.394	2.298	0.619	0.058	70
10 ($22,000)	7.577	2.204	0.468	0.046	97
11 ($59,900)	8.098	2.322	0.346	0.036	115
Colombia ($12,300)	8.186	2.582	0.532	0.070	73

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

The WBES dataset surveys establishments with more than 5 employees. As a result, for each country in the sample, we impute the missing support for firm size distribution by fitting a Pareto distribution to the observed firm size (number of full-time employees) data. We first estimate the shape parameter for a scale parameter of 5 employees. Then, we use the estimated shape parameters to obtain a value for the average firm size and size dispersion (interquartile range), imposing a scale parameter equal to 1 employee. Table C7 reports the resulting targets for average firm size and size dispersion. Table C8 reports the

Table C9: 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)	0.97	227.95	1.58	1501.07	9.6	1.08
	(0.567)	(56.191)	(0.004)	(0.25)	(0.878)	(0.0)
9 ($8,100)	1.39	517.56	1.9	7540.64	4.56	1.37
	(0.419)	(32.636)	(0.002)	(0.149)	(1.319)	(0.0)
10 ($22,000)	1.93	734.97	2.39	34480.16	4.17	1.12
	(0.332)	(25.267)	(0.001)	(0.078)	(2.159)	(0.0)
11 ($59,900)	3.16	931.32	2.89	144024.74	4.76	1.09
	(0.253)	(17.539)	(0.001)	(0.05)	(0.346)	(0.0)
Colombia ($12,300)	2.19	597.59	2.14	15366.88	6.03	1.17
	(0.292)	(16.866)	(0.001)	(0.107)	(0.337)	(0.0)

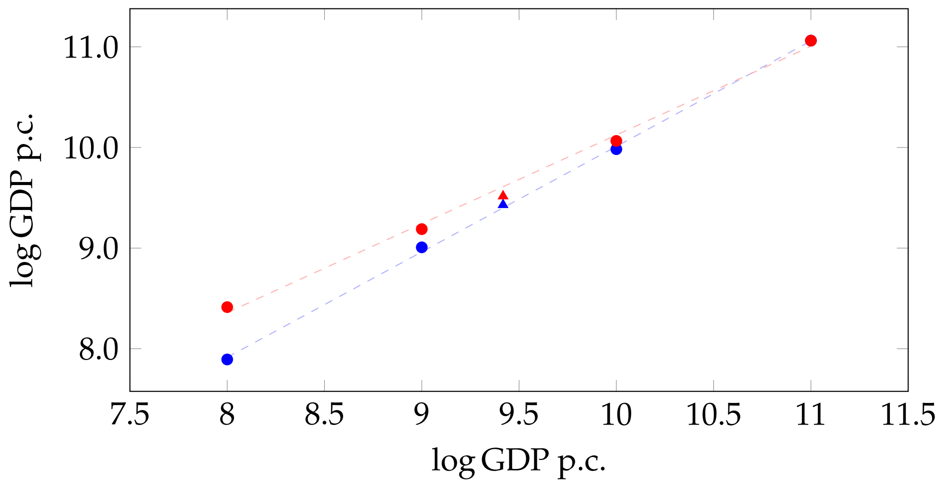
Notes: This table reports the estimate of the labor supply elasticity ϵ^L, measure of workers, L, Pareto shape, α, Pareto scale, θ, dispersion of amenities, b, and entry cost c_e, for 4 synthetic targeted countries. The entry cost is reported as a fraction of the Pareto scale, θ. Standard errors in parenthesis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

model-based simulated moments.

Table C9 reports the parameter values estimated using WBES targets for average firm size and firm size dispersion.

Figure C.4: Counterfactual Results (WBES)

(a) GDP per capita



Notes: Blue dots show the baseline (log) GDP per capita, and red dots show the counterfactual (log) GDP per capita. Baseline and counterfactual moments for Colombia are represented by triangles.

Compared to our baseline estimates in Table 1 of the main text, the estimates for the labor supply elasticity are largely unchanged. For the poorest country, we estimate a value of 0.97 against 0.84. For the richest country, we estimate a value of 3.16 against 3.14. The estimates of labor supply elasticity are still increasing with GDP per capita, suggesting the identification is robust to alternative targets for the average firm size and the size dispersion.

Using the estimates in Table C9 we also perform the same counterfactual exercise as in the main text. Keeping all the parameters constant, we increase the labor supply elasticity of each country to the value of the richest one. Figure C.4 reports baseline and counterfactual (log) GDP per capita across countries when parameters are estimated using moments from the WBES. The gains in GDP per capita are remarkably similar to those reported in the main text: the poorest countries, such as Zambia or Senegal, would see an increase in their GDP per capita of up to 52 percent if they had the same labor supply elasticity as countries at the top of the development ladder, such as the Netherlands or Denmark. The increase in GDP per capita for middle-income countries, such as Indonesia or Peru, would be approximately 18 percent. For Colombia, the increase in GDP per capita would be around 8 percent.

D. Counterfactual Appendix

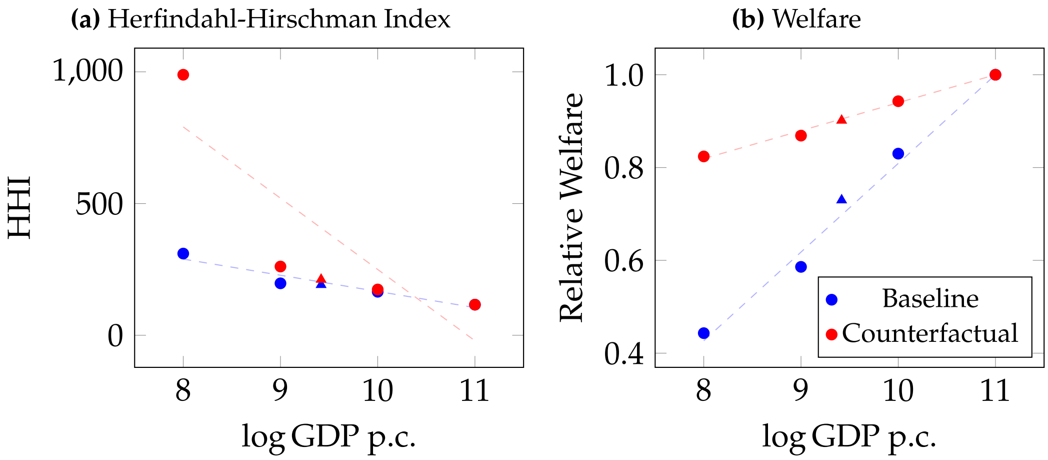
Figure D.1 reports how concentration, measured by the Herfindahl-Hirschman index (Panel A) and a measure of model-based welfare (Panel B) changes with development in the baseline and counterfactual. Welfare is computed as the expected worker-level utility, i.e.,

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

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 the elasticity of labor supply leads to a higher concentration and welfare, particularly in the poorest targeted countries.

Figure D.1: 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. Welfare is normalized with respect to the richest country.

Tables D1 and D2 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 when the number of firms is fixed at the baseline values (column 3).

Table D1: Counterfactual outcomes

Countries	Baseline (1)	Counterfactual General Equilibrium (2)	Counterfactual Fixed Number of Firms (3)	Explained, % (4)
		A. GDP per capita		
8 ($2,900)	1	1.438	1.337	23.066
9 ($8,100)	1	1.169	1.147	13.299
10 ($22,000)	1	1.035	1.033	5.240
11 ($59,000)	1	1.000	1.000	-
Colombia ($12,300)	1	1.049	1.044	9.676
		B. Wage Dispersion		
8 ($2,900)	0.874	0.488	0.435	-13.864
9 ($8,100)	0.687	0.511	0.511	-0.150
10 ($22,000)	0.550	0.469	0.471	2.741
11 ($59,000)	0.404	0.404	0.404	-
Colombia ($12,300)	0.615	0.521	0.526	5.557
		C. Firm Size Dispersion		
8 ($2,900)	0.313	0.507	0.667	-82.740
9 ($8,100)	0.417	0.466	0.474	-17.284
10 ($22,000)	0.475	0.494	0.493	6.003
11 ($59,000)	0.464	0.464	0.464	-
Colombia ($12,300)	0.459	0.476	0.475	2.291
		D. Conditional Firm Size Wage Premium		
8 ($2,900)	1.189	0.314	0.314	-
9 ($8,100)	0.574	0.314	0.314	-
10 ($22,000)	0.383	0.314	0.314	-
11 ($59,000)	0.314	0.314	0.314	-
Colombia ($12,300)	0.403	0.314	0.314	-

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.

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

Table D2: Counterfactual outcomes

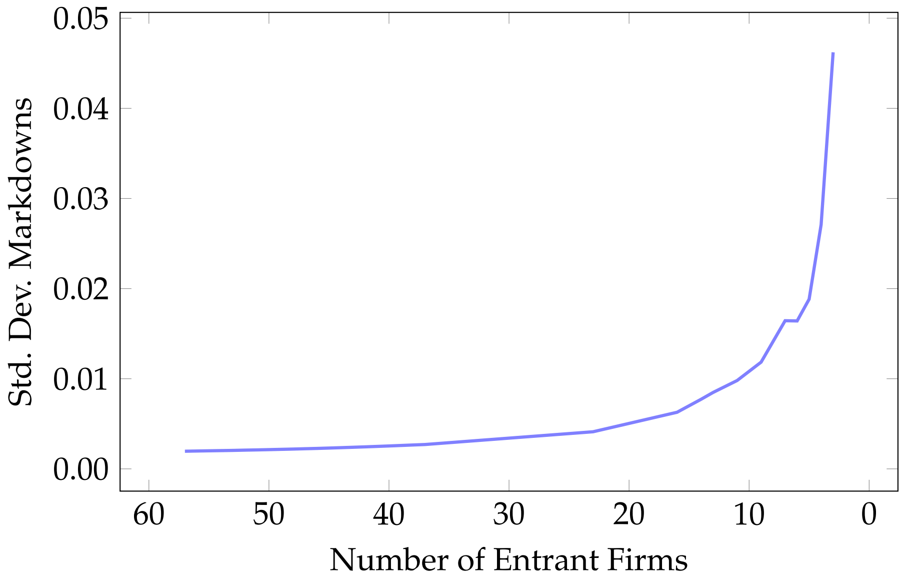
Countries	Baseline (1)	Counterfactual: General Equilibrium (2)	Counterfactual: Fixed Number of Firms (3)	Explained, % (4)
		A. Number of firms		
8 ($2,900)	37	13	37	-
9 ($8,100)	67	56	67	-
10 ($22,000)	93	92	93	-
11 ($59,000)	128	128	128	-
Colombia ($12,300)	74	72	74	-
		B. HH Index		
8 ($2,900)	308.13	983.37	459.03	77.65
9 ($8,100)	197.10	261.65	224.31	57.85
10 ($22,000)	162.66	172.58	170.81	17.89
11 ($59,000)	117.19	117.19	117.19	-
Colombia ($12,300)	195.67	211.39	206.26	32.59
		C. Average Wage		
8 ($2,900)	1	1.648	1.841	-29.928
9 ($8,100)	1	1.337	1.375	-11.516
10 ($22,000)	1	1.112	1.107	3.976
11 ($59,000)	1	1.000	0.996	-
Colombia ($12,300)	1	1.134	1.130	2.992
		D. Welfare		
8 ($2,900)	16.89	31.88	33.76	-12.56
9 ($8,100)	22.62	33.89	34.25	-3.24
10 ($22,000)	31.26	36.38	36.39	-0.12
11 ($59,000)	39.09	39.09	39.08	-
Colombia ($12,300)	29.16	35.01	35.05	-0.66

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.

D2: Strategic Interaction

Figure D.2 reports the standard deviation of markdowns across firms for counterfactual economies that differ in the number of firms. The parameters used to solve the model are those associated with the poorest artificial country. A different number of firms is obtained as an equilibrium outcome by changing the entry cost.

Figure D.2: Markdown Dispersion vs. Number of Firms



Notes: The figure shows the dispersion of markdowns across firms as a function of the number of entrant firms. The parameters used are those of the lowest GDP per capita artificial country, changing only the entry costs to go from a high number of firms to a low number of firms.

Markdowns have a higher dispersion when the number of firms is low and strategic interaction among them is strong. On the other hand, when evaluated at the targeted number of firms (i.e., 37), strategic interaction is likely to play a limited role, as the dispersion in markdown is lower than 1 percent.

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