Labor Market Power and Self-Employment Around the World*

Francesco Amodio†
Emanuele Brancati‡
Peter Brummund§
Nicolás de Roux¶
Michele Di Maio‖

August 14, 2025

Abstract

We estimate the labor market power of manufacturing firms in 82 low- and middle-income countries using over 13,000 observations from a harmonized global dataset. Wage markdowns—the gap between a worker's marginal revenue product and their wage—vary widely across countries and show a robust hump-shaped association with the share of self-employed workers. We interpret this pattern using a simple oligopsonistic labor market model with frictions, in which self-employment and wage markdowns are jointly determined, and unemployment protection dictates whether their relationship is positive or negative. Consistent with the model, wage markdowns rise with self-employment in countries with such protection, but fall in those without it. These findings underscore how labor market frictions and regulations shape the link between self-employment and labor market power across countries.

Keywords: labor market power, self-employment, development.

JEL Codes: J20, J30, J42, L11.

---

*We thank Lucy Besch, Ricky Andrés Carrillo, Hai Ma, Tristan Montgomery, and Reese Oberski for excellent research assistance. We also thank Tsenguunjav Byambasuren, James Lake, Monica Morlacco, Sergio Ocampo, Hoang Pham, Markus Poschke, and participants in the 2024 DevSouth Workshop, NEUDC, and the 2024 BSE Summer Forum "Advances in Micro Development" Workshop for their comments and suggestions. We gratefully acknowledge financial support from the Social Sciences and Humanities Research Council (SSHRC) of Canada—Insight Grant Program.

†Department of Economics and Institute for the Study of International Development, McGill University, CEPR and BREAD, francesco.amodio@mcgill.ca.

‡Department of Economics and Law, Sapienza University of Rome and IZA, emanuele.brancati@uniroma1.it.

§Department of Economics, Finance, and Legal Studies, Culverhouse College of Business, University of Alabama, pbrummund@ua.edu.

¶Department of Economics, Universidad de Los Andes, Colombia, nicolas.de.roux@uniandes.edu.co.

‖Department of Economics and Law, Sapienza University of Rome and IZA, michele.dimaio@uniroma1.it.

1 Introduction

Imperfect competition in the labor market can reduce wages, aggregate output, and overall welfare. This has been well documented in the United States and other high-income countries, where employers wield substantial market power over labor (Azar, Berry and Marinescu, 2022; Bassier, Dube and Naidu, 2022; Berger, Herkenhoff and Mongey, 2022; Berger et al., 2023). Despite a few notable exceptions, evidence from low- and middle-income countries remains scarce. This gap matters because structural differences between economies can shape both the extent and the nature of labor market power. In poorer countries, job creation and wage employment rates are lower (Rud and Trapeznikova, 2021), yet labor markets tend to be highly dynamic. Labor market flows—such as job-finding and employment exit rates—are higher, with workers frequently transitioning between low-paying jobs and self-employment (Donovan, Lu and Schoellman, 2023).

The high prevalence of self-employment—even within manufacturing—is a defining feature of labor markets in low-income countries (Gollin, 2008; Poschke, 2025; Breza and Kaur, 2025). By offering an alternative to wage employment, self-employment may increase workers' responsiveness to wage changes, thereby limiting firms' wage-setting power (Amodio, Medina and Morlacco, 2025). The strength of this mechanism likely depends on other features of the labor market, such as employment protection legislation and unemployment benefits, which provide formal workers with a buffer against job loss and reduce the relative appeal of self-employment. Understanding the interaction between labor market power, self-employment, and contextual factors is therefore essential for designing policies that constrain firms' wage-setting power and foster inclusive economic growth.

In this paper, we measure the labor market power of manufacturing firms across 82 low- and middle-income countries, using more than 13,000 observations from a harmonized global dataset. Our primary data source is the World Bank Enterprise Survey (WBES), which applies a standardized methodology and remains the only truly comparable source of firm-level data on a global scale.[1] We quantify labor market power as measured by the wage markdown, i.e., the gap between the marginal revenue product of labor and the wage paid. Under standard profit-maximization assumptions, this markdown corresponds to the ratio of the revenue–labor elasticity to the wage-bill share of revenues (Morlacco, 2020; Brooks et al., 2021*b*; Yeh, Macaluso and Hershbein, 2022; Brummund and Makowsky, 2024). To obtain consistent estimates of the revenue-labor elasticity, we exploit the panel structure of our data and apply proxy-variable methods commonly used to estimate production functions. This approach provides comparable cross-country measures of labor

[1] We discuss and assess the representativeness of the WBES in Section 5.1, where we compare the firm-size distribution in our sample to external benchmarks and explore potential sources of bias.

market power within a unified empirical framework.

We conduct two main validation exercises to assess the reliability of our markdown estimates. First, we examine how our measure of labor market power relates to firm-level characteristics by comparing firms within the same sector and local labor market. Consistent with previous studies, we find that firms with higher wage markdowns tend to be larger, in line with an oligopsonistic labor market model. We also find that foreign-owned firms exhibit higher markdowns than their domestic counterparts. While not the main focus of the paper, this analysis serves as a useful validity check, indicating that—despite the known limitations of the production function approach—our measure generates findings consistent with the literature. Second, we estimate markdowns using a completely different dataset—ORBIS, the other main cross-country dataset at the firm level.[2] For countries covered in both datasets, the ORBIS-based estimates exhibit a high correlation (52%) with those from WBES, indicating broad consistency despite differences in sampling and coverage.

The main advantage of applying a single methodology to a globally harmonized dataset is that it provides a systematic way to measure and compare labor market power across countries. Using the median wage markdown in each country, we document substantial cross-country heterogeneity: markdowns are lowest in most of Africa, moderately high in Latin America, and highest in several countries in Eastern Europe and the Middle East. While our results show a negative association between GDP per capita and wage markdowns across much of the income spectrum, this relationship reverses at very low income levels, where markdowns tend to rise with income.

We build on this cross-country heterogeneity to explore the relationship between labor market power and self-employment, a defining feature of labor markets in low- and middle-income countries. Recent single-country studies show that self-employment shapes both the extent and nature of labor market power, yet little is known about how this relationship varies across the development spectrum. Using our global dataset, we uncover a robust hump-shaped relationship between labor market power and the share of self-employed workers across countries. This quadratic fit accounts for a remarkable 24% of the cross-country variation in wage markdowns. We also find that structural features of the labor market play a central role in shaping this relationship. In countries lacking unemployment protection, self-employment is more widespread and negatively associated with labor market power. The opposite holds in countries with unemployment protection, where self-employment is less common and positively correlated with wage markdowns. These findings are robust to a range of checks, including alternative sample restrictions, different moments of the

[2] ORBIS provides broader coverage within some countries but spans fewer economies overall. Moreover, the countries included in ORBIS tend to be relatively higher-income and less heterogeneous, and therefore exhibit limited variation in national characteristics. See Section 5.1 for details.

within-country wage markdown distribution, various revenue production function specifications and estimation methods, and controlling for other key country characteristics, like GDP per capita. We also replicate the analysis using the ORBIS dataset and find the same patterns among countries with sufficient coverage.

To explain these facts, we develop a simple oligopsonistic labor market model with frictions. In the model, firms compete *à la* Cournot for workers. Workers are heterogeneous in their self-employment abilities and choose whether to pursue self-employment or work for a wage. Because of labor market frictions, a subset of potential wage workers remains unemployed. For a given wage level, when the job-finding probability decreases, the expected value of wage employment falls, and more workers opt for self-employment. At the same time, workers on the margin between wage work and self-employment are highly responsive to changes in the wage paid, reducing firms' wage-setting power. When unemployment protection is available, the expected payoff from wage work includes an insurance component that makes workers less sensitive to wage changes—particularly when the job-finding rate is lower and self-employment prevalence is higher. Overall, and in line with our empirical findings, the share of self-employment correlates with the elasticity of labor supply to the wage paid and, consequently, with wage markdowns, with unemployment protection potentially reversing the sign of this relationship. Our theoretical and empirical analysis suggests that the hump-shaped relationship between labor market power and the self-employment share across countries is driven by labor supply-side mechanisms, particularly by how potential wage workers respond to wage changes. This behavior is shaped by the features of the labor market, namely the presence of frictions and the availability of unemployment protection.

This paper contributes to the growing literature on labor market power and its determinants. While seminal studies have examined the extent and consequences of employer wage-setting power in the United States and other high-income countries (see, e.g., Azar, Marinescu and Steinbaum 2022; Berger, Herkenhoff and Mongey 2022; Bassier, Dube and Naidu 2022; Yeh, Macaluso and Hershbein 2022), recent work has begun to measure labor market power in low- and middle-income countries such as Brazil (Felix, 2022; Galindo da Fonseca and Santarrosa, 2025), China (Pham, 2023; Brooks et al., 2021*b*), Colombia (Amodio and de Roux, 2024), Costa Rica (Méndez-Chacón and Van Patten, 2022; Alfaro-Ureña, Manelici and Vasquez, 2021), India (MacKenzie, 2021; Brooks et al., 2021*b*; Muralidharan, Niehaus and Sukhtankar, 2023), Indonesia (Brummund and Makowsky, 2024; Calí and Presidente, 2023), Mexico (Estefan et al., 2024), Peru (Amodio, Medina and Morlacco, 2025), and South Africa (Bassier, 2023). However, all of these are single-country studies that rely on different data sources and methodologies, limiting comparability across settings.[3]

[3]In a meta-analysis of 53 studies, Sokolova and Sorensen (2021) highlight methodological heterogeneity as a key

There are only a few papers that measure labor market power across countries, and they all rely on the WBES dataset. Armangué-Jubert, Guner and Ruggieri (2025) develop a general equilibrium model of imperfect labor market competition and calibrate it to five (artificial) representative economies at different income levels. Eslava, García-Marín and Messina (2025) and Amodio et al. (2025) both measure markdowns in a set of Latin American and Caribbean countries.

We make three main contributions. First, to our knowledge, this is the first paper to estimate labor market power in a truly global, cross-country setting, using harmonized firm-level data and a consistent empirical strategy across 82 low- and middle-income countries. This approach allows us to document several empirical regularities on the firm-level determinants of labor market power that hold across countries, as well as novel facts about the geographical distribution of labor market power. Second, we provide new evidence on the role of self-employment in shaping the extent and nature of labor market power across countries. Finally, we contribute to the literature by highlighting the importance of country-specific labor market frictions and regulations. In particular, we show how unemployment protection shapes the relationship between labor market power and self-employment, and we develop a simple oligopsonistic labor market model that explains our empirical findings.

The remainder of the paper is organized as follows. Section 2 describes the data. Section 3 outlines the methodology used to estimate wage markdowns. Section 4 presents preliminary results on firm-level correlates and basic cross-country patterns. Section 5 explores the relationship between labor market power and self-employment. Section 6 introduces a stylized theoretical model and presents empirical evidence in support of its mechanisms. Section 7 concludes.

2 Data

Our main data source is the World Bank Enterprise Survey (WBES), a harmonized dataset covering firms in 155 countries. The WBES provides internationally comparable establishment-level data that are nationally representative of privately owned firms with at least five employees operating in the formal (non-agricultural) sector.[4] Each wave of the survey follows a globally standardized methodology, making the WBES the only available source of truly comparable firm-level informa-

barrier to comparability. Moreover, while one could theoretically combine the datasets used in these country-specific studies, this approach is not feasible for the vast majority of the 82 countries in our sample, as nationally representative surveys suitable for computing wage markdowns simply do not exist for most of them.

[4]Firms in each country are interviewed face-to-face and selected using random sampling techniques with three levels of stratification to ensure representativeness across firm size (5–19 employees; 20–99 employees; and 100+ employees), sector (manufacturing, retail, and other services, with further sub-sectors in selected economies), and subnational region.

tion across countries. In terms of coverage, most countries in the sample are classified as low- or middle-income economies.

Although the original dataset is structured as a repeated cross-section, several firms are interviewed in multiple waves. This panel component is essential for estimating production functions (see Section 3). For this purpose, we rely on the Global Panel component of the WBES, which covers 91 countries between 2006 and 2019 and includes approximately 42,000 firm-year observations. These firms report data on total sales, employment, labor costs, capital (measured as the value of machinery), raw materials and intermediate inputs, operating sector, and a range of additional variables used in the analysis.[5] From this initial sample, we restrict our attention to firms in the manufacturing sector. The confidential version of the WBES dataset, to which we have access, includes information on each firm's geo-localization. We combine this information with a global map of sub-national administrative units, which we use to define local labor markets in each country. Online Appendix B provides further details on the dataset, and Appendix Table B.3 lists the countries, survey waves, and number of observations included in our final sample—that is, the manufacturing subset of the WBES Global Panel.

Potential concerns about representativeness are addressed in Section 5.1. First, we compare moments of the firm-size distribution in the sample for which estimated wage markdowns are available to those from the full Global Panel and from the Global Entrepreneurship Monitor (GEM; Poschke, 2018). Second, we use ORBIS (Bureau van Dijk)—a widely used firm-level dataset that contains detailed balance sheet information—as a complementary data source. While its cross-country coverage is narrower and more concentrated in higher-income economies, ORBIS provides rich within-country detail, particularly for larger firms. We use it to compute median wage markdowns and validate parts of our analysis, allowing us to assess the robustness of our results across data sources.

For all economies represented in our firm-level data, we collect a broad set of country-level correlates from three primary sources. From the World Bank, we obtain data on real GDP per capita across countries. Measures of self-employment prevalence, agricultural and manufacturing employment shares, and the share of informal employment come from the International Labour Organization (ILO). The availability of unemployment protection—defined as whether workers are eligible for any form of unemployment scheme after one year of continuous employment—comes from the World Bank's Employing Workers (WBEW) project. This dataset evaluates the flexibility of employment regulation, focusing on hiring practices, working hours, and the rules and costs related to redundancy. These schemes encompass a variety of measures, including income-security

[5] All monetary values are expressed in 2002 US dollars, using nominal exchange rates and inflation data from the IMF, Bank of Italy, World Bank, and OECD.

benefits (regardless of format), and may be supported by active labor market policies and employment services aimed at helping the unemployed find suitable work. Further details on the main variables used in the analysis are provided in Online Appendix B.

3 Estimating labor market power

We measure labor market power at the firm-year level by comparing a firm's marginal revenue product of labor (MRPL) to the wage it pays. This wage markdown captures the gap between a worker's value to the firm and their cost, and is therefore independent of the source of employer market power. Its origins trace back to Robinson's (1933) original formulation and have been the focus of recent empirical work on labor market power.

The WBES data directly report information on the wage bill and employment for each firm, from which we compute the average wage w_{it} paid by firm i in year t. The MRPL, however, is not directly observed and must be estimated. We begin by assuming a Cobb-Douglas revenue production function of the form:

$$\ln r_{it} = \alpha \ln n_{it} + \beta \ln k_{it} + \gamma \ln m_{it} + \omega_{it} + \varepsilon_{it} \tag{1}$$

where r_{it} denotes firm revenues or sales, and the inputs are labor n_{it}, capital k_{it}, and materials m_{it}. The term ω_{it} captures a combination of firm-level productivity differences and demand-side factors that affect output prices. The residual term ε_{it} reflects unobserved idiosyncratic revenue shocks, distributed as white noise. Since ω_{it} is observed by the firm but not by the econometrician, it raises well-known identification concerns in production function estimation.

Exploiting the panel dimension of our firm-level data, we estimate the parameters of the revenue production function in equation (1) using proxy-variable methods that are standard in the industrial organization literature (Levinsohn and Petrin, 2003; Ackerberg, Caves and Frazer, 2015). These methods rely on three key assumptions: (i) the term ω follows a first-order Markov process; (ii) ω is the only unobservable in the firm's input demand function; and (iii) the input demand function is invertible in ω. Together, these assumptions allow us to control for unobserved productivity and demand shocks and to estimate the production function parameters using additional moment conditions implied by the Markov process. We use materials as the proxy variable.

Our baseline approach follows Ackerberg, Caves and Frazer (2015), which applies most directly to a value-added production function or to a gross output specification with Leontief materials. We show below that our results are robust to alternative specifications, including a structural Cobb-

Douglas value-added function and a translog revenue production function. They are also robust to using the Levinsohn and Petrin (2003) method while maintaining the Cobb-Douglas specification.

One limitation of all these approaches is the assumption that the production function is identical across firms, differing only through a factor-neutral productivity term. To allow for greater flexibility, prior studies typically estimate equation (1) separately by industry, relying on rich datasets from one or two countries (see Pham, 2023; Brooks et al., 2021*b*; Yeh, Macaluso and Hershbein, 2022; Brummund and Makowsky, 2024 for analyses of China, India, the US, and Indonesia, respectively). Given the structure of the WBES—with smaller sample sizes within each country but broad cross-country coverage—we adopt a modified estimation strategy tailored to this setting.

Our aim is to estimate revenue production functions as narrowly as possible over groups of *similar* firms. The primary constraint to this goal is sample size. When a country has a sufficiently large sample, we estimate separate revenue production functions within 2-digit manufacturing industries at the country level. When the sample size is insufficient, we expand along the geographic dimension by grouping firms in the same industry located in nearby countries within the same world region.[6] This strategy rests on the assumption that firms in a given industry are more likely to share similar production technologies and demand conditions with firms in the same industry in nearby countries than with firms in other industries within the same country. Finally, if the regional sample remains too small for reliable estimation, we further expand the grouping to include all firms in that industry across the WBES sample. The choice of a minimum number of observations per industry-country cell is necessarily arbitrary; we use a threshold of 100 observations (following Huneeus, Koike-Mori and Martner 2024) but show robustness to a lower threshold of 50. Using this strategy, 44% of our wage markdown estimates are based on industry $\times$ country-level estimations, 52% on industry $\times$ region, and 4% on industry only.

Once the parameters of the revenue production function are estimated, we derive the marginal revenue product of labor (MRPL) as

$$mrpl_{it} = \frac{\partial r_{it}}{\partial n_{it}} = \alpha \frac{r_{it}}{n_{it}}. \tag{2}$$

We then compute the wage markdown as

$$\psi_{it} = \frac{mrpl_{it}}{w_{it}} = \alpha \left(\frac{w_{it} n_{it}}{r_{it}} \right)^{-1}, \tag{3}$$

where ψ_{it} is the firm-level wage markdown, equal to the ratio of the revenue–labor elasticity α to

[6] We use the six regions defined by the World Bank: Africa; East Asia and the Pacific; Europe and Central Asia; Latin America and the Caribbean; Middle East and North Africa; and South Asia.

the labor share of revenues.

Notice that if a firm also has market power in the product market, it may set a price of output above marginal cost. This price markup does not confound the wage markdown estimate obtained from equation (3), because α represents the revenue–labor elasticity (Pham, 2023). This is a reduced-form parameter that reflects both production and demand and is related to the physical output–labor elasticity α^y through the identity $\alpha = \alpha^y \mu_{it}^{-1}$, where μ_{it} is the price markup (De Loecker, 2011). An alternative approach in the literature is to estimate physical output–input elasticities, exploit the presence of a flexible input (typically materials) that is assumed not to be subject to monopsony forces, and infer the wage markdown by taking the ratio of ψ_{it} to its analogue for materials (Brooks et al., 2021*b*; Morlacco, 2020; Yeh, Macaluso and Hershbein, 2022; Estefan et al., 2024). However, this method requires estimating physical elasticities and relies on detailed price deflators—ideally at the firm level (Syverson, 2004; Calí and Presidente, 2023; de Roux et al., 2021)—which are generally unavailable for the countries and industries in our sample. Our approach, based on the revenue–labor elasticity in equation (3), addresses the markup issue under two key assumptions: (i) that markups are constant, as in standard horizontal product differentiation models (e.g., constant elasticity of substitution, CES); and (ii) that the unobserved productivity and demand shocks embedded in the ω term jointly satisfy the assumptions for production function estimation outlined above. Nonetheless, we show that our cross-country findings are robust to using the alternative approach based on the ratio of wage to material markdowns.[7]

4 Results

Before turning to the relationship between labor market power and self-employment, we begin by examining patterns in wage markdowns across firms and countries with different GDP per capita.

4.1 Firm-level wage markdowns

To validate our markdown estimates, we study their correlates at the firm level and compare them with previous results in the literature. Appendix Table A.1, Panel A, reports summary statistics

[7] Notice also that if the production function is Cobb–Douglas, one can measure differences in the wage markdown (relative to its analogue for materials) across firms within a given reference group by taking the ratio of the labor to the material share of revenues. This is the approach adopted by Amodio and Di Maio (2018) to measure input market distortions in Palestine, later recommended by Bond et al. (2021) and used by Brooks et al. (2021*a*) and Estefan et al. (2024). While suitable for comparing the wage markdown between firms—even over time—this method is not appropriate for cross-country comparisons, as the measure is relative to a reference group of firms with the same production technology (e.g., firms in the same industry and country).

for the estimated firm-level wage markdowns obtained using the methods described in the previous section. Using our preferred production function approach (Ackerberg, Caves and Frazer, 2015), we estimate markdowns for 13,205 firm-year observations, corresponding to 9,089 firms across 82 countries.[8] The median estimated wage markdown is 2.33, indicating that workers at the median firm receive roughly 43% of their marginal revenue product as wages. As discussed in Section 3, we construct alternative measures of the wage markdown using different revenue production function specifications—namely, a structural Cobb-Douglas in value-added form and a translog—alongside an alternative estimation method (Levinsohn and Petrin, 2003). The resulting median markdown values, reported in Table A.1, range from 1.75 to 5.06. The direction and magnitude of these differences are consistent with patterns documented in the literature. For example, both Pham (2023) and Brooks et al. (2021*b*) find that structural value-added specifications estimated using the Ackerberg, Caves and Frazer (2015) method yield substantially higher markdowns. As noted earlier, we use all these alternative measures throughout the analysis to assess the robustness of our results.

Table A.1 also reports descriptive statistics for several firm-level characteristics. The median firm employs 28 workers, is 18 years old, and pays an average annual real wage of USD 2,180 (in 2002 dollars). Foreign-owned firms account for 11% of the sample. The data span 932 distinct local labor markets and 1,207 country-sector cells. Approximately 18% of firms are located in the national capital, and 30% operate in cities with over one million inhabitants. A detailed discussion of the sample's representativeness is provided in Section 5.1.

Table 1 presents results from regressions of the log wage markdown on various firm-level characteristics.[9] Columns 1 and 2 show that, within sectors and local labor markets, firms with higher sales and employment exhibit significantly higher wage markdowns. A 10-percentage-point increase in sales (employment) is associated with a 2.2 (0.8) percentage-point increase in the markdown. Columns 3 and 4 indicate that markdowns are also higher among firms with greater sales per worker and those employing a larger share of local employment. In contrast, column 5 shows

[8]We exclude 9 countries from the initial set of 91 due to insufficient sample size (fewer than 30 firm observations with valid markdown estimates).

[9]Specifically, we estimate the following regression specification:

$$\ln \psi_{it} = \theta_{sc} + \gamma_{mc} + \delta_t + \beta X_{it} + u_{it}. \tag{4}$$

The dependent variable is the log of the wage markdown of firm i, located in local labor market m, operating in sector s in country c, and surveyed in year t. θ_{sc} denotes a set of sector $\times$ country fixed effects, capturing average differences across ISIC 2-digit sectors within and across countries. γ_{mc} denotes local labor market fixed effects, and δ_t year fixed effects. The variable X_{it} represents the firm-level characteristic of interest, while u_{it} captures residual variation in wage markdowns. Identification of local labor markets is made possible by access to the confidential version of the WBES, which includes geolocation data for surveyed firms. This allows us to define spatially disaggregated labor markets within countries and to control for local labor market conditions in the analysis.

Table 1: Labor market power and firm characteristics

	Log of Wage Markdown						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log of Sales	0.224***						
	(0.009)						
Log of Employment		0.079***					
		(0.011)					
Log of Sales per Worker			0.481***				
			(0.016)				
Log of Share of Local Empl.				0.068***			
				(0.010)			
Log of Wage					-0.299***		
					(0.019)		
Started Informal						-0.076**	
						(0.037)	
Foreign-Owned							0.265***
							(0.045)
Year FE	✓	✓	✓	✓	✓	✓	✓
Sector $\times$ Country FE	✓	✓	✓	✓	✓	✓	✓
Local Labor Market FE	✓	✓	✓	✓	✓	✓	✓
Observations	12300	12532	12299	12532	12270	12533	12483
R^2	0.545	0.455	0.629	0.454	0.497	0.449	0.453

Notes: OLS estimates. The unit of observation is a manufacturing firm in a year. The dependent variable is the log of the wage markdown. Sales and wages are measured in 2002 US dollars. Sector $\times$ country fixed effects correspond to dummies for each 2-digit ISIC Rev. 3.1 manufacturing sector within each country. All variables are defined in Tables B.1 and B.2. Standard errors (in parentheses) are clustered at the local labor market level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

that firms paying higher wages tend to exhibit lower markdowns: a 10-percentage-point increase in average wages is associated with a 3-percentage-point decline in the markdown. Column 6 reveals that firms with higher markdowns are also less likely to have started as informal enterprises. Finally, column 7 shows that foreign-owned firms exhibit greater labor market power than their domestic counterparts.[10] Appendix Table A.4 confirms the robustness of these patterns using alternative methods to estimate revenue input elasticities, including (i) a structural Cobb-Douglas value-added production function, (ii) a translog revenue production function, and (iii) the Levinsohn and Petrin (2003) method under a Cobb-Douglas specification.

Appendix Table A.5 reports variation in wage markdowns across ISIC 2-digit sectors, focusing on those with at least 500 firm-level observations. Firms in the food, chemicals, rubber and plastics, and machinery sectors consistently exhibit higher markdowns relative to others. By contrast, labor market power appears lower in textiles, apparel, and publishing and printing.

Taken together, these results suggest that labor market power tends to rise with firm size, consis-

[10] Appendix Table A.3 reports results from specifications including firm fixed effects, focusing on time-varying firm characteristics. The findings are broadly consistent with those in Table 1, with the exception of employment and local employment share, likely due to limited within-firm variation.

tent with predictions from oligopsonistic labor market models. The positive association between wage markdowns and sales per worker further indicates that distortions from labor market power increase with firm size, underscoring their potential to impair aggregate output through misallocation. Sectoral patterns support this interpretation: wage markdowns are higher in capital- and technology-intensive sectors—such as chemicals, machinery, and plastics—and lower in sectors like textiles, apparel, and publishing.[11] Although the production function approach has known limitations, the consistency of our firm-level correlates of labor market power with prior single-country studies (e.g., Alfaro-Ureña, Manelici and Vasquez, 2021, Amodio and de Roux, 2024, Estefan et al., 2024) and across alternative specifications suggests that our markdown estimates capture robust cross-firm and cross-sector patterns in labor market power.

4.2 Country-level wage markdowns

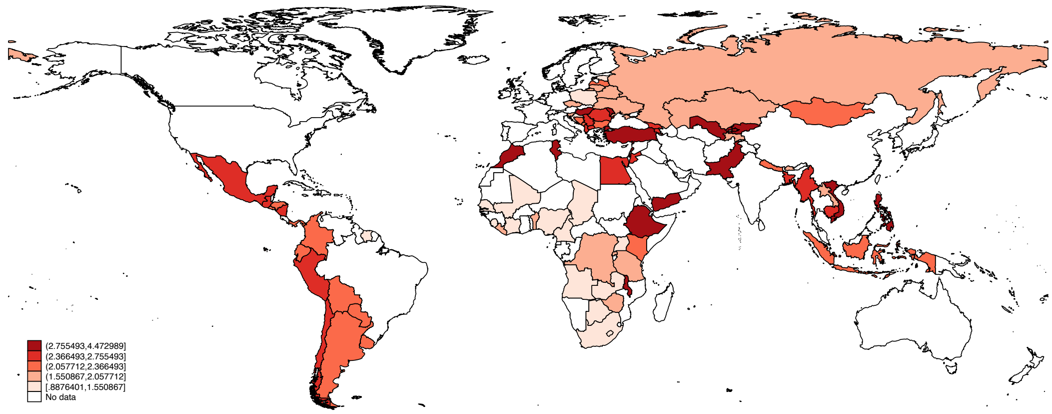
The main advantage of applying a consistent methodology to a globally harmonized dataset is that it provides a clearly comparable measurement of labor market power across countries. Appendix Table A.2 reports wage markdowns for each of the 82 countries in our sample, presenting key moments of the distribution along with the corresponding number of firm-year observations. Markdowns vary substantially both within and across countries. In many cases, the 25th percentile of the distribution implies that workers earn more than 90% of their marginal product—a pattern that also holds for the median firm in several African economies.

Appendix Table A.1, Panel B, presents summary statistics for the estimated country-level wage markdowns obtained using the different methods described in Section 3. For the 82 countries in our sample, the median markdown based on our preferred production function estimation method (Ackerberg, Caves and Frazer, 2015) is 2.27, with a standard deviation of 0.8. The same table also reports descriptives for the set of country-level variables used in our analysis. Across the 82 economies, the median real GDP per capita (in 2010 USD) is $2,885. The median share of self-employed workers is 48%, and the median unemployment rate is 6%. Unemployment protection is available in roughly one-third of these countries.

Figure 1 presents the global distribution of median wage markdowns across the 82 countries in our sample, shaded by quintiles. The geographic patterns indicate that labor market power is lowest in most of Africa, moderately high in Latin America, and highest in several countries in Eastern Europe and the Middle East. These patterns are broadly consistent with the firm-level markdown distributions by world region shown in Appendix Figure A.1: the distribution appears left-skewed

[11] In light of these results, Section 5.1 assesses the robustness of the relationship between country-level wage markdowns and self-employment by accounting for cross-country differences in sectoral and workforce composition.

Figure 1: Labor market power by country



Notes. The figure displays the distribution of median wage markdowns across countries, with shading by quintiles. Darker shades indicate greater labor market power.

in Africa and more right-skewed in Asia, with Latin America and Europe lying in between.[12]

Our wage markdown estimates are broadly in line with those reported in the literature. The overall median estimate is similar to that found by Felix (2022) for Brazil during the pre-1990 trade liberalization period, where the markdown was approximately 2. In Indonesia, we estimate a median markdown of 2.3, close to the 2.15 reported by Calí and Presidente (2023). For South Africa, our median markdown is 1.3, somewhat lower than the range implied by the separation-based labor supply elasticity estimates of Bassier (2023).[13] For Colombia and Peru, our estimated markdowns are higher than those implied by inverse labor supply elasticity estimates in Amodio and de Roux (2024) and Amodio, Medina and Morlacco (2025), respectively. However, the latter also show that in local labor markets characterized by high concentration and low self-employment rates, the wage share of MRPL can be as low as 57%. In Mexico, Estefan et al. (2024) estimate a median wage share of 80%, compared to the 42% we find. This discrepancy partly reflects differences in data coverage: their analysis relies on the economic census, which includes all formal firms—including single-person establishments—whereas the WBES is designed to be representative of employers, specifically firms with at least five employees. Interestingly, for many African firms and countries, we estimate wage markups rather than markdowns, with values below one. This implies that the marginal product of labor is somewhat lower than the wage paid. This finding is consistent with Macchi and Stalder (2025), who show that firms may continue to hire under such conditions for redistributive motives.

[12]The median wage markdown is 2.05 in Africa, 2.37 in Latin America, 2.55 in Europe, and 2.58 in Asia.

[13]The labor supply elasticity estimates in Bassier (2023) range from 1.3 to 1.6. As shown below in equation (6), the wage markdown equals one plus the inverse of the labor supply elasticity faced by the firm (Manning, 2003). The implied markdown for South Africa thus falls between $1 + (1.6)^{-1} = 1.64$ and $1 + (1.3)^{-1} = 1.77$.

Finally, we explore how labor market power varies across the development spectrum, using GDP per capita as a proxy. Appendix Figure A.2 plots the log of the median wage markdown against the log of GDP per capita, with the quadratic fit suggesting a mild hump-shaped relationship. While our results indicate a negative association between GDP per capita and wage markdowns across much of the income spectrum, this relationship reverses at very low income levels, where markdowns increase as income rises. The next section investigates whether the weak non-linear link with income per capita masks a stronger relationship with self-employment, a feature that varies systematically with economic development.

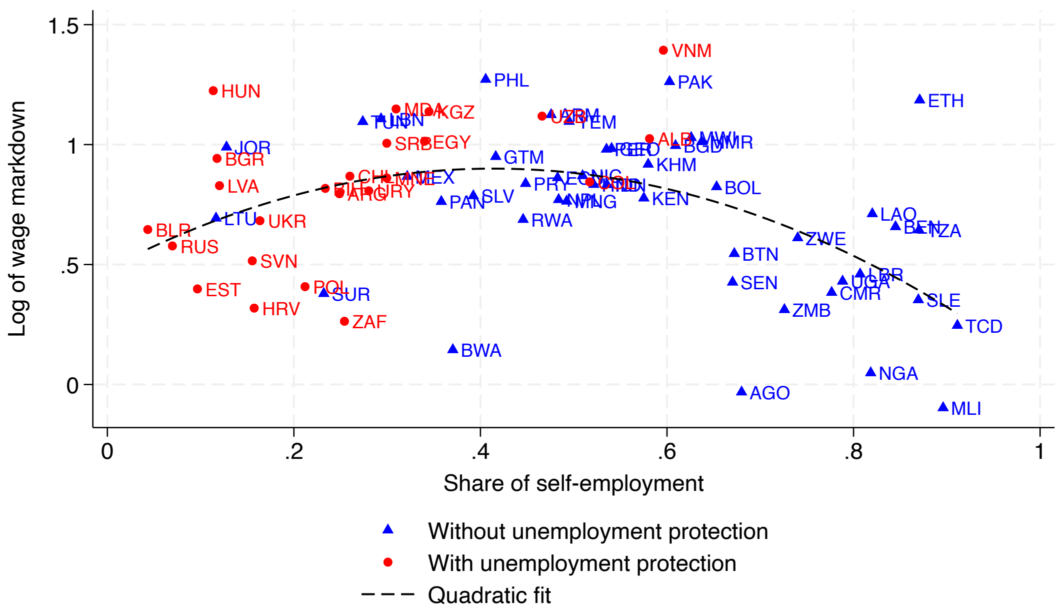
5 Self-employment and labor market power across countries

Labor markets differ significantly between low- and high-income countries. A key distinction is that in poorer countries, self-employment is more prevalent and protections against unemployment are limited (Breza and Kaur, 2025). As an alternative to wage employment, self-employment offers a readily available outside option for workers, which constrains firms' wage-setting power. This is consistent with Felix (2022), who show that in Brazil, firms in local labor markets with higher self-employment rates tend to face more elastic labor supply, and with Amodio, Medina and Morlacco (2025), who find that in Peru, wage-setting power rises with labor market concentration but less so where self-employment is more common. The mechanisms underlying these relationships are likely to depend on policies—such as employment protection legislation and unemployment benefits—that provide formal workers with a buffer against job loss and reduce the attractiveness of self-employment as an outside option. In this section, we examine the relationship between labor market power and self-employment at the global level, focusing on how it varies with the availability of unemployment protection.

Figure 2 presents evidence of a pronounced hump-shaped relationship between the (log) median wage markdown and the share of self-employment at the country level. Column 1 of Table 2 shows that this relationship is significant at the 1% level, with the quadratic specification explaining 24% of the cross-country variation in median wage markdowns. When both the self-employment share and the log of GDP per capita—along with their squared terms—are included in the regression (column 2), the self-employment variables remain highly significant. Moreover, column 3 shows that this effect goes above and beyond what can be accounted for by the unemployment rate. In low- and middle-income countries, (subsistence) self-employment often serves as a substitute for unemployment, and indeed, the two are strongly negatively correlated in the data.[14] Taken

[14] A simple regression of the unemployment rate on the self-employment share yields a coefficient of -0.094 with a

Figure 2: Labor market power, self-employment, and unemployment protection across countries



Notes. The figure plots the log of the median wage markdown against the share of self-employed workers across countries in our sample, along with a quadratic fit. Countries are classified according to whether unemployment protection is available after one year of continuous employment, based on national labor regulations.

together, the evidence suggests that—even after accounting for differences in GDP per capita and unemployment—the prevalence of self-employment remains a strong and non-linear correlate of labor market power: wage markdowns initially increase with the self-employment share, but then decline at higher levels.[15]

Figure 2 also shows that the availability of unemployment protection helps explain this pattern. Unemployment benefits provide formal workers with a buffer against job loss, reducing the attractiveness of self-employment as a fallback option or safety net. In countries where such protection is available (shown in red), self-employment is less prevalent and positively associated with labor market power. In contrast, where unemployment protection is absent (in blue), self-employment tends to be more widespread and negatively associated with wage markdowns. Columns 4–7 of Table 2 confirm that these relationships are robust and hold even after controlling for the unemployment rate.

t-statistic of -4.28.

[15]Equation (3) defines the wage markdown as the ratio between the MRPL and the wage paid. Appendix Figure A.3 shows that both the median MRPL and the median wage decrease as the self-employment share rises. The decline is initially faster for the wage paid, but then more rapid for the MRPL, which leads to the hump-shaped relationship illustrated in Figure 2.

Table 2: Labor market power, self-employment, and unemployment protection

	Log of Wage Markdown						
	All countries			With unemployment protection		Without unemployment protection	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Share of Self-Employment	2.022***	1.531**	2.076***	1.071***	1.118***	-0.700***	-0.933***
	(0.602)	(0.688)	(0.587)	(0.341)	(0.318)	(0.223)	(0.257)
Share of Self-Employment Sq.	-2.442***	-2.417***	-2.658***				
	(0.605)	(0.658)	(0.597)				
Log of GDP per capita		-0.111					
		(0.563)					
Log of GDP per capita Sq.		-0.002					
		(0.036)					
Unemployment Rate			-1.651**		-1.906**		-2.002*
			(0.754)		(0.906)		(1.165)
Observations	73	73	73	24	24	46	46
R^2	0.240	0.302	0.289	0.310	0.430	0.183	0.235

Notes. OLS estimates. The unit of observation is a country. The dependent variable is the log of the median wage markdown. Columns 5 and 6 restrict the sample to countries with unemployment protection, while columns 7 and 8 include only countries without unemployment protection. All variables are defined in Tables B.1 and B.2. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

5.1 Robustness

The hump-shaped relationship between wage markdowns and a country's self-employment share is robust to a range of checks, which we summarize below and report in Online Appendix A. We begin by examining alternative measures of wage markdowns and various subsamples. We then explore different methods for production function estimation and markdown computation. Finally, we address concerns related to sectoral and workforce composition, sample representativeness, and external validity using the ORBIS dataset.

5.1.1 Alternative wage markdown measures and sub-samples

Panel (a) of Appendix Figure A.4 shows that using the median wage markdown in levels, rather than logs, leaves the results in Figure 2 unchanged.[16] Panel (b) shows that the pattern also holds when using the (log of the) average wage markdown instead of the median. Panels (c) and (d) demonstrate that using the 25th or 75th percentile of the markdown distribution yields similar cross-country patterns. In Panels (e) and (f), we restrict the sample to countries with at least 50 and 100 firm-year observations, respectively. Despite the smaller sample, the hump-shaped relationship between wage markdowns and self-employment shares remains robust, suggesting that the results are not driven by variation in the number of observations used for estimation across countries.

To further address this concern, we examine the relationship between the (log) median wage markdown and the number of firm-level observations per country. Column 1 of Appendix Table A.7 shows no systematic correlation between the two. This result remains unchanged after controlling for all country-level covariates used in our analysis (columns 2–7). In addition, Appendix Table A.8 shows that the hump-shaped relationship between wage markdowns and self-employment prevalence persists when markdowns are estimated using a random 75% subsample of firm-level observations within each country, further confirming that our results are not driven by sample size variation.[17]

Next, we assess the robustness of our findings to alternative assumptions about the revenue production function and to different methods for estimating revenue-input elasticities. Appendix Figure A.5 plots the relationship between the (log) median wage markdown and self-employment shares under several specifications: a structural Cobb-Douglas value-added production function, a translog revenue production function, and the Levinsohn and Petrin (2003) estimation method

[16] This is confirmed by Appendix Table A.6, which closely mirrors Table 2.

[17] Specifically, we draw a random 75% subsample of firm-level observations within each country, estimate wage markdowns using this subsample, and compute the country-level median. We repeat this procedure 200 times and use the average of the resulting medians as the final estimate for each country.

applied to a Cobb-Douglas structure. We also vary the level of aggregation used to estimate the production function and consider an alternative markdown measure based on the ratio of wage to material markdowns. While these methodological choices affect the levels of estimated markdowns (see Table A.1), they do not materially alter the relationship between markdowns and self-employment shares across countries. Appendix Table A.9, which mirrors Table 2, reports the corresponding regression estimates using these alternative markdown measures and confirms the robustness of our main result.

5.1.2 Sectoral and workforce composition across countries

A potential concern with our findings is that the observed hump-shaped relationship between labor market power and the share of self-employment could be confounded by other country-level characteristics. While the self-employment share declines with GDP per capita, so does the share of agricultural employment, whereas the manufacturing employment share tends to rise—at least to some extent. The results in Appendix Table A.10 show that both agricultural and manufacturing employment shares are also correlated with labor market power in a non-linear way. Yet, when all three employment shares and their squared terms are included in the same regression, only the self-employment share remains statistically significant and accounts for most of the explanatory power. The same result holds when we consider the share of informal employment—which includes both informal self-employed and informal wage workers—as an alternative country-level variable. Although data limitations reduce the sample size in this case, the results confirm the distinct and dominant role of self-employment in shaping cross-country variation in labor market power, setting it apart from other structural employment characteristics.

Another potential concern is that the observed relationship may be driven by cross-country differences in sectoral composition within manufacturing. As discussed earlier and shown in Appendix Table A.5, wage markdowns vary systematically across ISIC 2-digit sectors. If the prevalence of certain sectors correlates with national self-employment rates, this could confound the relationship between self-employment and median wage markdowns at the country level. To address this, we regress firm-level (log) wage markdowns on the full set of 2-digit sector fixed effects and compute the country-level median of the resulting residuals. Appendix Figure A.6 plots these residual medians against self-employment shares and reveals the same hump-shaped pattern observed in our baseline results. This confirms that the relationship is not driven by differences in sectoral composition within manufacturing, reinforcing the central role of self-employment in shaping cross-country variation in employer wage-setting power.

An additional potential concern is that cross-country differences in workforce skill composition may be influencing our results. Firms in poorer countries—where self-employment rates are typically higher—also tend to employ less-skilled workers, which could be driving the hump-shaped relationship between wage markdowns and self-employment observed in Figure 2. To assess this possibility, Appendix Figure A.7 plots the log of the median wage markdown against the median share of unskilled workers across firms in each country, using data from the WBES. The two measures appear uncorrelated, suggesting that differences in workforce skill composition are unlikely to account for our main finding.

5.1.3 Representativeness and comparison with ORBIS

A further issue relates to the representativeness of our sample. In particular, the median firm in each country may differ from the median manufacturing employer in ways that systematically correlate with GDP per capita or the share of self-employment. Moreover, the final sample of firms with estimated wage markdowns may not be representative even of manufacturing employers with five or more employees. To examine this possibility, we compare our final sample to the full WBES Global Panel. In both datasets, we compute the share of manufacturing firms with fewer than 10 and fewer than 50 employees, and then take the ratio of these shares between the two samples. We regress these ratios on log GDP per capita and the share of self-employment across countries. Appendix Table A.11 shows that variation in the representation of small firms is unrelated to either GDP per capita or self-employment, allaying concerns that sample representativeness might be driving our results.[18]

Finally, we replicate our analysis using the ORBIS Global Company Database by Bureau van Dijk, a widely used firm-level dataset with broad coverage and a harmonized structure. Despite its nominal global reach, ORBIS exhibits substantial variation in data availability and quality across countries. Differences in national disclosure and filing requirements introduce systematic biases: the dataset tends to overrepresent older, larger, and foreign-owned firms, while SMEs and privately held domestic firms are often underrepresented—particularly where filing thresholds are high or reporting mandates weak. As a result, coverage is relatively strong in some European economies (see Kalemli-Özcan et al., 2024), but in many others, firm-level data are sparse or key variables—such as sector, revenues, employment, inputs, capital, and labor costs—are missing or incomplete. These limitations are especially pronounced in lower-income and emerging contexts. By contrast, the WBES is explicitly designed for representativeness, using stratified random sam-

[18] As an additional robustness check, we replicate this comparison using data from the Global Entrepreneurship Monitor (GEM; Poschke, 2018). While GEM data are available for only 33 countries in our sample, Appendix Table A.12 shows that the results are consistent: differences in the share of small firms between WBES and GEM are not systematically related to GDP per capita or the share of self-employment.

pling by firm size, sector, and location, making it better suited to capturing firm dynamics across a wide range of income levels and market structures.

Despite these limitations, we use ORBIS to complement our analysis and validate key empirical patterns. After applying data quality and sample size filters, we obtain a sample of only 36 countries suitable for estimation—less than half the size of the WBES sample, which covers 82 countries.[19] Of these, 16 overlap with the WBES sample. The correlation between median wage markdowns in the two datasets is approximately 52%, indicating broad consistency despite differences in sampling and coverage. As expected, median markdowns from ORBIS tend to be systematically higher, reflecting the dataset's overrepresentation of larger firms, which typically exhibit higher markdowns (see Appendix Figure A.8).

Using the full ORBIS sample, we also examine the relationship between labor market power and self-employment shares. In the WBES data, we documented a robust hump-shaped relationship, largely driven by cross-country differences in unemployment protection. Among the 36 countries in the ORBIS sample, however, only Pakistan lacks such protection, limiting our ability to test the full non-linear pattern. Nonetheless, as shown in Appendix Figure A.9, the ORBIS data reveal a clear positive relationship between markdowns and self-employment—consistent with the upward-sloping segment of the inverse-U pattern observed in the WBES sample.

6 A simple model

We have shown that labor market power exhibits a hump-shaped relationship with the share of self-employment across countries. In countries without unemployment protection, self-employment is more prevalent and correlates negatively with labor market power. The opposite holds where unemployment protection is in place: self-employment is less common and correlates positively with wage markdowns.

To interpret these findings, we develop a simple partial equilibrium model of an oligopsonistic labor market with frictions. The ease with which potential wage earners find jobs influences their choice between wage work and self-employment, and determines the elasticity of labor supply to the wage paid. In the model, the presence of unemployment protection mediates these relationships in a way that is consistent with the empirical patterns documented above.

[19] We restrict the ORBIS sample to countries with sufficiently populated variables and a large enough number of firm-level observations to support estimation.

6.1 Market structure and wage markdowns

Consider a finite number of firms that compete *à la* Cournot in the labor market. All firms pay the same unit wage w, and workers view them as perfect substitutes, giving rise to an oligopsonistic market structure. Each firm i chooses its employment level n_i to maximize profits:

$$\max_{n_i} \; r_i - wn_i \tag{5}$$

where r_i denotes firm revenues. The corresponding first-order condition is:

$$\frac{\partial r_i}{\partial n_i} = w\left(1 + \frac{\partial w}{\partial n_i}\frac{n_i}{w}\right) = w\psi_i \tag{6}$$

implying that the wage w is a markdown $\psi_i \geq 1$ below the MRPL. The wage markdown is exactly equal to one plus the inverse elasticity of the labor supply curve faced by the individual firm (Manning, 2003). When the labor supply to the firm is very elastic, the wage markdown is close to one. In this case, even a small decrease in the unit wage would drive all workers away, and firms set the wage equal to its competitive level. Conversely, when labor supply is less elastic, the wage markdown exceeds one, and firms pay workers less than their MRPL—that is, they exercise labor market power.

Let $n^w = \sum_i n_i$ be the aggregate labor supply in the wage employment sector. In equilibrium, and given the oligopsonistic labor market structure, the wage markdown is equal to:

$$\psi_i = 1 + \frac{\partial w}{\partial n_i}\frac{n_i}{w}\frac{\partial n^w}{n^w}\frac{n^w}{\partial n^w} = 1 + \frac{s_i}{\epsilon(w)} \tag{7}$$

where the second equality follows from $\partial n_i/\partial n^w = 1$. Here, $s_i \equiv n_i/n^w$ denotes firm i's share of total wage employment, and $\epsilon(w) \equiv \frac{\partial n^w}{\partial w} \cdot \frac{w}{n^w}$ is the elasticity of aggregate labor supply in the wage employment sector—i.e., the wage work supply elasticity. As such, s_i and $\epsilon(w)$ capture the demand- and supply-side determinants of labor market power, respectively (Amodio, Medina and Morlacco, 2025).

Let $\tilde{\psi}$ be the median of the wage markdown across firms in this economy. From equation (7) it follows that:

$$\ln(\tilde{\psi} - 1) = \ln \tilde{s} - \ln \epsilon(w) \tag{8}$$

which shows that the median wage markdown is uniquely determined by the median firm-level share of wage employment and the aggregate wage work supply elasticity.

6.2 Labor supply

Consider a measure-one continuum of workers. Each worker chooses whether to work for a wage or be self-employed, with the share of self-employment denoted by n^s. All workers are endowed with one efficiency unit of labor for use in the wage employment sector, but are heterogeneous in their endowment of efficiency units $a \in \mathbb{R}_+$ that can be used when self-employed. These values are independently drawn from a log-normal distribution, $\log a \sim \mathcal{N}(\mu, 1)$, and determine the productivity of the worker in the self-employment sector.

The wage employment labor market is frictional: potential wage workers find jobs with an exogenous probability $q < 1$, and unmatched workers remain unemployed. In the absence of unemployment benefits, the payoff from unemployment is zero. Let earnings from self-employment per efficiency unit be normalized to one. Given the relative wage w offered by firms, a given worker self-selects into wage work if and only if $qw \geq a$.

The (effective) aggregate labor supply in the wage employment sector is therefore equal to:

$$n^w = q\Phi(\log q + \log w - \mu) = q\Phi(c_u) \tag{9}$$

where $\Phi(\cdot)$ is the c.d.f. of the standard normal distribution and $c_u = \log q + \log w - \mu$. The elasticity of supply of wage work is:

$$\epsilon(w) = \frac{\partial \log n^w}{\partial \log w} = \frac{\phi(c_u)}{\Phi(c_u)} = \lambda(c_u) > 0 \tag{10}$$

where $\lambda(x) \equiv \frac{\phi(x)}{\Phi(x)} \geq 0$ is the inverse Mills ratio. Note that the share of unemployed workers is equal to $n^u = (1-q)\Phi(c_u)$, and that $n^w + n^u = 1 - n^s = \Phi(c_u)$ so that $c_u = \Phi^{-1}(1 - n^s)$.

To begin, let's hold fixed the number of operating firms and their employment shares, as well as the wage w. Consider a decrease in the wage job-finding rate q, which lowers c_u and increases n^s. Taking the derivative of $\epsilon(w)$ with respect to the self-employment share n^s we obtain:

$$\frac{\partial \epsilon(w)}{\partial n^s} = \lambda'(c_u)\frac{\partial c_u}{\partial n^s} = \lambda'(c_u)\frac{\partial \Phi^{-1}(1 - n^s)}{\partial n^s} > 0 \tag{11}$$

which implies that the aggregate elasticity of wage work increases with the share of self-employment n^s. It follows that the median wage markdown decreases when the share of self-employment increases.

This result is consistent with the negative relationship between the median wage markdown and self-employment in the descending part of the curve shown in Figure 2. It also aligns with the evidence in Amodio, Medina and Morlacco (2025) and Felix (2022) showing that firms in local labor markets with higher self-employment prevalence face more elastic labor supply curves. In other words, a large self-employment sector reduces the wage-setting power of firms.

6.3 Labor supply with unemployment protection

When unemployment protection is available, unemployed workers receive unemployment benefits equal to $b < w$. In this case, a worker self-selects into wage employment if and only if $qw + (1 - q)b \geq a$. The (effective) aggregate labor supply in the wage employment sector and its elasticity are given by:

$$\begin{aligned} n^w &= q\Phi\left(\log\left[b + q(w-b)\right] - \mu\right) = q\Phi(c_p) \\ \epsilon(w) &= \lambda(c_p)\frac{qw}{b + q(w-b)} = qw\lambda(c_p)e^{-(c_p+\mu)} > 0 \end{aligned} \tag{12}$$

with $c_p = \log\left[b + q(w-b)\right] - \mu$ and $1 - n^s = \Phi(c_p)$, so that $c_p = \Phi^{-1}(1 - n^s)$. Consider again a decrease in the wage job-finding rate q, which decreases c_p and increases n^s. Holding w and b constant, we can express the wage job-finding rate as a decreasing (inverse) function of the share of self-employment:

$$q(n^s) = \frac{e^{\Phi^{-1}(1-n^s)+\mu} - b}{w - b} \qquad q'(n^s) = \frac{e^{\Phi^{-1}(1-n^s)+\mu}}{w-b}\frac{\partial \Phi^{-1}(1-n^s)}{\partial n^s} < 0 \tag{13}$$

Taking the derivative of $\epsilon(w)$ with respect to n^s we get

$$\frac{\partial \epsilon(w)}{\partial n^s} = -\epsilon(w)\frac{\partial \Phi^{-1}(1-n^s)}{\partial n^s}\left(c_p + \lambda(c_p) + 1 - \frac{e^{\Phi^{-1}(1-n^s)+\mu}}{e^{\Phi^{-1}(1-n^s)+\mu} - b}\right) \tag{14}$$

where we substituted $\lambda'(x) = -x\lambda(x) - \lambda^2(x)$. The relationship between n^s and $\epsilon(w)$ is now ambiguous and can be negative. A decrease in the wage job-finding rate q makes workers both more willing to substitute self-employment for wage work and, given the availability of unemployment protection, less responsive to changes in the wage offered by firms. This is because, as q falls, the benefit component $(1-q)b$ increasingly dominates the expected payoff from wage work, making the wage w less salient in workers' decision-making. Indeed, equation (14) shows that the aggregate elasticity of wage work can decline—and the median wage markdown can rise—as the share of self-employment n^s increases. In other words, when unemployment protection is available, a larger self-employment sector may be associated with greater, rather than lesser, wage-setting power for employers. This is consistent with the positive relationship between the median wage markdown and self-employment observed in the left-hand side of Figure 2.

6.4 Labor demand

The previous discussion focuses on the supply side of the labor market, holding fixed the number of operating firms, their employment shares, and the wage paid. We now consider the opposite exercise: holding fixed the aggregate elasticity of wage work and focusing instead on changes in labor demand. From equation (8), it follows that in order to generate the hump-shaped relationship shown in Figure 2, the median firm-level share of wage employment $\tilde{s}$ must first increase and then decrease with the share of self-employment n^s. This occurs if changes in n^s are associated with shifts in the firm size distribution among wage-paying firms.

For instance, at low levels of n^s, an increase in self-employment may coincide with the exit of smaller firms, raising the median firm-level employment share and thus the median wage markdown. However, as n^s rises further, a growing share of self-employed workers may transition into becoming employers and begin hiring workers. This expansion at the bottom of the size distribution leads to the entry of smaller firms, thereby reducing the median firm-level employment share and lowering the median wage markdown. We examine this hypothesis empirically in the next section.

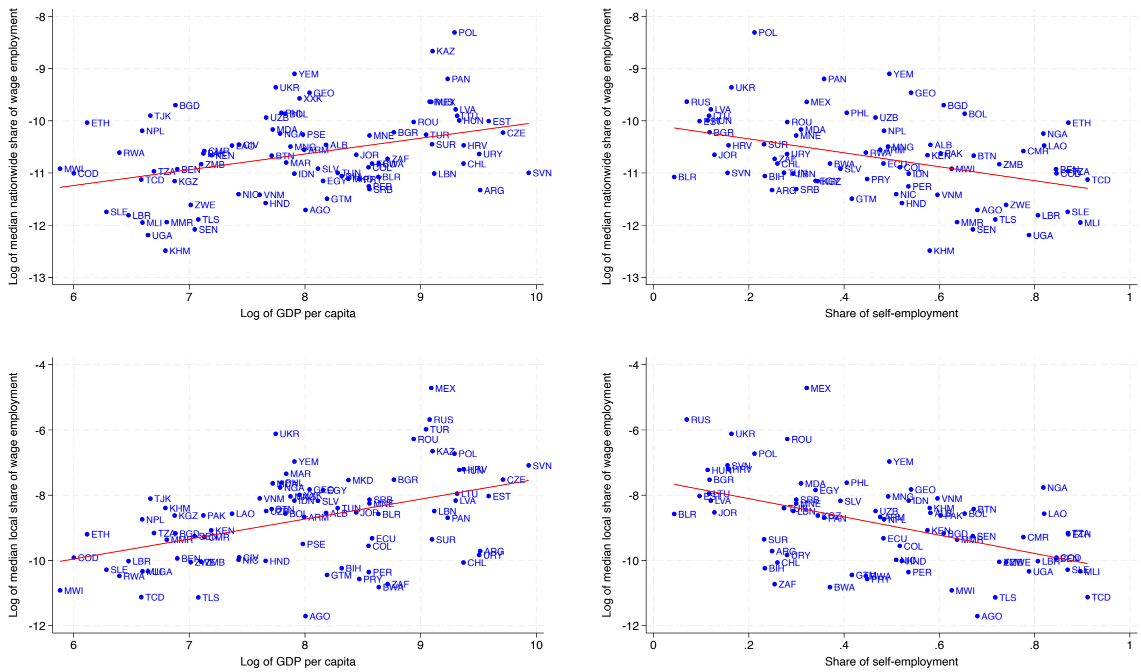
6.5 Additional evidence and discussion

In the partial equilibrium analyses above, we have deliberately examined the demand and supply sides of the labor market separately, exploring how changes on either side affect the median wage markdown while holding the other side—and prices—constant. This naturally raises the question of which of these scenarios is more empirically relevant.

To address this question, we build on the previous subsection and examine how the firm size distribution varies with GDP per capita and the share of self-employment. We focus in particular on the median firm-level share of wage employment in manufacturing, measured both at the national level and relative to a firm's local labor market. Figure 3 shows that the median wage employment share increases monotonically with GDP per capita and decreases monotonically with the self-employment share across countries. The regression results in Appendix Table A.13 confirm these patterns. They also show that, in a regression of a firm's wage employment share on both GDP per capita and self-employment, only the latter is statistically significant.

Taken together, our theoretical results and empirical findings suggest that changes in labor demand alone cannot account for the hump-shaped relationship between labor market power and the share of self-employment. Instead, changes on the supply side—in particular, the sensitivity of potential

Figure 3: Wage employment shares across countries



Notes. The left panels plot the log of the median firm-level national wage employment share (top) and the log of the median firm-level local wage employment share (bottom) against the log of GDP per capita across countries, along with the corresponding linear fit. The left panels plot the same variables against the national share of self-employment.

wage workers to the wage offered—play a central role in explaining our results.

7 Conclusion

A growing body of research has renewed interest in documenting the extent and nature of labor market power in the US and other high-income countries, but evidence from the rest of the world remains limited and fragmented. Labor markets in low- and middle-income countries have distinctive features, and studying labor market power in these settings requires alternative theoretical frameworks informed by new empirical facts.

To make progress, we leverage a global firm-level dataset and implement a consistent methodology to estimate labor market power for over 13,000 manufacturing firm observations across 82 countries. We show that the share of self-employment is a strong, non-linear predictor of labor market power across countries, and that the presence or absence of unemployment protection is central to understanding this relationship. Wage markdowns increase with the self-employment share in countries with unemployment protection, while the opposite holds in countries without it.

To interpret these findings, we present a simple oligopsonistic labor market model with frictions. Our analysis indicates that the hump-shaped relationship is mainly a supply-side phenomenon, reflecting how potential wage workers respond to wages and how this responsiveness varies with the availability of unemployment protection.

Our findings underscore the role of labor market frictions and regulations in shaping labor market outcomes in low- and middle-income countries. These factors influence wage markdowns in ways that affect the allocation of labor between wage work and self-employment, the distribution of wage employment across firms, and potentially firm selection at entry. Further research is needed to explore these mechanisms and quantify their implications for aggregate output, welfare, and income gap—both within and across countries.

References

Ackerberg, Daniel A., Kevin Caves, and Garth Frazer. 2015. "Identification Properties of Recent Production Function Estimators." *Econometrica*, 83(6): 2411–2451.

Alfaro-Ureña, Alonso, Isabela Manelici, and Jose P. Vasquez. 2021. "The Effects of Multinationals on Workers: Evidence from Costa Rican Microdata." *Mimeo*.

Amodio, Francesco, and Michele Di Maio. 2018. "Making Do With What You Have: Conflict, Input Misallocation and Firm Performance." *The Economic Journal*, 128(615): 2559–2612.

Amodio, Francesco, and Nicolás de Roux. 2024. "Measuring Labor Market Power in Developing Countries: Evidence from Colombian Plants." *Journal of Labor Economics*, 42(4): 949–977.

Amodio, Francesco, Emanuele Brancati, Nicolas De Roux, and Michele Di Maio. 2025. "Labor Market Institutions and Wage-Setting Power: Evidence from Latin America and the Caribbean." *CEPR Discussion Papers*, 20539.

Amodio, Francesco, Pamela Medina, and Monica Morlacco. 2025. "Labor Market Power, Self-Employment, and Development." *American Economic Review*, forthcoming.

Armangué-Jubert, Tristany, Nezih Guner, and Alessandro Ruggieri. 2025. "Labor market power and development." *American Economic Review: Insights*, 7(2): 177–195.

Azar, José, Ioana Marinescu, and Marshall Steinbaum. 2022. "Labor Market Concentration." *Journal of Human Resources*, 57(S): 167–199.

Azar, José, Steven T Berry, and Ioana Marinescu. 2022. "Estimating Labor Market Power." *NBER Working Paper*, 30365.

Bassier, Ihsaan. 2023. "Firms and inequality when unemployment is high." *Journal of Development Economics*, 161: 103029.

Bassier, Ihsaan, Arindrajit Dube, and Suresh Naidu. 2022. "Monopsony in Movers: The Elasticity of Labor Supply to Firm Wage Policies." *Journal of Human Resources*, 57(S): 50–86.

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

Berger, David W., Kyle F. Herkenhoff, Andreas R. Kostøl, and Simon Mongey. 2023. "An Anatomy of Monopsony: Search Frictions, Amenities, and Bargaining in Concentrated Markets." *NBER Macroeconomics Annual*, 38.

Bond, Steve, Arshia Hashemi, Greg Kaplan, and Piotr Zoch. 2021. “Some unpleasant markup arithmetic: Production function elasticities and their estimation from production data.” *Journal of Monetary Economics*, 121(C): 1–14.

Breza, Emily, and Supreet Kaur. 2025. “Labor Markets in Developing Countries.” *Annual Review of Economics*, 17.

Brooks, Wyatt J., Joseph P. Kaboski, Illenin O. Kondo, Yao Amber Li, and Wei Qian. 2021*a*. “Infrastructure Investment and Labor Monopsony Power.” *IMF Economic Review*, 69(3): 470–504.

Brooks, Wyatt J., Joseph P. Kaboski, Yao Amber Li, and Wei Qian. 2021*b*. “Exploitation of labor? Classical monopsony power and labor’s share.” *Journal of Development Economics*, 150: 102627.

Brummund, Peter, and Michael D. Makowsky. 2024. “Monopsony and Local Religious Clubs: Evidence from Indonesia.” *IZA Discussion Papers*, 16999.

Calí, Massimiliano, and Giorgio Presidente. 2023. “Product Market Monopolies and Labor Market Monopsonies.” *World Bank Policy Research Working Paper*, 10388.

De Loecker, Jan. 2011. “Product Differentiation, Multiproduct Firms, and Estimating the Impact of Trade Liberalization on Productivity.” *Econometrica*, 79(5): 1407–1451.

de Roux, Nicolás, Marcela Eslava, Santiago Franco, and Eric Verhoogen. 2021. “Estimating production functions in differentiated-product industries with quantity information and external instruments.” *NBER Working Paper*, 28323.

Donovan, Kevin, Will Jianyu Lu, and Todd Schoellman. 2023. “Labor Market Dynamics and Development.” *The Quarterly Journal of Economics*, 138(4): 2287 – 2325.

Eslava, Marcela, Alvaro García-Marín, and Julián Messina. 2025. “Inequality and market power in Latin America and the Caribbean.” *Oxford Open Economics*, 4(Supplement 1): i416–i425.

Estefan, Alejandro, Roberto Gerhard, Joseph P. Kaboski, Illenin O. Kondo, and Wei Qian. 2024. “Outsourcing Policy and Worker Outcomes: Causal Evidence from a Mexican Ban.” *NBER Working Paper*, 32024.

Felix, Mayara. 2022. “Trade, Labor Market Concentration, and Wages.” Mimeo.

Galindo da Fonseca, João, and Rogerio Santarrosa. 2025. "Identifying Labor Market Power: A Quasi-Experimental Approach." *Inter-American Development Bank, IDB Working Paper*, 1681.

Gollin, Douglas. 2008. "Nobody's business but my own: Self-employment and small enterprise in economic development." *Journal of Monetary Economics*, 55(2): 219 – 233.

Huneeus, Federico, Yasutaka Koike-Mori, and Antonio Martner. 2024. "Growth Accounting in Open Economies with Distortions." *Mimeo*.

Kalemli-Özcan, Şebnem, Bent E Sørensen, Carolina Villegas-Sanchez, Vadym Volosovych, and Sevcan Yeşiltaş. 2024. "How to construct nationally representative firm-level data from the ORBIS global database: New facts on SMEs and aggregate implications for industry concentration." *American Economic Journal: Macroeconomics*, 16(2): 353–374.

Levinsohn, James, and Amil Petrin. 2003. "Estimating Production Functions Using Inputs to Control for Unobservables." *The Review of Economic Studies*, 70(2): 317–341.

Macchi, Elisa, and Jeremia Stalder. 2025. "Informal Redistribution Through Work." *Mimeo*.

MacKenzie, Gaelan. 2021. "Trade and Market Power in Product and Labor Markets." *Bank of Canada Working Papers*, 21-17.

Manning, Alan. 2003. *Monopsony in Motion: Imperfect Competition in Labor Markets.* Princeton University Press.

Méndez-Chacón, Esteban, and Diana Van Patten. 2022. "Multinationals, Monopsony and Local Development: Evidence from the United Fruit Company." *Econometrica*, 90(6): 2685–2721.

Morlacco, Monica. 2020. "Market Power in Input Markets: Theory and Evidence from French Manufacturing." *Mimeo*.

Muralidharan, Karthik, Paul Niehaus, and Sandip Sukhtankar. 2023. "General Equilibrium Effects of (Improving) Public Employment Programs: Experimental Evidence From India." *Econometrica*, 91(4): 1261–1295.

Pham, Hoang. 2023. "Trade reform, oligopsony, and labor market distortion: Theory and evidence." *Journal of International Economics*, 144: 103787.

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

Poschke, Markus. 2025. "Wage employment, unemployment and self-employment across countries." *Journal of Monetary Economics*, 149: 103684.

Robinson, Joan. 1933. *The Economics of Imperfect Competition.* Macmillan, London UK.

Rud, Juan Pablo, and Ija Trapeznikova. 2021. "Job creation and wages in least developed countries: Evidence from Sub-Saharan Africa." *The Economic Journal*, 131(635): 1331–1364.

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

Syverson, Chad. 2004. "Market Structure and Productivity: A Concrete Example." *Journal of Political Economy*, 112(6): 1181–1222.

Yeh, Chen, Claudia Macaluso, and Brad Hershbein. 2022. "Monopsony in the US Labor Market." *American Economic Review*, 112(7): 2099–2138.

Online Appendix

A Additional tables and figures

Table A.1: Summary statistics

Variable	Obs.	Mean	Median	St. Dev.
Firm-Level Variables				
Wage Markdown				
– Cobb-Douglas, ACF (Baseline)	13205	5.769	2.332	13.467
– Cobb-Douglas Struct. Value Added, ACF	13205	13.693	5.059	34.207
– Translog, ACF	11859	4.247	1.746	15.137
– Cobb-Douglas, LP	13205	4.398	1.804	9.934
Employment	13203	123.654	28	366.390
Log of Employment	13203	3.541	3.332	1.456
Sales	12967	3781622	446782	1.08×10^{7}
Log of Sales	12967	12.968	13.010	2.313
Sales per Worker	12965	43240	14604	202642
Log of Sales per Worker	12965	9.443	9.589	1.658
Wage	12937	4157	2180	5519
Log of Wage	12937	7.541	7.687	1.490
Share of Local Empl.	13203	0.003	0.000	0.013
Share of Unskilled Workers	11696	0.298	0.2	0.316
Age	13123	22.405	18	18.458
Started Informal	13205	0.111	0	0.314
Located in >1 Million City	13205	0.299	0	0.458
Located in Capital	13205	0.176	0	0.381
Foreign-Owned	13154	0.110	0	0.313
Sectors and Local Labor Markets				
ISIC 2-digit Sector $\times$ Countries	1207			
Local Labor Markets	932			
Country-Level Variables				
Median Wage Markdown				
– Cobb-Douglas, ACF (Baseline)	82	2.304	2.272	0.800
– Cobb-Douglas Struct. Value Added, ACF	82	5.065	4.868	1.615
– Translog, ACF	82	1.683	1.642	0.851
– Cobb-Douglas, LP	82	1.756	1.775	0.739
– Labor/Materials Markdown, ACF	82	1.358	1.309	0.681
Obs. per Country	82	161.037	104	189.326
GDP per Capita	82	4569	2886	4347
Share of Self-Employment	73	0.472	0.483	0.243
Share of Agricultural Employment	76	0.311	0.288	0.194
Share of Manufacturing Employment	76	0.108	0.107	0.050
Share of Informal Employment	56	0.709	0.791	0.207
Unemployment Rate	76	0.072	0.061	0.049
Unemployment Protection	77	0.351	0	0.480

Notes. The table reports summary statistics for the variables used in the empirical analysis, presented at the firm-year and country levels. Sales and wages are expressed in 2002 US dollars.

Table A.2: Wage markdown distribution across countries

Country Code	Country Name	Observations	p25	p50	p75
ALB	Albania	43	1.10	2.79	7.37
AGO	Angola	92	0.65	0.97	1.43
ARG	Argentina	560	1.38	2.21	3.72
ARM	Armenia	51	1.58	3.08	8.32
BGD	Bangladesh	206	1.59	2.71	4.65
BLR	Belarus	95	1.16	1.91	3.39
BEN	Benin	47	1.13	1.93	3.76
BTN	Bhutan	86	1.07	1.73	4.38
BOL	Bolivia	101	1.28	2.28	4.93
BIH	Bosnia and Herzegovina	76	1.48	2.26	3.76
BWA	Botswana	81	0.70	1.16	2.05
BGR	Bulgaria	51	1.03	2.57	4.85
KHM	Cambodia	46	1.16	2.50	6.39
CMR	Cameroon	55	0.90	1.47	2.95
TCD	Chad	54	0.82	1.28	2.48
CHL	Chile	469	1.58	2.38	3.60
COL	Colombia	573	1.51	2.33	3.89
HRV	Croatia	48	1.01	1.37	2.14
CZE	Czech Republic	54	1.21	2.09	4.30
CIV	Côte d'Ivoire	68	0.29	0.89	2.16
COD	DRC	107	1.09	1.95	4.46
ECU	Ecuador	126	1.48	2.37	4.39
EGY	Egypt	1403	1.47	2.76	6.62
SLV	ElSalvador	187	1.29	2.20	4.30
EST	Estonia	54	0.96	1.49	3.44
ETH	Ethiopia	156	1.19	3.27	6.47
GEO	Georgia	54	1.15	2.67	4.69
GTM	Guatemala	386	1.54	2.59	4.43
HND	Honduras	120	1.20	2.30	5.37
HUN	Hungary	45	1.58	3.40	6.62
IDN	Indonesia	531	1.30	2.30	6.29
JOR	Jordan	87	1.56	2.69	5.51
KAZ	Kazakhstan	34	1.45	1.99	5.52
KEN	Kenya	301	1.04	2.18	4.79
XXK	Kosovo	35	2.21	4.60	8.32
KGZ	Kyrgyz Republic	59	1.85	3.12	7.11
LAO	LaoPDR	103	1.26	2.04	3.83
LVA	Latvia	44	1.06	2.29	3.66
LBN	Lebanon	155	1.71	3.03	5.73
LBR	Liberia	48	0.16	1.58	6.11
LTU	Lithuania	54	0.70	1.78	3.17
MWI	Malawi	54	1.00	2.80	5.38
MLI	Mali	149	0.08	0.91	2.95
MEX	Mexico	257	1.32	2.38	4.50
MDA	Moldova	77	1.41	3.15	4.94
MNG	Mongolia	112	1.20	2.15	3.02
MNE	Montenegro	43	1.26	2.37	5.11
MAR	Morocco	79	1.91	3.73	8.27
MMR	Myanmar	236	1.56	2.75	5.09
NPL	Nepal	164	1.20	2.16	5.49
NIC	Nicaragua	203	1.31	2.39	4.85
NGA	Nigeria	239	0.52	1.05	2.62
MKD	North Macedonia	120	1.20	2.49	5.53
PAK	Pakistan	135	1.76	3.53	10.39
PAN	Panama	42	0.96	2.14	3.54
PRY	Paraguay	126	1.37	2.31	4.57
PER	Peru	476	1.59	2.67	4.36
PHL	Philippines	182	2.07	3.57	8.58
POL	Poland	31	0.83	1.50	4.12
ROU	Romania	86	1.33	2.58	7.86
RUS	Russia	256	1.03	1.78	3.39
RWA	Rwanda	92	0.96	1.99	5.89
SEN	Senegal	188	0.95	1.53	3.00
SRB	Serbia	116	1.60	2.73	5.59
SLE	Sierra Leone	35	0.48	1.42	10.40
SVN	Slovenia	88	1.22	1.67	2.35
ZAF	SouthAfrica	173	0.76	1.30	2.48
SUR	Suriname	37	1.11	1.46	1.94
TJK	Tajikistan	31	1.21	2.10	6.22
TZA	Tanzania	155	0.88	1.90	4.40
TLS	Timor-Leste	104	0.73	1.11	2.64
TUN	Tunisia	150	1.42	2.99	6.79
TUR	Türkiye	468	2.41	4.29	8.04
UGA	Uganda	151	0.87	1.54	3.23
UKR	Ukraine	140	1.07	1.98	4.04
URY	Uruguay	189	1.30	2.24	3.66
UZB	Uzbekistan	108	1.58	3.06	6.47
VNM	Vietnam	272	2.04	4.03	10.37
PSE	West Bank And Gaza	62	2.19	4.47	11.56
YEM	Yemen	59	1.49	2.99	6.89
ZMB	Zambia	248	0.78	1.37	2.82
ZWE	Zimbabwe	327	0.82	1.84	3.67

Notes. The table reports the number of firm-year observations for each country, along with the 25th, 50th (median), and 75th percentiles of the wage markdown distribution (Ackerberg, Caves and Frazer, 2015) within each country.

Table A.3: Labor market power and firm characteristics — Exploiting variation within firms over time

	Log of Wage Markdown									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log of Sales	0.224***	0.370***								
	(0.009)	(0.023)								
Log of Employment			0.079***	0.025						
			(0.010)	(0.033)						
Log of Sales per Worker					0.481***	0.440***				
					(0.016)	(0.027)				
Log of Share of Local Empl.							0.068***	0.011		
							(0.009)	(0.022)		
Log of Wage									-0.299***	-0.421***
									(0.019)	(0.039)
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Sector × Country FE	✓		✓		✓		✓		✓	
Local Labor Market FE	✓		✓		✓		✓		✓	
Firm FE		✓		✓		✓		✓		✓
Observations	12,300	7,695	12,532	7,957	12,299	7,693	12,532	7,957	12,270	7,674
R^2	0.545	0.729	0.455	0.671	0.629	0.740	0.454	0.671	0.497	0.724

Notes: OLS estimates. The unit of observation is a manufacturing firm in a year. The dependent variable is the log of the wage markdown. Sales and wages are in 2002 US dollars. Sector × country fixed effects correspond to dummies for each 2-digit ISIC Rev. 3.1 manufacturing sector within each country. All variables are defined in Tables B.1 and B.2. Standard errors (in parentheses) are clustered at the local labor market level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.4: Labor market power and firm characteristics —
Robustness to alternative production function specifications and estimation methods

	Log of Wage Markdown						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A: Cobb-Douglas Structural Value Added – Ackerberg, Caves and Frazer (2015)						
Log of Sales	0.225*** (0.009)						
Log of Employment		0.079*** (0.011)					
Log of Sales Per Worker			0.481*** (0.016)				
Log of Share of Local Empl.				0.068*** (0.010)			
Log of Wage					-0.301*** (0.019)		
Started Informal						-0.081** (0.037)	
Foreign-Owned							0.267*** (0.046)
	Panel B: Translog – Ackerberg, Caves and Frazer (2015)						
Log of Sales	0.158*** (0.017)						
Log of Employment		0.053*** (0.020)					
Log of Sales Per Worker			0.368*** (0.021)				
Log of Share of Local Empl.				0.049*** (0.018)			
Log of Wage					-0.418*** (0.025)		
Started Informal						-0.050 (0.049)	
Foreign-Owned							0.188*** (0.055)
	Panel C: Cobb-Douglas – Levinsohn and Petrin (2003)						
Log of Sales	0.225*** (0.009)						
Log of Employment		0.079*** (0.010)					
Log of Sales per Worker			0.481*** (0.016)				
Log of Share of Local Empl.				0.068*** (0.010)			
Log of Wage					-0.301*** (0.019)		
Started Informal						-0.081** (0.037)	
Foreign-Owned							0.267*** (0.045)
Year FE	✓	✓	✓	✓	✓	✓	✓
Sector × Country FE	✓	✓	✓	✓	✓	✓	✓
Local Labor Market FE	✓	✓	✓	✓	✓	✓	✓

Notes: OLS estimates. The unit of observation is a manufacturing firm in a year. The dependent variable is the log of the wage markdown, estimated using revenue-input elasticities obtained through the different methods specified in the panel headings. Sales and wages are measured in 2002 US dollars. Sector × country fixed effects refer to dummies for each 2-digit ISIC Rev. 3.1 manufacturing sector within each country. All variables are defined in Tables B.1 and B.2. Standard errors (in parentheses) are clustered at the local labor market level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.5: Labor market power across sectors

	Log of Wage Markdown									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Food	0.291***									
	(0.036)									
Textile		-0.282***								
		(0.042)								
Apparel			-0.850***							
			(0.151)							
Publishing & Printing				-0.314***						
				(0.066)						
Chemicals					0.216***					
					(0.034)					
Rubber and Plastic						0.137***				
						(0.047)				
Non-Metallic Mineral Products							-0.057			
							(0.051)			
Metal Products								0.058		
								(0.046)		
Machinery & Equipment									0.139***	
									(0.051)	
Furniture										0.102
										(0.074)
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Country FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Local Labor Market FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	12,972	12,972	12,972	12,972	12,972	12,972	12,972	12,972	12,972	12,972
R^2	0.190	0.185	0.230	0.184	0.184	0.182	0.182	0.182	0.182	0.182

Notes: OLS estimates. The unit of observation is a manufacturing firm in a year. The dependent variable is the log of the wage markdown. Each independent variable is a dummy equal to one if the firm operates in the corresponding 2-digit ISIC Rev. 3.1 sector. All variables are defined in Tables B.1 and B.2. Standard errors (in parentheses) are clustered at the local labor market level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.6: Labor market power, self-employment, and unemployment protection — Wage markdowns in levels

	Wage Markdown						
	All countries			With unemployment protection		Without unemployment protection	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Share of Self-Employment	4.189***	3.035**	4.287***	2.585***	2.699***	-1.301***	-1.633***
	(1.262)	(1.448)	(1.241)	(0.772)	(0.706)	(0.447)	(0.523)
Share of Self-Employment Sq.	-4.927***	-4.706***	-5.319***				
	(1.268)	(1.385)	(1.263)				
Log of GDP per Capita		0.104					
		(1.184)					
Log of GDP per Capita Sq.		-0.024					
		(0.075)					
Unemployment Rate			-2.995*		-4.689**		-2.855
			(1.595)		(2.014)		(2.375)
Observations	73	73	73	24	24	46	46
R^2	0.212	0.271	0.251	0.338	0.473	0.162	0.189

Notes: OLS estimates. The unit of observation is a country. The dependent variable is the median wage markdown. Columns 5 and 6 include only countries with unemployment protection, while columns 7 and 8 include only those without it. All variables are defined in Tables B.1 and B.2. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.7: Wage markdowns and number of observations per country

	Log of Wage Markdown						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log of Number of Observations	0.049 (0.049)	0.064 (0.047)	0.048 (0.049)	0.050 (0.047)	0.051 (0.046)	0.048 (0.045)	0.065 (0.051)
Share of Self-Employment		-0.357** (0.155)					
Log of GDP per Capita			0.030 (0.040)				
Unemployment Rate				0.042 (0.778)			
Share of Agricultural Empl.					-0.298 (0.194)		
Share of Manufacturing Empl.						1.856** (0.727)	
Share of Informal Empl.							-0.430** (0.204)
Observations	82	73	82	76	76	76	56
R^2	0.012	0.087	0.019	0.015	0.046	0.096	0.106

Notes: OLS estimates. The unit of observation is a country. The dependent variable is the log of median wage markdown in each country. All variables are defined in Tables B.1 and B.2. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.8: Labor market power and share of self-employment —
Robustness to alternative sample sizes

	Log of Wage Markdown					
	All countries		With unemployment protection		Without unemployment protection	
	(1)	(2)	(3)	(4)	(5)	(6)
Share of Self-Employment	1.978***	2.018***	1.005***	1.042***	-0.524**	-0.667**
	(0.564)	(0.550)	(0.300)	(0.249)	(0.215)	(0.253)
Share of Self-Employment Sq.	-2.258***	-2.442***				
	(0.571)	(0.564)				
Unemployment Rate		-1.532**		-2.392***		-1.231
		(0.726)		(0.751)		(1.146)
Observations	68	68	22	22	46	46
R^2	0.212	0.263	0.359	0.582	0.119	0.142

Notes: OLS estimates. The unit of observation is a country. The dependent variable is the log of the average median wage markdown in each country. To construct this variable, we repeatedly draw random subsamples of 75% of firm-level observations within each country, estimate wage markdowns for each subsample, compute the country-level median, and average the resulting medians over 200 repetitions. Columns 3 and 4 restrict the sample to countries with unemployment protection, while columns 5 and 6 restrict the sample to those without it. All variables are defined in Tables B.1 and B.2. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.9: Labor market power, self-employment, and unemployment protection — Robustness to alternative production function specifications and estimation methods

	Log of Wage Markdown						
				Unempl. Protection		No Unempl. Protection	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A: Cobb-Douglas Structural Value Added – Ackerberg, Caves and Frazer (2015)						
Share of Self-Employment	1.698***	1.324*	1.756***	1.109***	1.147***	-0.526**	-0.845***
	(0.594)	(0.674)	(0.575)	(0.310)	(0.294)	(0.223)	(0.249)
Share of Self-Employment Sq.	-1.941***	-2.046***	-2.173***				
	(0.596)	(0.645)	(0.585)				
Log of GDP per Capita		-0.363					
		(0.552)					
Log of GDP per Capita Sq.		0.014					
		(0.035)					
Unemployment Rate			-1.770**		-1.566*		-2.748**
			(0.739)		(0.839)		(1.130)
	Panel B: Translog – Ackerberg, Caves and Frazer (2015)						
Share of Self-Employment	2.642**	2.169	2.799**	1.400***	1.467***	-0.714	-1.508***
	(1.206)	(1.430)	(1.145)	(0.489)	(0.455)	(0.493)	(0.537)
Share of Self-Employment Sq.	-3.227***	-2.742**	-3.808***				
	(1.210)	(1.366)	(1.164)				
Log of GDP per Capita		0.938					
		(1.175)					
Log of GDP per Capita Sq.		-0.059					
		(0.074)					
Unemployment Rate			-4.355***		-2.761**		-6.885***
			(1.471)		(1.297)		(2.443)
	Panel C: Cobb-Douglas – Levinsohn and Petrin (2003)						
Share of Self-Employment	2.148***	1.716*	2.220***	0.869**	0.920***	-1.315***	-1.678***
	(0.764)	(0.903)	(0.742)	(0.331)	(0.300)	(0.306)	(0.349)
Share of Self-Employment Sq.	-3.078***	-2.894***	-3.367***				
	(0.768)	(0.864)	(0.755)				
Log of GDP per Capita		0.266					
		(0.739)					
Log of GDP per Capita Sq.		-0.021					
		(0.047)					
Unemployment Rate			-2.210**		-2.093**		-3.123*
			(0.953)		(0.855)		(1.581)

Notes: OLS estimates. The unit of observation is a country. The dependent variable is the log of median wage markdown in each country obtained upon estimating revenue-input elasticities using the different methods specified in the panel headings. The sample in columns 5 and 6 consists of countries with unemployment protection. The sample in columns 7 and 8 consists of countries without unemployment protection. All variables are defined in Tables B.1 and B.2. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.10: Labor market power, self-employment, and agriculture, manufacturing, and informal employment shares

	Log of Wage Markdown						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Share of Self-Employment	2.022***		1.664*		2.111***		2.096*
	(0.602)		(0.912)		(0.650)		(1.217)
Share of Self-Employment Sq.	-2.442***		-2.401***		-2.247***		-2.219**
	(0.605)		(0.832)		(0.637)		(1.040)
Share of Agricultural Empl.		1.295*	0.590				
		(0.707)	(1.074)				
Share of Agricultural Empl. Sq.		-2.302**	-0.224				
		(0.985)	(1.303)				
Share of Manufacturing Empl.				10.116***	5.716*		
				(3.006)	(3.132)		
Share of Manufacturing Empl. Sq.				-35.415***	-16.524		
				(12.556)	(12.753)		
Share of Informal Empl.						1.949*	0.493
						(1.163)	(1.292)
Share of Informal Empl. Sq.						-1.922**	-0.585
						(0.922)	(1.111)
Observations	73	76	73	76	73	56	56
R^2	0.240	0.098	0.253	0.172	0.300	0.148	0.230

Notes: OLS estimates. The unit of observation is a country. The dependent variable is the log of the median wage markdown in each country. All variables are defined in Tables B.1 and B.2. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.11: Firm-size distribution in markdown sample vs. full WBES Global Panel

	f^{10}/f^{10}_{GP}			f^{50}/f^{50}_{GP}		
	(1)	(2)	(3)	(4)	(5)	(6)
Log of GDP per Capita	0.010		-0.036	0.006		-0.003
	(0.028)		(0.049)	(0.007)		(0.013)
Share of Self-Employment		-0.199	-0.323		-0.042	-0.053
		(0.121)	(0.207)		(0.031)	(0.053)
Observations	82	73	73	82	73	73
R^2	0.002	0.037	0.044	0.011	0.025	0.026

Notes: OLS estimates. The unit of observation is a country. The dependent variable is the ratio between the share of firms f^X with fewer than X employees in our final sample (for which wage markdowns are estimated) and the corresponding share f^X_{GP} in the full Global Panel component of the WBES, restricted to manufacturing firms. All variables are defined in Tables B.1 and B.2. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.12: Firm-size distribution in markdown sample vs. GEM

	f^{10}/f^{10}_{GEM}			f^{50}/f^{50}_{GEM}		
	(1)	(2)	(3)	(4)	(5)	(6)
Log of GDP per Capita	0.044		0.047	0.012		0.011
	(0.044)		(0.086)	(0.024)		(0.048)
Share of Self-Employment		-0.195	-0.036		-0.049	-0.010
		(0.191)	(0.350)		(0.107)	(0.196)
Observations	33	27	27	33	27	27
R^2	0.031	0.040	0.052	0.008	0.008	0.011

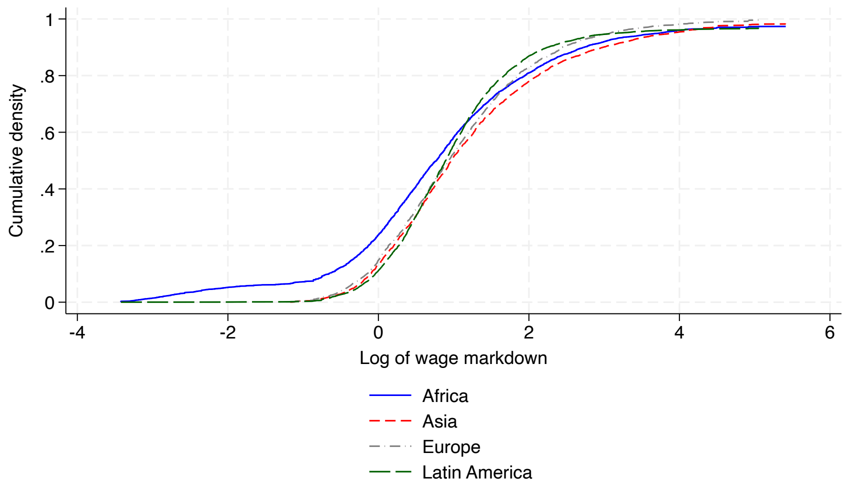
Notes: OLS estimates. The unit of observation is a country. The dependent variable is the ratio between the share of firms f^X with fewer than X employees in our final sample (with estimated wage markdowns) and the corresponding share f^X_{GEM} in the GEM data, restricted to manufacturing firms and excluding self-employed workers. All variables are defined in Tables B.1 and B.2. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.13: Firm-level share of wage employment across countries

	Log Share of Wage Employment			Log Local Share of Wage Employment		
	(1)	(2)	(3)	(4)	(5)	(6)
Log of GDP per Capita	0.302***		0.137	0.612***		0.098
	(0.082)		(0.143)	(0.137)		(0.237)
Share of Self-Employment		-1.335***	-0.865		-2.802***	-2.466**
		(0.354)	(0.605)		(0.583)	(1.001)
Observations	82	73	73	82	73	73
R^2	0.147	0.166	0.177	0.200	0.245	0.247

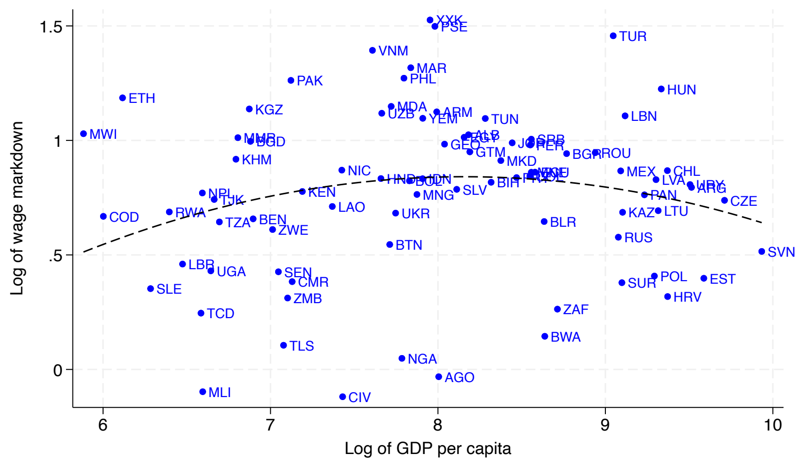
Notes: OLS estimates. The unit of observation is a country. The dependent variable is the median log share of wage employment in manufacturing, measured either at the national level (columns 1 to 3) or relative to the local labor market (columns 4 to 6). All variables are defined in Tables B.1 and B.2. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Figure A.1: Labor market power distribution within and across continents



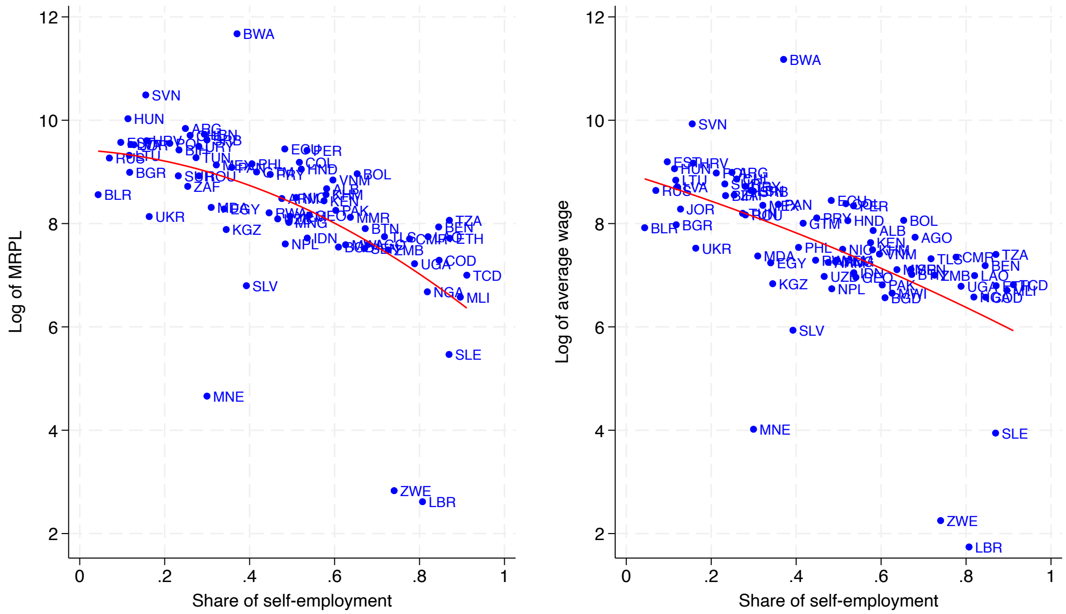
Notes. The figure plots the cumulative distribution function of the log of wage markdowns across firm-year observations, separately by world region.

Figure A.2: Labor market power and GDP per capita across countries



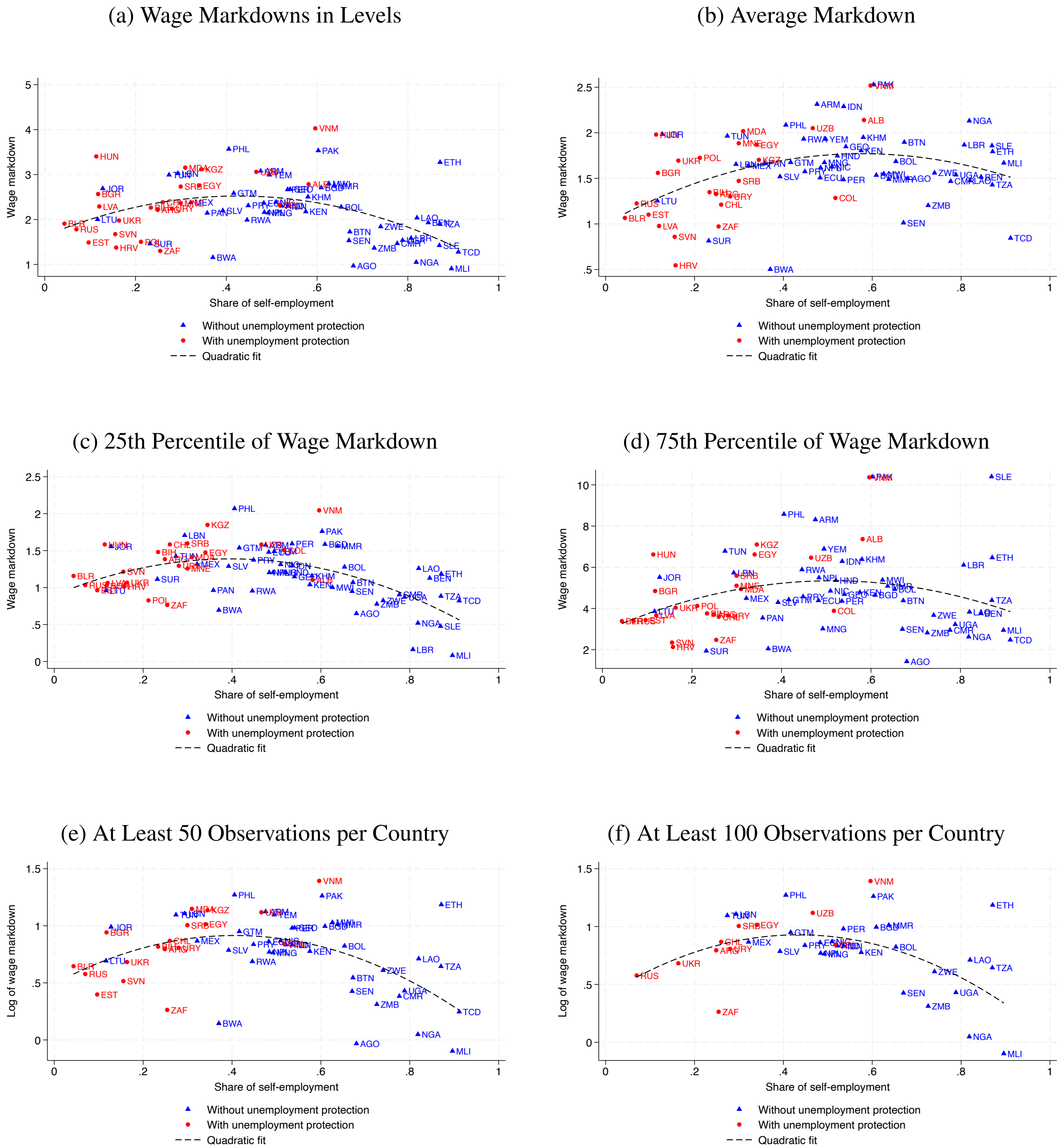
Notes. The figure plots the log of the median wage markdown against the log of GDP per capita (2010) across countries, along with a quadratic fit.

Figure A.3: MRPL, average wage, and share of self-employment across countries



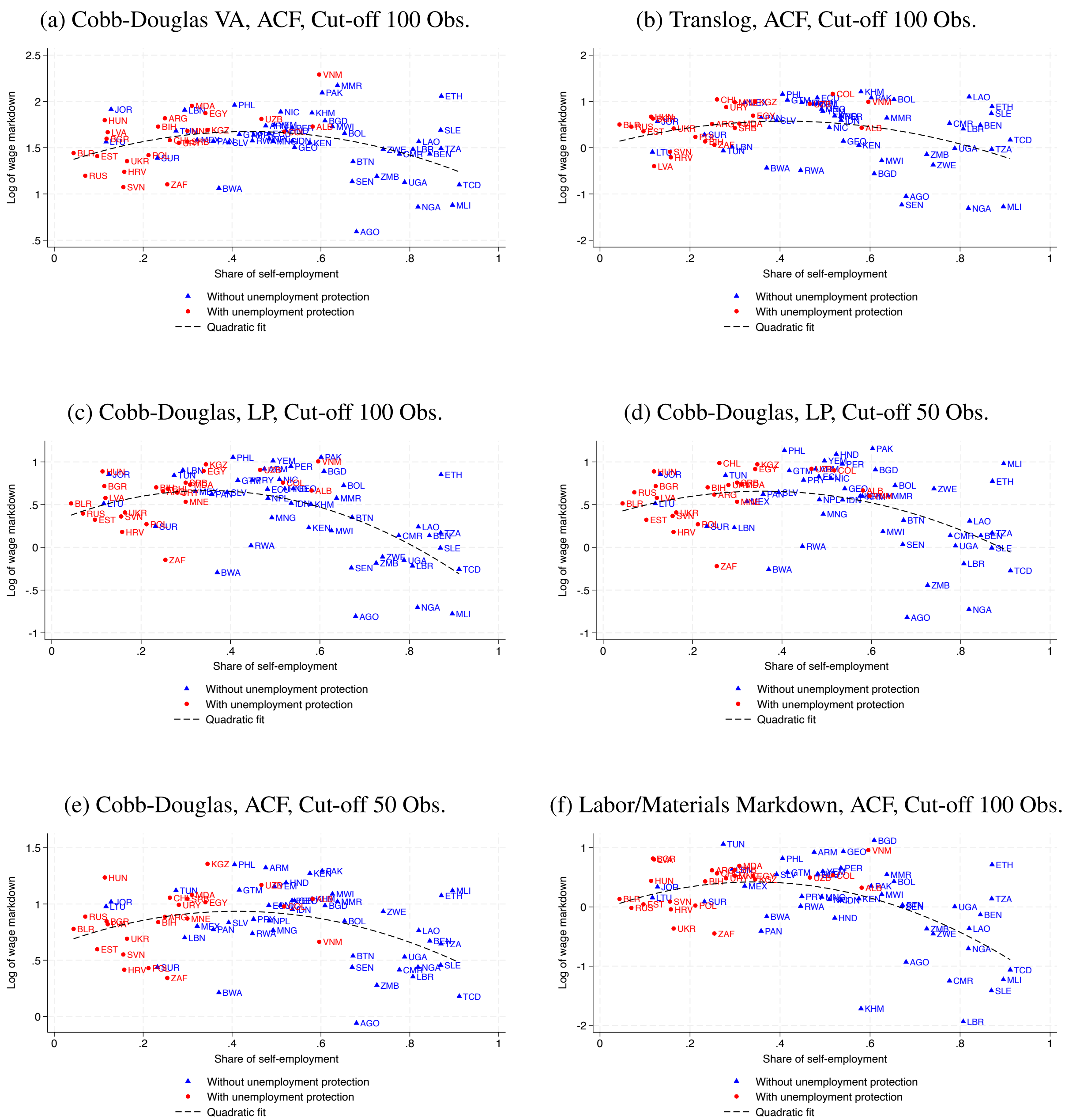
Notes. The figure plots the log of the median MRPL (left) and the log of the median average wage (right) against the share of self-employment across countries, along with a quadratic fit.

Figure A.4: Robustness — Markdown measure



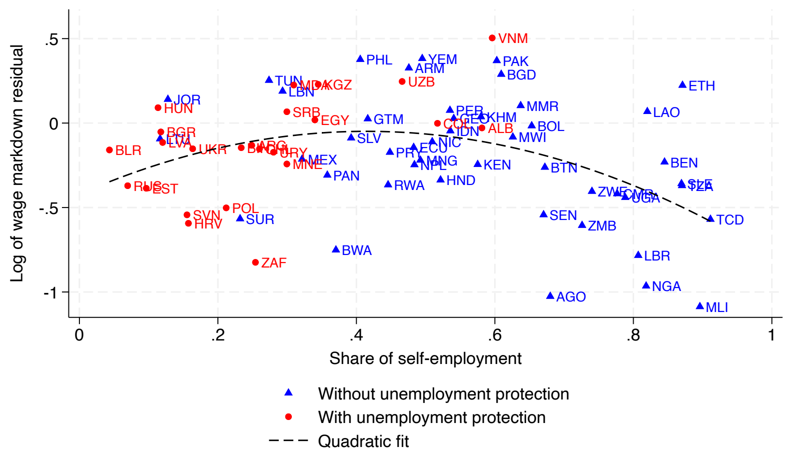
Notes. Panel (a) plots the median wage markdown against the share of self-employed workers across countries. Panel (b) shows the log of the average wage markdown by country, while Panels (c) and (d) display the 25th and 75th percentiles of the wage markdown distribution, respectively, each plotted against the share of self-employment. Panel (e) plots the log of the median wage markdown against the share of self-employment for countries with at least 50 firm-level observations, and Panel (f) restricts to countries with at least 100 such observations. All panels include a quadratic fit and highlight countries based on the availability of unemployment protection after one year of continuous job tenure, according to national labor regulations.

Figure A.5: Robustness — Revenue production function estimation method



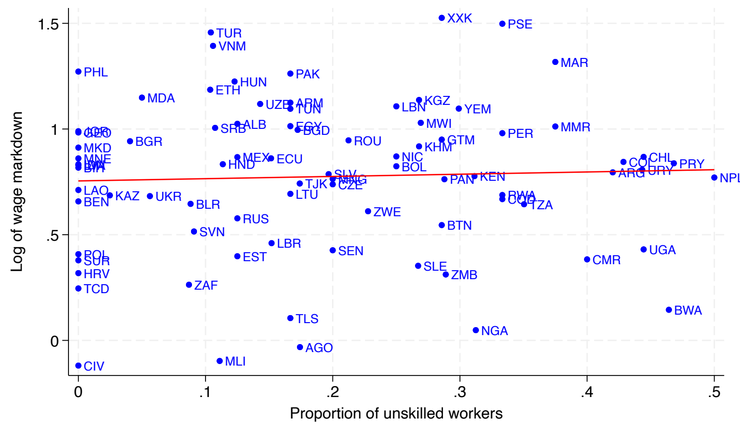
Notes. All figures plot the log of median wage markdown against the share of self-employed workers across countries. Each figure varies by the method used to estimate revenue production functions and by the observation threshold (or cut-off) used to determine the level of industry × country aggregation for markdown estimation—see Section 3 for details.

Figure A.6: Residual wage markdown net of sector fixed effects



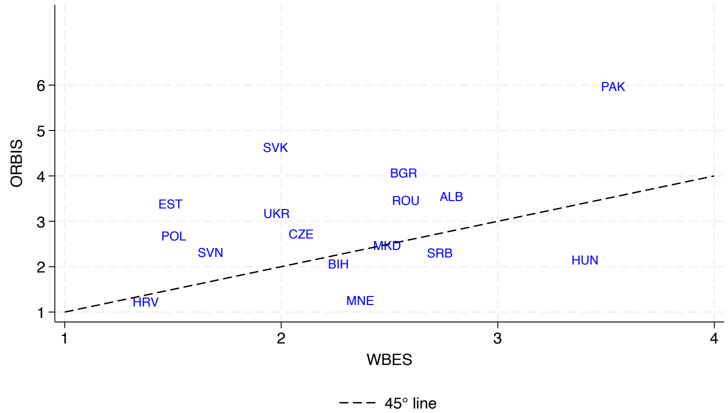
Notes. The figure plots the log of the median residual wage markdown—obtained from a regression of log markdowns on the full set of ISIC 2-digit sector fixed effects—against the share of self-employed workers across countries. A quadratic fit is shown. Countries are also highlighted based on the availability of unemployment protection after one year of job tenure, according to national employment regulations.

Figure A.7: Median wage markdown and proportion of unskilled workers



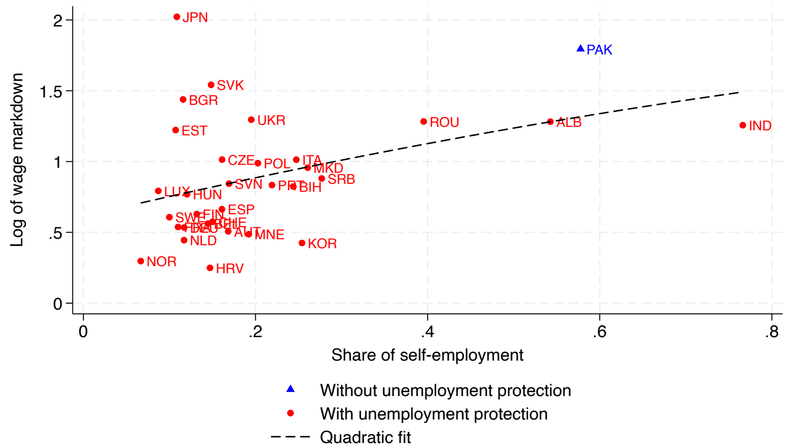
Notes. The figure plots the log of the median wage markdown against the median share of unskilled workers across countries, together with a linear fit.

Figure A.8: Median markdowns in WBES vs. ORBIS



Notes. The figure plots the estimated median wage markdowns from the ORBIS dataset against those from the WBES for the 16 countries present in both samples. Each point represents a country. The correlation between the two measures is approximately 52%. The 45-degree line is shown for reference; countries above the line exhibit higher median markdowns in ORBIS than in WBES.

Figure A.9: Labor market power and self-employment across countries — ORBIS



Notes. The figure plots the log of median wage markdowns against the share of self-employed workers across countries in the ORBIS sample. Countries are distinguished based on the availability of unemployment protection after one year of job tenure, according to national employment regulations. For countries with unemployment protection, the slope of the linear fit is 0.84, which is close to the one reported for the WBES sample in column 4 of Table 2.

B Data Appendix

This section complements Section 2 by providing additional detail on the variables used in the empirical analysis. Table B.1 defines the main firm-level variables, which we construct using data from the Global Panel component of the World Bank Enterprise Survey (WBES). Table B.2 describes the country-level variables. Finally, Table B.3 lists the countries and survey waves included in the final firm-level dataset.

Table B.1: Firm-level variables

Variable name	**Definition**
Wage Markdown	Wage markdowns estimated as described in Section 3. Unless otherwise noted, this variable is constructed using the approach of Ackerberg, Caves and Frazer (2015), applied to a value-added or gross output specification with Leontief materials. We also explore alternative specifications, including a structural Cobb–Douglas value-added function, a translog revenue production function, and the Levinsohn and Petrin (2003) method.
Sales	Total sales in the last fiscal year, expressed in constant 2002 USD using nominal exchange rates and U.S. CPI data. The top and bottom 1% of the distribution are trimmed. Source: WBES.
Employment	Number of permanent, full-time employees at the end of the last fiscal year. Source: WBES.
Sales per worker	Computed by dividing *Sales* by *Employment*.
Wage bills	Total annual cost of labor, including wages, salaries, bonuses, and social security payments. Expressed in constant 2002 USD using nominal exchange rates and U.S. CPI data. Source: WBES.
Wage	Average wage computed by dividing *Wage bills* by *Employment*.
Share of Local Empl.	Firm's share in local manufacturing employment within its local labor market and year, weighted by normalized sampling weights.
Age	Number of years since the firm's establishment, calculated as the difference between the survey year and the reported year of firm founding. Source: WBES.
Started Informal	Dummy equal to 1 if the firm initially operated without formal registration. Source: WBES.
Located in >1 Million City	Dummy equal to 1 if the firm is located in a city with more than one million inhabitants. Source: WBES.
Located in Capital	Dummy equal to 1 if the firm is located in the country's capital city. Source: WBES.
Foreign Owned	Dummy equal to 1 if the firm has private foreign ownership above 10%. Source: WBES.
Share of Wage Employment	Calculated by dividing *Employment* at the firm by the weighted (using weights `wt_rs`) sum of employment across firms. For nationwide employment shares, the denominator is the sum of employment across all manufacturing firms in each country and survey wave; for local shares, the denominator is the sum of employment across all manufacturing firms in each local labor market (see below) and survey wave.
Share of Unskilled Workers	Share of unskilled production workers among all permanent, full-time production employees. Source: WBES.

Table B.2: Country-level variables

Variable name	Definition
GDP per Capita	Real GDP per capita in constant 2015 USD. Data refer to the year 2010 to allow for consistent cross-country comparisons. Source: World Bank.
Share of Self-Employment	Share of self-employed workers obtained by dividing the number of self-employed workers by the number of employed workers. According to ILOSTAT definitions, the employed comprise all persons of working age who, during a specified brief period, were in one of the following categories: a) paid employment (whether at work or with a job but not at work); or b) self-employment (whether at work or with an enterprise but not at work). Self-employment refers to jobs lacking an explicit employer–employee relationship, where earnings directly depend upon the (actual or potential) profits derived from goods or services produced. It includes employers, own-account workers, members of producer cooperatives, and contributing family workers, as defined in the International Classification of Status in Employment (ICSE-93). Source: ILO (LFS and STLFS), averaged across all available years between 2008 and 2023.
Share of Agricultural Employment	Share of workers employed in agriculture out of total employment. Data disaggregated by economic activity are provided according to the latest version of the International Standard Industrial Classification of All Economic Activities (ISIC) available for each year. Data may have been regrouped from national classifications, which may not be strictly compatible with ISIC. For more information, refer to the Labour Force Statistics (LFS and STLFS) database description. Source: ILO (LFS and STLFS), averaged across all available years between 2008 and 2023.
Share of Manufacturing Employment	Share of workers employed in manufacturing out of total employment. Data disaggregated by economic activity are provided according to the latest version of the International Standard Industrial Classification of All Economic Activities (ISIC) available for each year. Data may have been regrouped from national classifications, which may not be strictly compatible with ISIC. For more information, refer to the Labour Force Statistics (LFS and STLFS) database description. Source: ILO (LFS and STLFS), averaged across all available years between 2008 and 2023.
Share of Informal Employment	Share of informal employment in total employment, covering all informal jobs regardless of sector or employment status. Employment comprises all persons of working age who, during a specified brief period, were either in paid employment (whether at work or with a job but not at work) or in self-employment (whether at work or with an enterprise but not at work). Informal employment includes (a) own-account workers, employers, and members of producers' cooperatives employed in their own informal sector enterprises; (b) own-account workers producing goods exclusively for own final use by their household (e.g., subsistence farming); (c) contributing family workers; and (d) employees holding informal jobs, whether employed by formal or informal sector enterprises, or as paid domestic workers. Data disaggregated by economic activity are classified using the most recent ISIC revision available and may be regrouped from national classifications. For more information, refer to the Labour Market-related SDG Indicators (ILOSDG) database description. Source: ILO (ILOSDG), averaged across all available years between 2008 and 2023.
Unemployment Rate	Share of unemployed individuals in the labor force (i.e., the employed plus the unemployed). According to ILO definitions, the unemployed comprise all persons of working age who: (a) were without work during the reference period (i.e., not in paid employment or self-employment); (b) were currently available for work during that period; and (c) had taken specific steps in a recent period to seek paid employment or self-employment. For more information, refer to the Labour Market-related SDG Indicators (ILOSDG) database description. Source: ILO (ILOSDG), averaged across all available years between 2008 and 2023.
Unemployment Protection	Dummy equal to 1 if the country has formal unemployment protection mechanisms in place, including unemployment insurance or social assistance. Information is sourced from the World Bank Employing Workers (WBEW) project, which provides systematically comparable data across 191 economies between 2004 and 2020. The data are collected through multiple rounds of communication with local legal experts and government officials, and are based on a review of national laws concerning employment, social insurance, unemployment security acts, and related regulations. Source: World Bank Employing Workers dataset.

Local Labor Markets To define the local labor market of a firm, we proceed as follows. First, we use the geolocation of the firm in conjunction with a shapefile that encompasses the various administrative unit levels of each country. With these two sources of information, we determine for each firm the code of the administrative unit at each respective level of administration.

Next, for each country, we determine which administrative unit level most accurately reflects local labor markets. To achieve this, we start by conducting a web search for documents—such as papers, policy briefs, etc.—that enumerate and detail each country's local labor markets. During this search, we use the country's name and one of the following keywords: "Metropolitan Area,", "Metropolitan Zone," "Metropolitan Region," "Functional Urban Areas," "Local Labor Market," "Labor Commuting Zone," and "Local Labor Agglomerations."

In many of these sources, the definition of a local labor market aligns with or mirrors that of the OECD.[20] According to this definition, a local labor market, which the OECD calls a Functional Urban Area (FUA), consists of a city along with its surrounding areas or commuting zones, forming an integrated labor market with the city. This integration means that individuals within the local labor market can work in the city without residing there, facilitated by commuting. The OECD employs population density and travel-to-work flows as criteria to define local labor markets. Using these sources, we proceed to identify which level of administrative unit most accurately encapsulates the local labor market.

[20]https://www.oecd.org/regional/regional-statistics/functional-urban-areas.htm.

Table B.3: Sample Composition

Country	Waves	Firms	Obs.	Country	Waves	Firms	Obs.
Afghanistan	08-14	12	19	Lithuania	09-13-19	51	95
Albania	13-19	59	95	Malawi	09-14	64	81
Angola	06-10	101	182	Mali	07-10-16	120	255
Argentina	06-10-17	497	1079	Mexico	06-10	160	310
Armenia	09-13-20	68	133	Moldova	09-13-19	86	158
Azerbaijan	09-13-19	47	91	Mongolia	09-13-19	80	161
Bangladesh	07-13	118	229	Montenegro	09-13-19	45	92
Belarus	08-13-18	93	194	Morocco	13-19	71	116
Benin	09-16	41	72	Myanmar	14-16	178	327
Bhutan	09-15	50	93	Nepal	09-13	106	211
Bolivia	06-10-17	128	258	Nicaragua	06-10-16	154	275
Bosnia and Herzegovina	09-13-19	88	172	Niger	09-17	30	46
Botswana	06-10	66	115	Nigeria	07-14	177	317
Bulgaria	09-13-19	56	113	North Macedonia	09-13-19	102	200
Cambodia	13-16	47	90	Pakistan	07-13	76	152
Cameroon	09-16	47	83	Panama	06-10	70	122
Chad	09-18	36	71	Paraguay	06-10-17	125	229
Chile	06-10	337	644	Peru	06-10-17	391	837
Colombia	06-10-17	379	784	Philippines	09-15	301	578
Cote d'Ivoire	09-16	63	105	Poland	09-13-19	94	166
Croatia	13-19	32	57	Romania	09-13-19	76	146
Czech Republic	09-13-19	40	76	Russia	09-12-19	316	623
DRC	06-10-13	95	181	Rwanda	06-11-19	56	114
Dominican Republic	10-16	36	60	Senegal	07-14	145	270
Ecuador	06-10-17	88	168	Serbia	09-13-19	87	173
Egypt	13-16-20	844	1811	Slovak Republic	09-13-19	20	30
El Salvador	06-10-16	174	267	Slovenia	09-13-19	58	125
Estonia	09-13-19	49	94	SouthAfrica	07-20	104	179
Ethiopia	11-15	198	344	Suriname	10-18	30	49
Georgia	08-13-19	55	110	Tajikistan	08-13-19	84	134
Ghana	07-13	24	43	Tanzania	06-13	87	165
Guatemala	06-10-17	264	508	Timor-Leste	09-15-21	62	124
Honduras	06-10-16	112	182	Togo	09-16	26	35
Hungary	09-13-19	50	100	Tunisia	13-20	143	267
Indonesia	09-15	410	801	Turkey	08-13-19	542	1083
Jordan	13-19	122	220	Uganda	06-13	138	263
Kazakhstan	09-13-19	77	144	Ukraine	08-13-19	253	501
Kenya	07-13-18	236	455	Uruguay	06-10-17	220	441
Kosovo	09-13-19	55	93	Uzbekistan	08-13-19	88	195
Kyrgyz Republic	09-13-19	71	139	Venezuela	06-10	65	109
Lao PDR	09-12-16-18	65	131	Vietnam	09-15	239	446
Latvia	09-13-19	58	113	West Bank And Gaza	13-19	61	121
Lebanon	13-19	118	213	Yemen	10-13	70	127
Lesotho	09-16	33	63	Zambia	07-13-19	200	388
Liberia	09-17	55	91	Zimbabwe	11-16	190	352

Notes. Composition of the firm-level dataset. This table provides information on the Global Panel fraction of the WBES and considering only the manufacturing sector. For each country included in the sample, we report the years of the survey waves, the number of single panel firms interviewed, as well as the overall observations available.