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DISCUSSION PAPER SERIES

IZA DP No. 16823

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ABSTRACT

Global Labor Market Power*

We estimate the labor market power of over 13,000 manufacturing establishments across 82 low and middle-income countries around the world. Within local labor markets, larger and more productive firms have higher wage markdowns and pay lower wages. Labor market power across countries exhibits a mild non-linear relationship with GDP per capita, entirely driven by a strong hump-shaped relationship with the share of self-employed workers. Labor market institutions fully account for the hump shape: in countries with unemployment protection, wage markdowns increase with the share of self-employment while the opposite is true in countries without it. We explain this finding through the lens of a simple oligopsonistic labor market model with frictions. Self-employment prevalence correlates with the elasticity of labor supply to the wage paid, and labor market institutions can change the sign of this relationship.

JEL Classification: J20, J30, J42, L11

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

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1 Introduction

Imperfect competition in the labor market can lower wages, aggregate output, and welfare. This is true for the United States and other high-income countries, where employers have been found to wield significant market power over labor (Azar, Berry and Marinescu, 2022; Bassier, Dube and Naidu, 2022; Berger, Herkenhoff and Mongey, 2022; Berger et al., 2023). With a few notable exceptions, there is significantly less knowledge about these issues in low and middle-income countries. Their economies differ systematically from those of high-income countries along several dimensions that are potentially related to labor market power. Job creation and wage employment rates are lower in poor countries (Rud and Trapeznikova, 2021), yet they exhibit a high degree of labor market dynamism. Labor market flows, such as the job-finding or employment exit rate, are higher in developing countries, with workers frequently switching between low-paying jobs and (informal) self-employment (Donovan, Lu and Schoellman, 2023).

The high prevalence of self-employment, even in manufacturing, is a key feature of labor markets in low-income countries (Gollin, 2008; Poschke, 2022). Its availability as an alternative can make workers highly responsive to changes in the wage paid, decreasing the wage-setting power of firms (Amodio, Medina and Morlacco, 2022). This may change with labor market institutions, such as employment protection legislation and unemployment benefits, that provide formal workers with a buffer against the risk of job loss and reduce reliance on self-employment as a safety net. The study of these issues is essential for shaping policies that seek to foster inclusive economic growth, and calls for the gathering of systematic evidence on the market power of employers (or its absence) across countries with different characteristics.

In this paper, we measure the labor market power of over 13,000 manufacturing establishments across 82 low and middle-income countries around the world. We use data from the World Bank Enterprise Survey to build a large, comprehensive global dataset of establishments. We then estimate their wage markdown (or labor wedge), thereby quantifying the extent to which wages fall below their competitive level. Under standard profit maximization conditions, this is equivalent to the ratio between the revenue-labor elasticity and the wage-bill share of revenues (Morlacco, 2020; Brooks et al., 2021*b*; Yeh, Macaluso and Hershbein, 2022; Brummund and Makowsky, 2023). To obtain consistent estimates of the revenue-labor elasticity, we exploit the panel dimension of our data and rely on proxy methods that are standard in the industrial organization literature (Levinsohn and Petrin, 2003; Ackerberg, Caves and Frazer, 2015). We thus measure labor market power over a harmonized global dataset of establishments and implement the same methodology consistently across countries.

Using this measure, we first explore the correlates of labor market power at the firm level by comparing establishments within sectors and local labor markets. We find that firms with higher wage markdowns are larger and more productive, yet pay differentially lower wages. This suggests that labor market power increases with firm size, consistent with an oligopsonistic labor market model. We also find that foreign-owned and state-owned firms have more market power over labor than their domestic and privately owned counterparts.

Second, we compare labor market power across countries. We consider the median wage markdown estimated in each country and find that it is lowest in most of Africa, moderately high in Latin America, and highest for several countries in Eastern Europe and the Middle East. We then show that labor market power exhibits a mild hump-shaped correlation with GDP per capita, while displaying a robust hump-shaped relationship with the share of self-employed workers. The quadratic fit explains a remarkable 24% of the variation in the median wage markdown across countries, and explains away the hump-shaped relationship of labor market power with development. We also find that labor market institutions are key to explain this pattern. In countries with weak labor regulation and no unemployment protection, self-employment is more prevalent and correlates negatively with labor market power. The opposite is true where labor market regulation is stronger and unemployment protection is present, where self-employment is less prevalent and correlates positively with wage markdowns. These findings stand up to a battery of robustness checks such as considering different moments of the wage markdown distribution, using different revenue production function specifications and estimation methods, conditioning on other salient country characteristics, and restricting the sample to countries with hundreds of establishment-level observations.

Third, 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 heterogenous 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 remain unemployed. For a given wage level, when the job finding probability decreases the expected value of wage employment decreases, and more workers opt for self-employment. At the same time, workers on the margin between sectors become more elastic to changes in the wage paid, decreasing the wage-setting power of firms. When unemployment protection is available, workers' sensitivity to wage changes is lower and can decrease with the job finding probability, thus increasing with self-employment prevalence. Overall, and in accordance with our empirical findings, self-employment prevalence correlates with the elasticity of labor supply to the wage paid and thus wage markdowns, with labor market institutions possibly changing the sign of this relationship. Our theoretical and empirical investigation suggests that the hump-shaped relationship between labor market power and self-employment share across countries is due to labor supply-side mechanisms, and specifically the sensitivity of potential wage workers to the wage paid.

This paper contributes to the expanding literature on labor market power. A large amount of new research has sparked new interest over labor market power in the US and other high-income countries, but evidence on these issues in the rest of the world is scant and fragmented. Existing studies focus on Brazil (Felix, 2022), China (Pham, 2023; Brooks et al., 2021*b*), Colombia (Amodio and de Roux, 2022), 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, 2023), Mexico (Estefan et al., 2024), Peru (Amodio, Medina and Morlacco, 2022), and South Africa (Bassier, 2023), all using different data and methodologies and thus not directly comparable to each other.[1] The fundamental contribution of this paper is that we leverage a global dataset of establishments and implement a consistent methodology to estimate the labor market power of firms across 82 countries. We show that this exhibits a hump-shaped relationship with the share of self-employed workers. We further document the role of labor market institutions for this relationship, and propose a simple oligopsonistic labor market model that is consistent with these findings.

More related to ours is Armangué-Jubert, Guner and Ruggieri (2023), who quantify the extent to which differences in labor market competitiveness can help explain differences in GDP per capita across countries. They develop a simple general equilibrium model with imperfect competition in the labor market and endogenous firm entry, and calibrate it using World Bank Enterprise Survey data. They find that output per capita in the poorest countries would increase by up to 69 percent if their labor markets were as competitive as in the richest countries. Using a different methodology based on production function estimation and panel data, we find that the median wage markdown among manufacturing establishments exhibits a hump-shaped relationship with GDP per capita and, more significantly, with self-employment prevalence across countries.

The remainder of the paper is organized as follows. Section 2 introduces the data, Section 3 explains how we estimate wage markdowns and presents summary statistics, Section 4 shows the results at the firm-level, and Section 5 focuses on cross-country comparisons. Section 6 sketches the theoretical model, with some additional empirical results. Section 7 concludes.

[1] Using wage-setting power estimates from 53 studies, Sokolova and Sorensen (2021) emphasize in their meta-analysis how heterogeneity in methods is a key challenge to comparability across studies.

2 Data

The data on firms come from the World Bank Enterprise Survey (WBES), an establishment-level dataset of unique global coverage providing information on about 192,000 firms in 155 countries. The survey is representative at the national level for the population of privately-owned firms with at least five employees operating in the formal (non-agricultural) sector.[2] In terms of coverage, most of the countries in the sample belong to low and middle-income economies. Importantly, each survey administration follows a standardized and consolidated methodology which makes the WBES the only available dataset providing truly comparable information on a wide range of firms' activities worldwide.

Although the original dataset is a repeated cross-section, several firms in the sample are interviewed in multiple waves. This is key to estimate production functions (see Section 3). For this purpose, we use the Global Panel component of the WBES. This covers 90 countries from 2006 to 2021 and consists of approximately 42,000 firm-year observations for which we have information on total sales, number of workers, labor cost, value of machineries, cost of raw materials and intermediate goods employed in production, operating sector, along with a wealth of additional information used in the analysis.[3] Out of this initial sample, we focus on the manufacturing sector. Online Appendix B provides additional information on the data we use, with Table B.1 providing a detailed list of the countries, waves, and number of observations included in this firm-level dataset, i.e., the Global Panel fraction of the WBES further restricted to manufacturing. Importantly, in Section 5.1, we tackle explicitly potential representativity issues by comparing moments of the firm-size distribution in our final sample with those derived from the Global Entrepreneurship Monitor (GEM), following Poschke (2018).

The confidential version of the WBES dataset, which we have access to, includes information on each firm's geo-localization. We combine this information with the world map of sub-national administrative units, which we use to define local labor markets in each country.

For all economies represented in our firm-level data, we retrieve a large set of correlates from three primary sources. From the World Bank, we obtain data on real GDP per capita across countries and over time. We derive data on self-employment prevalence, agricultural employment share, and manufacturing employment share from the International Labor Organization (ILO). For systematic

[2]Firms in each country are interviewed face to face and are selected using random sampling techniques with three stratification levels 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.

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

information on labor market institutions and regulations across countries, we rely on the World Bank Employing Workers (WBEW) project dataset, which measures the flexibility of regulation of employment, specifically as it relates to the areas of hiring, working hours, and redundancy rules and cost. We focus in particular on the availability of unemployment protection, meaning whether workers are eligible to unemployment schemes of any kind after one year of continuous employment. These schemes encompass a variety of measures including income-security benefits (regardless of their format), and may be supported by active labor market measures and employment services to help the unemployed find suitable employment. We provide further details on each one of these country-level variables in Online Appendix B.

3 Measurement

We measure labor market power at the firm-year level by comparing the firm's marginal revenue product of labor (MRPL) to the wage paid. This wage markdown measure captures the gap between workers' value to the firm and their cost and is therefore independent of the source of employer market power. Its origins can be traced back to Robinson's (1933) original formulation and recent empirical work on labor market power (Brooks et al., 2021*b*; Yeh, Macaluso and Hershbein, 2022; Brummund and Makowsky, 2023).

The WBES data directly report information on wage-bill and employment for each firm, from which we can derive the average wage w_{it} paid by firm i in year t. The MRPL is instead not directly observed, and needs to be estimated. We begin by assuming a Cobb-Douglas revenue production function specification 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 is firm revenues or sales, the inputs are labor n and capital k, and materials m, and ω captures a combination of productivity differences across firms and demand-side factors which affect the output price. The ε term captures instead unobserved idiosyncratic shocks to revenues distributed as white noise. The ω term is observed by the firm but unobserved by the econometrician, raising well-known identification concerns in production function estimation.

Exploiting the panel dimension of our firm-level data, we can 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 main assumptions: (i) that the ω term evolves according to a first-order

Markov process, (ii) that this is the only unobservable in the firm's input demand function, and (iii) that the input demand function is invertible in ω. Together, these assumptions allow to control for unobserved productivity and demand shocks, and estimate the parameters of the production function. We use materials as the proxy variable.

Our preferred method is Ackerberg, Caves and Frazer (2015), which applies more directly to either a value-added production function or a gross output production function in which materials are Leontief. We show below that our findings are robust to assuming a structural Cobb-Douglas value added or a translog revenue production function. They are also robust to implementing the Levinsohn and Petrin (2003) method while keeping the Cobb-Douglas specification. One limitation of all these methods is that they assume a production function that is constant across firms and only differs by a factor-neutral productivity parameter. To allow for more flexibility, previous studies usually estimates the parameters of equation (1) separately for each industry, and this is done using rich data from only one or two countries (see Pham, 2023; Brooks et al., 2021*b*; Yeh, Macaluso and Hershbein, 2022; Brummund and Makowsky, 2023 on China, India, the US and Indonesia, respectively). The WBES has much smaller sample sizes for each country, but much broader coverage, leading us to adopt a modified approach.

The goal is to estimate revenue production functions as narrowly as possible over as *similar* firms as possible. The constraint to this goal is sample size. If a country has a large *enough* sample, we estimate separate revenue production functions within each ISIC 2-digit manufacturing industry within each country. However, if a country does not have enough observations, we expand on the geography dimension and group firms in the same industry and located in nearby countries that belong to the same world region.[4] This strategy builds on the presumption that firms in a specific industry have production technologies and demand structures that are more similar to firms in the same industry in a nearby country than they are to firms in a different industry in the same country. Finally, if there are still not enough observations in the region to estimate the revenue production function, we expand the catchment area to include all firms in that industry in the whole WBES data. The choice of enough observations per industry $\times$ country is arbitrary, so we start by using 100 observations as the relevant cut-off, but also show robustness to using a cut-off value of 50. Using this strategy, 44% of our wage markdown measures come from within industry $\times$ countries, 52% from within industry $\times$ regions, and 4% from industries only.

Once the parameters of the revenue production function are estimated, we derive the MRPL as

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

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

and 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 the latter is simply the ratio between the revenue-labor elasticity α and the labor share of revenues.

Notice that if a firm also has market power in the product market, then it could raise the price of output above its marginal cost. This price markup does not confound the wage markdown estimate obtained from equation (3) because α is the revenue-labor elasticity (Pham, 2023). Another approach in the literature is to estimate and use physical output-input elasticities, exploit the availability of a flexible input (materials) which is assumed to not be subject to monopsony forces, and obtain the wage markdown by taking the ratio between ψ_{it} and its homolog for materials (Brooks et al., 2021*b*; Morlacco, 2020; Yeh, Macaluso and Hershbein, 2022; Estefan et al., 2024). This approach, however, relies on obtaining and using in the estimation of physical output elasticities detailed information about price deflators, ideally at the firm level (Syverson, 2004). These are typically not available for the industries and countries in our sample. Our approach of using the revenue-labor elasticity in equation (3) directly addresses the markup issue, but under the assumption that the unobserved productivity and demand shocks embedded in the ω term jointly satisfy the assumptions for production function estimation specified above.

Notice also that if the production function is Cobb-Douglas, one can measure differences in the wage markdown (relative to its homolog for materials) across firms within a given reference group by taking the ratio between the labor and the material shares of revenues. This is the approach that Amodio and Di Maio (2018) adopt to measure input market distortions in Palestine, later recommended by Bond et al. (2021) and utilized 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 unsuitable for cross-country comparisons because the measure is relative to other firms with the same production technology such as those in the same industry and country.

3.1 Summary Statistics

Using our baseline method (Ackerberg, Caves and Frazer, 2015), we estimate the wage markdown for as many as 13,205 manufacturing establishments across 82 countries, all of them low or middle-income. Online Appendix Table A.1 reports the summary statistics for this sample. The median number of employees is 28 while the median firm age is 18 years. The median yearly average real wage is equal to 2,180 USD (using 2002 as the base year). 11% of the establishments in our sample are foreign-owned, and 1.5% are state-owned. Our sample covers 932 different local labor markets and 1,207 country-sectors. 18% of establishments are located in the country capital, and 30% in cities with more than one million inhabitants. We discuss extensively the representativity of our sample in Section 5.1.

The median wage markdown estimated using our baseline method is equal to 2.33, indicating that workers at the median establishment earn as wage about 43% of the value they produce on the margin. This is close to what, using a different method, Felix (2022) finds for Brazil in the pre-1990 trade liberalization period, i.e., a wage markdown of 2 and wage share of about 50%. In South Africa, we estimate a median wage markdown of 1.3, which is lower than what implied by the separation-based labor supply elasticity estimates of Bassier (2023).[5] Our markdown estimates for Colombia and Peru are instead higher than what implied by the inverse labor supply elasticity estimates of Amodio and de Roux (2022) and Amodio, Medina and Morlacco (2022), respectively, although the latter also show that the wage share of MRPL can be as low as 57% in local labor markets with high concentration and low self-employment rates. In Mexico, Estefan et al. (2024) estimate a median wage share of 80% which contrasts with the 42% we estimate. But, their data belong to the economic census which covers all establishments in the economy, including one-person firms (excluding ambulant vendors operating in the streets without a fixed location), while the WBES is built to be representative of employers and specifically firms with at least five employees.

Assuming alternative revenue production function specifications and using different estimation methods, we obtain different versions of the wage markdown, the median ranging from 1.75 to 5.06. Their ordering is similar to what has been found in the literature. For instance, both Pham (2023) and Brooks et al. (2021*b*) report that the structural value-added approach using the Ackerberg, Caves and Frazer (2015) method produces very large wage markdown estimates. As mentioned before, we will consider all these alternative wage markdown estimates to probe the robustness of our findings.

Online Appendix Table A.2 reports moments of the (baseline) wage markdown distribution in each country, together with the number of observations. There is substantial variation in wage markdowns both within and across countries. The 25th percentile of the wage markdown distribution in each country often implies a wage take-home share higher than 90%. This is also true for the median markdown in several countries in Africa. Figure A.1 shows the distribution of wage markdowns across firms and countries for different world regions. The distribution appears more

[5] The labor supply elasticity estimates in Bassier (2023) are in the range of 1.3 to 1.6. As shown below in equation (6), the wage markdown is exactly equal to one plus the inverse elasticity of the labor supply curve faced by the individual firm (Manning, 2003). The implied wage markdown for South Africa thus ranges from $1 + (1.6)^{-1} = 1.64$ to $1 + (1.3)^{-1} = 1.77$.

skewed to the left in Africa, more to the right in Asia, with Latin America and (Eastern) Europe in between.[6]

Finally, across the 82 countries in our sample, the median real GDP per capita in 2010 was 2,885 USD, as reported at the bottom of Table A.1. The median share of self-employed workers is 48%, and the median unemployment rate is 6%. Unemployment protection is available in about a third of the countries.

4 Firm-Level Correlates of Labor Market Power

Using this global dataset of establishments and their estimated wage markdowns, we can explore the correlates of labor market power at the firm level and unpack regularities across firms within local labor markets. We implement the following regression specification

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

where the dependent variable is the log of wage markdown of establishment i located in local labor market m and operating in sector s in country c, surveyed in year t. The set of fixed effects θ_{sc} captures and nets out average differences across ISIC 2-digit sectors within and across countries, γ_{mc} stand for local labor market fixed effects, while δ_t denotes year fixed effects. X_{imsct} is the establishment-level characteristic of interest and u_{imsct} captures any residual determinant of wage markdowns.

Table 1 shows the results of this descriptive analysis. Wage markdowns are obtained using the Ackerberg, Caves and Frazer (2015) method to estimate revenue-labor elasticities. Columns 1 and 2 show that, within sectors and local labor markets, firms with higher markdowns report systematically higher sales and employment. Columns 3 and 4 show that they also have higher sales per worker, and a higher share of local employment. Yet, column 5 shows that the average wage is lower at these firms. Column 6 shows that firms with more labor market power are also less likely to have started as informal firms. Columns 7 and 8 further show that foreign-owned and state-owned firms have more market power over labor than their domestic and privately owned counterparts. Online Appendix Table A.3 reports the results that we obtain when assuming alternative revenue production function specifications and using different methods to estimate revenue-input elasticities, showing very similar patterns.

These results indicate that labor market power increases with firm size, consistent with an oligop-

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

sonistic labor market model. The positive correlation between wage markdowns and sales per worker suggests that the distortions induced by labor market power increase with firm productivity, highlighting its misallocation implications and negative impact on aggregate output.

In Online Appendix Table A.4, we document variation in wage markdowns across ISIC 2-digit sectors, focusing on the most represented in our sample, i.e., those for which we have at least 500 observations. When taken separately one by one, establishments in the food, chemicals, rubber and plastics, and machinery producing sectors appear to have systematically higher wage markdowns than the rest of establishments. We find instead labor market power to be systematically lower in textiles, apparel, publishing and printing.

5 Labor Market Power Across Countries

The advantage of implementing a consistent methodology for markdown estimation over a global dataset of establishments is that we can compare the extent of labor maker power across countries. To do so, we consider the wage markdown of the median firm in each country. We begin with Figure 1 showing the world distribution of (log) median wage markdown across the 82 countries in our sample, with different shades for different quintiles. Consistent with Online Appendix Figure A.1 showing the distribution of firm-level markdowns by world regions, we find that labor market power is lowest in most of Africa, moderately high in Latin America, and highest for several countries in Eastern Europe and the Middle East.

The top panel of Figure 2 plots labor market power against the log of GDP per capita across countries. The quadratic fitting line shows some evidence of a hump-shaped relationship between the two. Column 1 of Table 2 shows that this relationship is statistically significant, but only at the 10% level.

It is well known that the share of self-employed workers decreases systematically with GDP per capita (Gollin, 2008; Poschke, 2022). At the same time, recent evidence highlights the role of self-employment opportunities in shaping labor market power in poor countries. Felix (2022) shows how in Brazil firms in local labor markets where self-employment is more prevalent face more elastic labor supply curves. Amodio, Medina and Morlacco (2022) show that in Peru wage-setting power increases with concentration, but less so in markets where self-employment rates are high. They conceptualize self-employment as a readily accessible outside option for workers which can make them more elastic to changes in the wage paid, decreasing the wage-setting power of firms. Motivated by this research, we ask the extent to which the relationship between GDP per capita and labor market power shown in the top panel of Figure 2 is driven by differences in the share of self-employment across countries.

The bottom panel of Figure 2 shows evidence of a strong hump-shaped relationship between labor market power and self-employment share. Column 2 of Table 2 shows that this relationship is significant at the 1% level, and that the quadratic fit explains a remarkable 24% of the variation in median wage markdown across countries. When considering together log of GDP per capita and self-employment share and their squares, only the self-employment share variables remain highly statistically significant, as shown in column 3. Column 4 shows that this relationship is robust to controlling for the unemployment rate. In these contexts, (subsistence) self-employment is often a substitute for unemployment, and the two are indeed strongly negatively correlated in the data.[7] Evidence shows that even after differences in GDP per capita and unemployment rate are accounted for, self-employment prevalence stands out as a strong (non-linear) correlate of labor market power: wage markdowns first increase and then decrease with the share of self-employment.

The bottom panel of Figure 2 also shows that labor market institutions are key to explain this pattern. In theory, labor market institutions can provide (formal) workers with a buffer against the risk of job loss and reduce reliance on self-employment as a safety net. Indeed, in countries where unemployment protection is available, self-employment is less prevalent and correlates positively with labor market power. The opposite is true where unemployment protection is absent, where self-employment is more prevalent and correlates negatively with wage markdowns. The results in columns 5 to 8 of Table 2 show that these relationships are systematic and hold true conditional on the unemployment rate.

5.1 Robustness

The hump-shaped relationship we document between wage markdowns and self-employment prevalence stands up to a battery of robustness checks. We report all these results in Online Appendix A.

Panel (a) of Figure A.2, together with Table A.5, shows that considering the median wage markdown in levels as opposed to its log does not affect any of the results in the bottom panel of Figure 2 and Table 2, respectively. Panel (b) and (c) of Figure A.2 illustrate how taking the 25th or 75th percentile of the wage markdown instead of the median yields the same cross-country patterns. In panel (d) and (e), we restrict the sample to those countries for which we can measure

[7] The estimated coefficient from a simple regression of unemployment rate over self-employment share is equal to -0.094 and its associated *t-statistic* is -4.28.

markdowns for at least 50 and 100 establishment-level observations, respectively. Despite the reduction in sample size, the hump-shaped relationship between wage markdowns and the share of self-employment remains.

Next, we investigate the robustness of our findings to assuming alternative revenue production function specifications and using different estimation methods to estimate revenue-input elasticities. Figure A.3 illustrates the relationship between the (log) median wage markdown and self-employment shares when assuming a structural Cobb-Douglas value added revenue production function, a translog revenue production function, or implementing the Levinsohn and Petrin (2003) method while keeping the Cobb-Douglas specification, and for different cut-offs used to determine the level of production function aggregation. These choices matter for the level of markdowns (see Table A.1), but do not affect the relationship between the latter and self-employment shares across countries. Table A.6 supports this conclusion by showing patterns that are very similar to those reported in Table 2.

A possible concern with our findings is that the hump-shaped relationship we find between labor market power and the share of self-employment could be driven by some other country characteristics. The share of self-employed workers decreases with GDP per capita, but so does the share of agricultural employment, while the opposite is true (to some extent) for the share of manufacturing employment. The results in Table A.7 show that both agricultural and manufacturing employment shares correlate with labor market power in a non-linear way. Yet, when considering them together with self-employment share and their squares, only the self-employment share variables remain statistically significant while carrying most of the explanatory power. This confirms the crucial role played by the prevalence of self-employment in influencing labor market power, distinguishing it from other correlated factors.

Another potential concern pertains to the nature of WBES data and the possibility that systematic differences in its representativity across countries could be correlated with country characteristics. For instance, the median establishment in each country in our data could differ from the median of the population of manufacturing employers in a way that relates systematically – and in a non-linear way – with GDP per capita or the share of self-employment across countries.

We address this concern as follows. First, notice that the WBES is built to be representative of firms with at least five employees. Therefore, it will not be representative of the full distribution of firms which includes the self-employed as one-person firms.[8] It could still be the case, however, that

[8]To illustrate this point, we use data from Bento and Restuccia (2017), who build a standardized database on establishment size for 134 countries based on individual-country data from manufacturing censuses and representative surveys and registries. We calculate the average firm size (employment) in our final manufacturing WBES sample with estimated wage markdowns and take the log difference between this and the mean employment size in Bento and

the restricted sample of establishments with estimated wage markdowns we end up working with is not representative of the population of manufacturing employers with at least five employees. To assuage this concern, we use data from the Global Entrepreneurship Monitor (GEM). This is a survey that focuses on entrepreneurship, includes information on firm's employment, and that Poschke (2018) shows can be used to derive moments of the firm size distribution in each country. Most importantly for our purposes, it allows us to derive such moments for the population of manufacturing employers thus excluding the self-employed. Based on Poschke (2018), we compare WBES and GEM data as follows. We use GEM data from 2006 to 2010 and derive the share of manufacturing employers with less than 10 and and less than 50 employees. We do the same in our final WBES sample, then take the ratio between these two shares and regress it over the log of GDP per capita and the share of self-employment across countries. One limitation of this exercise is that GEM data are available for only 33 of the countries in our sample. Yet, the results in Table A.8 show that differences in the ratio of small firms in WBES vs. GEM are unrelated to GDP per capita and self-employment share, assuaging the concern that differences in representativity across countries could be responsible for our findings.

6 Some Theory

Evidence shows that labor market power exhibits a hump-shaped relationship with the share of self-employment across countries. In countries with no unemployment protection, self-employment is more prevalent and correlates negatively with labor market power. The opposite is true where unemployment protection is present: self-employment is less prevalent and correlates positively with wage markdowns.

To interpret these findings, we present a simple partial equilibrium oligopsonistic labor market model with frictions. The ease with which potential wage earner find jobs matters for workers. It influences their choice between wage work and self-employment, and shapes the elasticity of the labor supply to the wage paid. The availability of unemployment protection mediates these relationships in a way that is consistent with the evidence presented above.

Restuccia (2017). Online Appendix Figure A.4 shows that the difference between the two decreases monotonically with GDP per capita and increases with self-employment share. This makes clear that our findings are built off a comparison between the median manufacturing employer with at least 5 employees in each country, and not the median firm.

6.1 Market Structure and Wage Markdowns

Consider a finite number of firms that engage in Cournot competition in the labor market. They all pay the same unit wage w and workers view them as perfect substitutes, establishing an oligopsonistic labor market structure. The problem of each firm i is to choose the level of employment n_i that maximizes profits, namely

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

where r_i is 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, so that all firms set the wage equal to its competitive level. When the labor supply is less elastic the wage markdown is higher than one, and firms pay their workers less than their MRPL, i.e., they have 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 since $\partial n_i/\partial n^w = 1$, $s_i \equiv n_i/n^w$ is the firm i's employment share, and $\epsilon(w) = \frac{\partial n^w}{\partial w}\frac{w}{n^w}$ is the elasticity of the aggregate labor supply in the wage employment sector, or wage work supply elasticity. As such, s_i and $\epsilon(w)$ capture respectively the demand and supply-side determinants of labor market power.

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

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

Equation (8) 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 one of them chooses whether to work for a wage or be self-employed, so that the share of self-employment is equal to $n^s = 1 - n^w$. All workers are endowed with one efficiency unit of labor to 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 are i.i.d. draws 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 some exogenous probability $q < 1$ and workers who do not match remain unemployed. In the absence of unemployment benefits, when unemployed the worker's payoff is equal to zero. Let the 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 equal to

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

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 decreases c_u and increases n^s. Taking the derivative of $\epsilon(w)$ with respect to the self-employment share n^s we get

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

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 right part of Figure 2. It also resonates with the evidence in Amodio, Medina and Morlacco (2022) and Felix (2022) showing that firms in local labor markets where self-employment is more prevalent face more elastic labor supply curves.

6.3 Labor Supply With Unemployment Protection

When unemployment protection is available, unemployed workers obtain unemployment benefits equal to $b < w$. Workers then self-select into wage work if and only if $qw + (1-q)b \geq a$. The (effective) aggregate labor supply in the wage employment sector and its elasticity are equal to

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

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, i.e.,

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

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 firms pay. As a result, equation (14) shows that the aggregate elasticity of wage work can decrease when the share of self-employment n^s increases, and the median wage markdown can increase with the share of self-employment. This is consistent with the positive relationship between the median wage markdown and self-employment in the left part of Figure 2.

6.4 Labor Demand

The previous discussion focuses on the supply side of the labor market while holding fixed the number of operating firms, their employment shares, and the wage paid. Consider now the opposite exercise, i.e., hold fixed the aggregate elasticity of wage work and focus on changes in labor demand. From equation (8) it follows that, to obtain the hump-shaped relationship depicted in Figure 2, the median firm-level share of wage employment $\tilde{s}$ has to first increase and then decrease with the share of self-employment n^s. This is the case if changes in n^s are associated with changes in the firm size distribution among those firms that hire workers.

For example, for low levels of n^s, an increase in self-employment may coincide with the exit of smaller firms and an increase in the median firm-level share of wage employment and thus the median wage markdown. However, as n^s increases, more and more of the self-employed workers may start becoming employers and hire more workers themselves, which leads to entry of smaller firms and to a decrease in the median firm-level share of wage employment and wage markdown. We put this hypothesis under empirical scrutiny in the next section.

6.5 Additional Evidence and Discussion

In the partial equilibrium analyses above, we have intentionally kept the demand and supply sides of the labor market separate, and explored how changes in either side of the market lead to changes in the median wage markdown holding the other side of the market as well as prices fixed. This leaves us with the question of which one of the two scenarios is more empirically relevant.

To answer this question, we build on the previous subsection and look at how the firm size distribution changes 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, both nationwide and in relation to its local labor market. Figure 3 shows that the median firm-level share of wage employment increases monotonically with GDP per capita, and decreases monotonically with self-employment share across countries. The regression results in Online Appendix Table A.9 confirm these results. They also show that the negative relationship between the median firm-level share of wage employment and the nationwide share of self-employment is the only one that holds significance when regressing the former over the latter and the log of GDP per capita as well.

The theoretical results in this section together with these empirical results suggest that changes in the demand side of the labor market alone cannot explain the hump-shaped relationship between labor market power and self-employment share across countries, and that changes in the labor supply – and specifically the sensitivity of potential wage workers to the wage paid – are key to explain our findings.

7 Conclusion

A substantial body of recent research has sparked new interest over labor market power in the US and other high-income countries, but evidence on these issues in the rest of the world is limited and disjointed. Labor markets in low and middle-income countries have distinctive, recurrent features, and the study of labor market power in these countries requires alternative theoretical models informed by new facts.

To make progress, we leveraged a global dataset of establishments and implemented a consistent methodology to estimate the labor market power of more than 13,000 manufacturing establishments across 82 countries around the world. We showed that labor market power across countries exhibits a hump-shaped relationship with the share of self-employed workers. Labor market institutions fully account for this pattern: wage markdowns increase with the share of self-employment in countries with unemployment protection while the reverse is true in countries without. To interpret these findings, we presented a simple oligopsonistic labor market model with frictions. Our partial equilibrium analyses, coupled with supplementary evidence, indicate that the hump-shaped relationship between labor market power and self-employment share across countries is due to labor supply-side mechanisms, specifically the sensitivity of potential wage workers to the wage paid and how that changes when unemployment protection is available.

Our findings highlight the combined role of labor market frictions, self-employment, and labor market institutions for labor market outcomes in low and middle-income countries. Their impact on wage markdown matters as it shapes the allocation of labor across wage and self-employment, the allocation of wage employment across firms, and potentially firm selection at entry (Amodio, Medina and Morlacco, 2022; Armangué-Jubert, Guner and Ruggieri, 2023). As a result, it affects aggregate output and income distribution. Further research is needed to explore these mechanisms and quantify them through developing and estimating a general equilibrium model with oligopsony in the labor market, worker sorting across wage work and self-employment, endogenous firm entry, and labor market frictions.

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Tables and Figures

Table 1: Labor Market Power and Firm Characteristics

	Log of Wage Markdown							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
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 Local Empl. Share				0.068***				
				(0.010)				
Log of Wage					-0.299***			
					(0.019)			
Started Informal						-0.076**		
						(0.037)		
Foreign-Owned							0.265***	
							(0.045)	
State-Owned								0.232**
								(0.105)
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Sector $\times$ Country FE	✓	✓	✓	✓	✓	✓	✓	✓
Local Labor Market FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	12300	12532	12299	12532	12270	12533	12483	12485
R^2	0.545	0.455	0.629	0.454	0.497	0.449	0.453	0.450

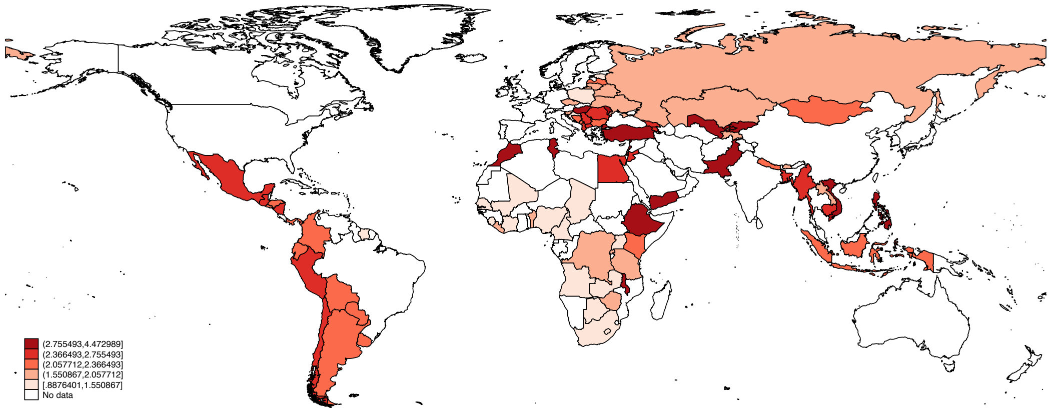
Notes. * p-value$<$ 0.1; ** p-value$<$0.05; *** p-value$<$0.01. The unit of observation is a manufacturing establishment. The dependent variable is the log of wage markdown. Sales and wages are in 2002 US dollars. Foreign-owned is a dummy equal to one if more than 10% of the ownership is foreign. State-owned is a dummy equal to one if more than 10% of the ownership belongs to the state. Sector $\times$ country fixed effects are dummies for each 2-digit ISIC Rev. 3.1 manufacturing sector in each country. Standard errors are clustered at the sector $\times$ country and local labor market level.

Table 2: Labor Market Power and Country Characteristics

	Log of Wage Markdown							
					Unempl. Protection		No Unempl. Protection	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log of GDP p.c.	1.037*		-0.111					
	(0.602)		(0.563)					
Log of GDP p.c. Sq.	-0.064*		-0.002					
	(0.038)		(0.036)					
Self-Employment Share		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)
Self-Employment Share Sq.		-2.442***	-2.417***	-2.658***				
		(0.605)	(0.658)	(0.597)				
Unemployment Rate				-1.651**		-1.906**		-2.002*
				(0.754)		(0.906)		(1.165)
Observations	82	73	73	73	24	24	46	46
R^2	0.041	0.240	0.302	0.289	0.310	0.430	0.183	0.235

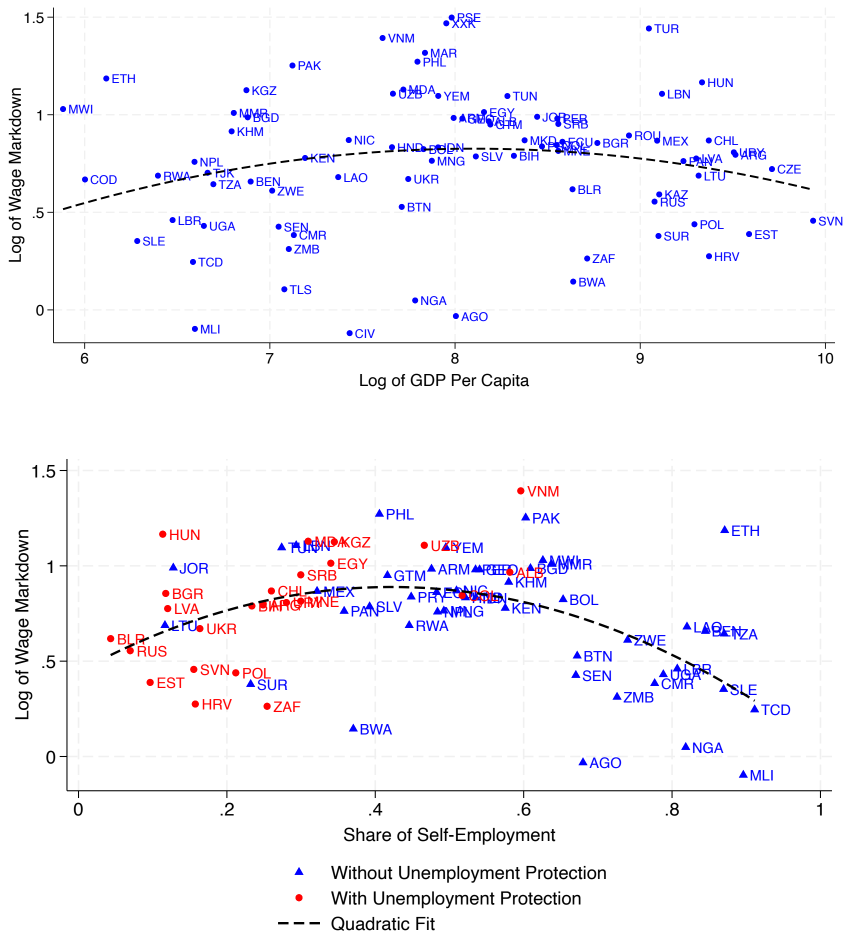
Notes. * p-value$<$ 0.1; ** p-value$<$0.05; *** p-value$<$0.01. The unit of observation is a country. The dependent variable is the log of median wage markdown in each country. The sample in columns 5 and 6 consists of countries with unemployment protection. The sample in columns 7 and 8 consists of countries without unemployment protection.

Figure 1: Labor Market Power by Country



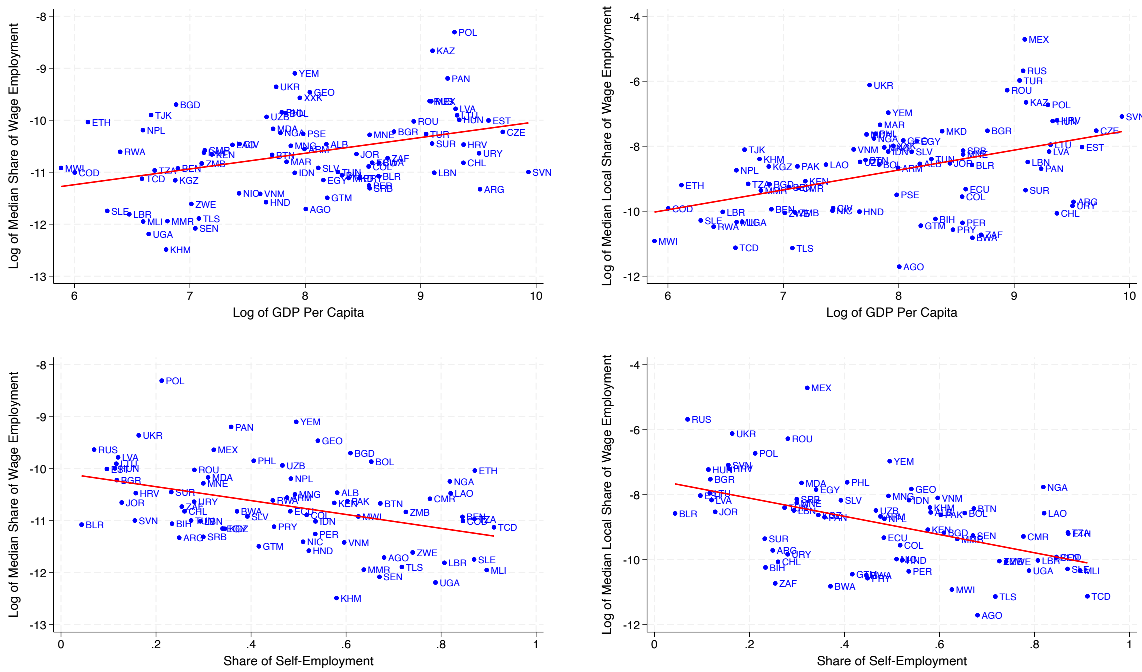
Notes. The figure shows the distribution of log median wage markdown across countries with different shades for different quintiles. Darker shades correspond to more labor market power.

Figure 2: Labor Market Power Across Countries



Notes. The top figure plots the log of median wage markdown against the log of GDP per capita in 2010 across countries together with a quadratic fit. The bottom figure plots the log of median wage markdown against the share of self-employed workers across countries in our sample together with a quadratic fit. It also highlights countries depending on the availability of unemployment protection after one year of job tenure according to national employment regulations.

Figure 3: Wage Employment Shares Across Countries



Notes. The top figures plot the log of the median firm-level nationwide share of wage employment (left) and the log of the median firm-level local share of wage employment (right) over the log of GDP per capita across countries, together with the linear fit. The bottom figures plot the same variables against the share of self-employment across countries.

Appendix for Online Publication

A Additional Tables and Figures

Table A.1: Summary Statistics

Variable	Obs.	Mean	Median	St. Dev.
Firm-Level Variables				
Employment	13203	123.654	28	366.390
Log of Employment	13203	3.541	3.332	1.456
Sales	12967	3781622	446782.400	1.08×10^{7}
Log of Sales	12967	12.968	13.010	2.313
Sales per Worker	12965	43240.420	14604.220	202641.600
Log of Sales per Worker	12965	9.443	9.589	1.658
Wage	12937	4156.809	2180.100	5518.725
Log of Wage	12937	7.541	7.687	1.490
Employment Share	13203	0.000	0.000	0.000
Local Employment Share	13203	0.003	0.000	0.013
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
State-Owned	13156	0.015	0	0.121
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
Sectors and Local Labor Markets				
ISIC 2-digit Sector × 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
Obs. per Country	82	161.037	103.500	189.326
2010 GDP per Capita	82	4568.805	2885.231	4347.340
Share of Self-Employment	73	0.472	0.483	0.243
Agricultural Share of Employment	76	0.311	0.288	0.194
Manufacturing Share of Employment	76	0.108	0.107	0.050
Unemployment Rate	76	0.072	0.061	0.049
Unemployment Protection	77	0.351	0	0.480

Notes. The table shows the summary statistics for firm and country-level variables. Sales and Wages are in 2002 US dollars.

Table A.2: Wage Markdown Distribution Across Countries

Country Code	Country Name	Observations	p25	p50	p75
ALB	Albania	43	1.05	2.63	6.95
AGO	Angola	92	0.65	0.97	1.43
ARG	Argentina	560	1.38	2.21	3.72
ARM	Armenia	51	1.55	2.67	7.64
BGD	Bangladesh	206	1.57	2.68	4.6
BLR	Belarus	95	1.16	1.86	3.1
BEN	Benin	47	1.13	1.93	3.76
BTN	Bhutan	86	1.06	1.7	4.3
BOL	Bolivia	101	1.28	2.28	4.93
BIH	Bosnia and Herzegovina	76	1.5	2.2	3.82
BWA	Botswana	81	0.7	1.16	2.05
BGR	Bulgaria	51	1.02	2.35	4.82
KHM	Cambodia	46	1.16	2.5	6.39
CMR	Cameroon	55	0.9	1.47	2.95
TCD	Chad	54	0.82	1.28	2.48
CHL	Chile	469	1.58	2.38	3.6
COL	Colombia	573	1.51	2.33	3.89
HRV	Croatia	48	1.03	1.32	2.11
CZE	Czech Republic	54	1.2	2.06	3.92
CIV	Côte d'Ivoire	68	0.29	0.89	2.16
COD	Democratic Republic of the Congo	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	El Salvador	187	1.29	2.2	4.3
EST	Estonia	54	0.95	1.47	3.3
ETH	Ethiopia	156	1.19	3.27	6.47
GEO	Georgia	54	1.08	2.67	4.6
GTM	Guatemala	386	1.54	2.59	4.43
HND	Honduras	120	1.2	2.3	5.37
HUN	Hungary	45	1.57	3.21	6.52
IDN	Indonesia	531	1.3	2.3	6.29
JOR	Jordan	87	1.56	2.69	5.51
KAZ	Kazakhstan	34	1.39	1.81	5.41
KEN	Kenya	301	1.04	2.18	4.79
XXK	Kosovo	35	2.16	4.34	8.05
KGZ	Kyrgyz Republic	59	1.71	3.08	6.51
LAO	Lao PDR	103	1.26	1.97	3.83
LVA	Latvia	44	1.07	2.17	3.42
LBN	Lebanon	155	1.71	3.03	5.73
LBR	Liberia	48	0.16	1.58	6.11
LTU	Lithuania	54	0.72	1.64	2.89
MWI	Malawi	54	1	2.8	5.38
MLI	Mali	149	0.08	0.91	2.95
MEX	Mexico	257	1.32	2.38	4.5
MDA	Moldova	77	1.46	3.09	4.71
MNG	Mongolia	112	1.18	2.15	2.98
MNE	Montenegro	43	1.21	2.26	5.01
MAR	Morocco	79	1.91	3.73	8.27
MMR	Myanmar	236	1.56	2.74	5.09
NPL	Nepal	164	1.19	2.14	5.41
NIC	Nicaragua	203	1.31	2.39	4.85
NGA	Nigeria	239	0.52	1.05	2.62
MKD	North Macedonia	120	1.11	2.38	5.06
PAK	Pakistan	135	1.74	3.5	10.29
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	0.85	1.55	3.96
ROU	Romania	86	1.28	2.44	7.86
RUS	Russia	256	1.02	1.74	3.28
RWA	Rwanda	92	0.96	1.99	5.89
SEN	Senegal	188	0.95	1.53	3
SRB	Serbia	116	1.46	2.59	5.38
SLE	Sierra Leone	35	0.48	1.42	10.4
SVN	Slovenia	88	1.21	1.58	2.32
ZAF	South Africa	173	0.76	1.3	2.48
SUR	Suriname	37	1.11	1.46	1.94
TJK	Tajikistan	31	1.2	2.05	6.02
TZA	Tanzania	155	0.88	1.9	4.4
TLS	Timor-Leste	104	0.73	1.11	2.57
TUN	Tunisia	150	1.42	2.99	6.79
TUR	Türkiye	468	2.36	4.23	8.04
UGA	Uganda	151	0.87	1.54	3.23
UKR	Ukraine	140	1.04	1.96	3.92
URY	Uruguay	189	1.3	2.24	3.66
UZB	Uzbekistan	108	1.5	3.03	6.31
VNM	Vietnam	272	2.04	4.03	10.14
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 shows the number of firm-level observations in each country together with the value of the wage markdown at the 25th, 50th, and 75th percentile of each country's distribution.

Table A.3: 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)	(8)
	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 Local Empl. Share				0.068***				
				(0.010)				
Log of Wage					-0.301***			
					(0.019)			
Started Informal						-0.081**		
						(0.037)		
Foreign-Owned							0.267***	
							(0.046)	
State-Owned								0.246**
								(0.106)
	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 Local Empl. Share				0.049***				
				(0.018)				
Log of Wage					-0.418***			
					(0.025)			
Started Informal						-0.050		
						(0.049)		
Foreign-Owned							0.188***	
							(0.055)	
State-Owned								0.406**
								(0.189)
	Panel C: Cobb-Douglas – Levinsohn and Petrin (2003)							
Log of Sales	0.225***							
	(0.009)							
Log of Employment		0.081***						
		(0.011)						
Log of Sales Per Worker			0.484***					
			(0.016)					
Log of Local Empl. Share				0.069***				
				(0.010)				
Log of Wage					-0.299***			
					(0.020)			
Started Informal						-0.089**		
						(0.039)		
Foreign-Owned							0.274***	
							(0.047)	
State-Owned								0.226**
								(0.107)
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Sector × Country FE	✓	✓	✓	✓	✓	✓	✓	✓
Local Labor Market FE	✓	✓	✓	✓	✓	✓	✓	✓

Notes. * p-value< 0.1; ** p-value<0.05; *** p-value<0.01. The unit of observation is a manufacturing establishment. The dependent variable is the log of wage markdown obtained upon estimating revenue-input elasticities using the different methods specified in the Panel headings. Sales and wages are in 2002 US dollars. Foreign-owned is a dummy equal to one if more than 10% of the ownership is foreign. State-owned is a dummy equal to one if more than 10% of the ownership belongs to the state. Sector × country fixed effects are dummies for each 2-digit ISIC Rev. 3.1 manufacturing sector in each country. Standard errors are clustered at the sector × country and local labor market level.

Table A.4: Labor Market Power Across Sectors

	Log of Wage Markdown									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Food	0.294***									
	(0.061)									
Textile		-0.280***								
		(0.051)								
Apparel			-0.851***							
			(0.196)							
Publishing & Printing				-0.311***						
				(0.078)						
Chemicals					0.218***					
					(0.043)					
Rubber and Plastics						0.138***				
						(0.050)				
Non-Metallic Mineral Products							-0.057			
							(0.063)			
Metal Products								0.060		
								(0.059)		
Machinery & Equipment									0.142**	
									(0.057)	
Furniture										0.102
										(0.097)
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Country FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Local Labor Market FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	12791	12791	12791	12791	12791	12791	12791	12791	12791	12791
R^2	0.192	0.186	0.232	0.185	0.185	0.184	0.183	0.183	0.183	0.183

Notes. * p-value$<$ 0.1; ** p-value$<$0.05; *** p-value$<$0.01. The unit of observation is a manufacturing establishment. The dependent variable is the log of wage markdown. Each independent variable is a dummy equal to one if the firm belongs to the corresponding 2-digit ISIC Rev. 3.1 sector. Standard errors are clustered at the sector $\times$ country and local labor market level.

Table A.5: Wage Markdowns in Levels and Country Characteristics

	Wage Markdown							
					Unempl. Protection		No Unempl. Protection	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log of GDP p.c.	2.739**		0.104					
	(1.327)		(1.184)					
Log of GDP p.c. Sq.	-0.170**		-0.024					
	(0.084)		(0.075)					
Self-Employment Share		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)
Self-Employment Share Sq.		-4.927***	-4.706***	-5.319***				
		(1.268)	(1.385)	(1.263)				
Unemployment Rate				-2.995*		-4.689**		-2.855
				(1.595)		(2.014)		(2.375)
Observations	82	73	73	73	24	24	46	46
R^2	0.053	0.212	0.271	0.251	0.338	0.473	0.162	0.189

Notes. * p-value$<$ 0.1; ** p-value$<$0.05; *** p-value$<$0.01. The unit of observation is a country. The dependent variable is the median wage markdown in each country. 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.

Table A.6: Labor Market Power and Country Characteristics
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)	(8)
	Panel A: Cobb-Douglas Structural Value Added – Ackerberg, Caves and Frazer (2015)							
Log of GDP p.c	0.695		-0.363					
	(0.552)		(0.552)					
Log of GDP p.c. Sq.	-0.044		0.014					
	(0.035)		(0.035)					
Self-Employment Share		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)
Self-Employment Share Sq.		-1.941***	-2.046***	-2.173***				
		(0.596)	(0.645)	(0.585)				
Unemployment Rate				-1.770**		-1.566*		-2.748**
				(0.739)		(0.839)		(1.130)
	Panel B: Translog – Ackerberg, Caves and Frazer (2015)							
Log of GDP p.c.	2.177**		0.938					
	(0.982)		(1.175)					
Log of GDP p.c. Sq.	-0.133**		-0.059					
	(0.062)		(0.074)					
Self-Employment Share		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)
Self-Employment Share Sq.		-3.227***	-2.742**	-3.808***				
		(1.210)	(1.366)	(1.164)				
Unemployment Rate				-4.355***		-2.761**		-6.885***
				(1.471)		(1.297)		(2.443)
	Panel C: Cobb-Douglas – Levinsohn and Petrin (2003)							
Log of GDP p.c.	1.705**		0.266					
	(0.756)		(0.739)					
Log of GDP p.c. Sq.	-0.099**		-0.021					
	(0.048)		(0.047)					
Self-Employment Share		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)
Self-Employment Share Sq.		-3.078***	-2.894***	-3.367***				
		(0.768)	(0.864)	(0.755)				
Unemployment Rate				-2.210**		-2.093**		-3.123*
				(0.953)		(0.855)		(1.581)

Notes. * p-value< 0.1; ** p-value<0.05; *** p-value<0.01. 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.

Table A.7: Labor Market Power, Self-Employment, and Employment Shares in Agriculture and Manufacturing

	Log of Wage Markdown					
	(1)	(2)	(3)	(4)	(5)	(6)
Agricultural Empl. Share	1.295*		0.590			
	(0.707)		(1.074)			
Agricultural Empl. Share Sq.	-2.302**		-0.224			
	(0.985)		(1.303)			
Manufacturing Empl. Share				10.116***		5.716*
				(3.006)		(3.132)
Manufacturing Empl. Share Sq.				-35.415***		-16.524
				(12.556)		(12.753)
Self-Employment Share		2.022***	1.664*		2.022***	2.111***
		(0.602)	(0.912)		(0.602)	(0.650)
Self-Employment Share Sq.		-2.442***	-2.401***		-2.442***	-2.247***
		(0.605)	(0.832)		(0.605)	(0.637)
Observations	76	73	73	76	73	73
R^2	0.098	0.240	0.253	0.172	0.240	0.300

Notes. * p-value$<$ 0.1; ** p-value$<$0.05; *** p-value$<$0.01. The unit of observation is a country. The dependent variable is the log of median wage markdown in each country.

Table A.8: Firm-size Distribution in Markdown Sample vs. GEM

	$f^{10}_{WBES}/f^{10}_{GEM}$			$f^{50}_{WBES}/f^{50}_{GEM}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Log of GDP p.c.	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

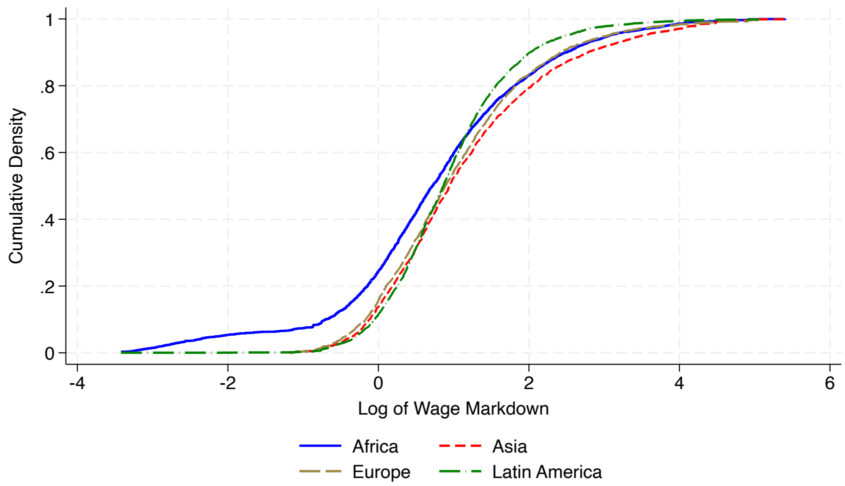
Notes. * p-value$<$ 0.1; ** p-value$<$0.05; *** p-value$<$0.01. The unit of observation is a country. The dependent variable is the ratio between the fraction of firms f^X_{WBES} with less than X employees in our sample divided by the corresponding fraction f^X_{GEM} in GEM data, focusing on manufacturing and excluding self-employed workers.

Table A.9: 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. * p-value$<$ 0.1; ** p-value$<$0.05; *** p-value$<$0.01. The unit of observation is a country. The dependent variable is the median log share of wage employment in manufacturing either nationwide (columns 1 to 3) or in relation to its local labor market.

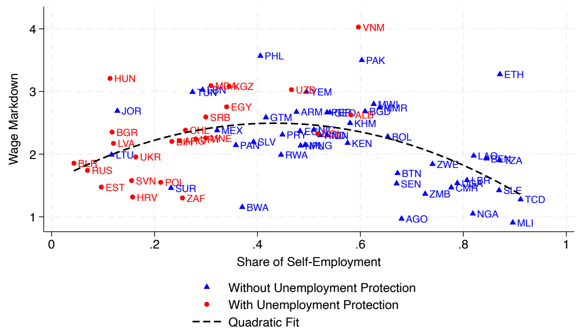
Figure A.1: Labor Market Power Distribution Within and Across Continents



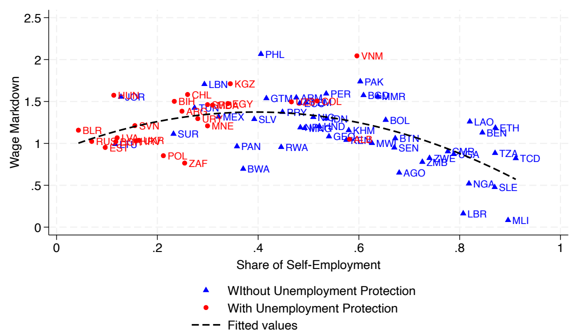
Notes. The figure plots the cumulative density function of the log of wage markdown across firms in different world regions.

Figure A.2: Robustness – Markdown Measure

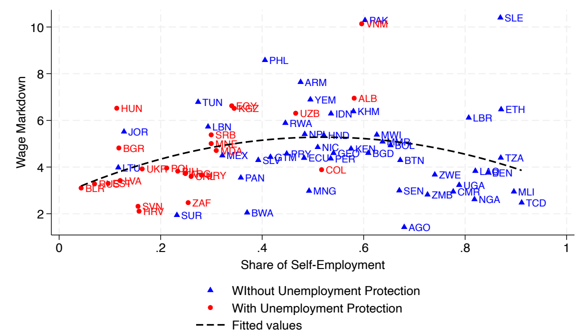
(a) Wage Markdowns in Levels



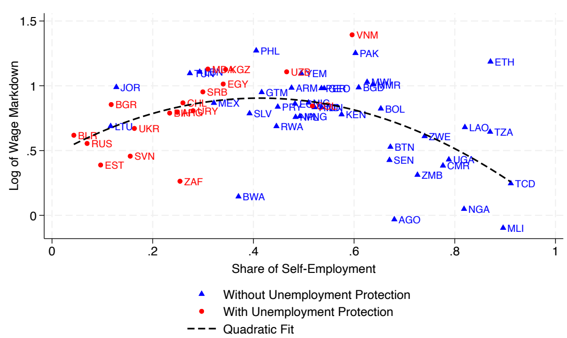
(b) 25th Percentile of Wage Markdown



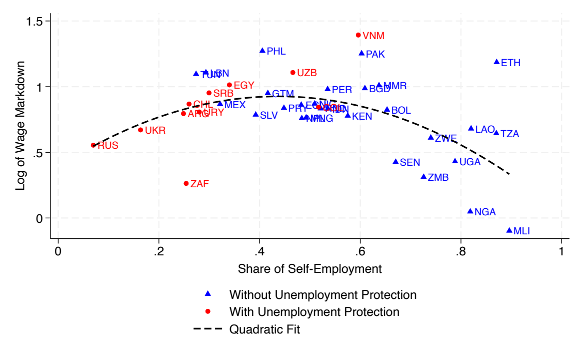
(c) 75th Percentile of Wage Markdown



(d) At Least 50 Observations per Country



(e) At Least 100 Observations per Country

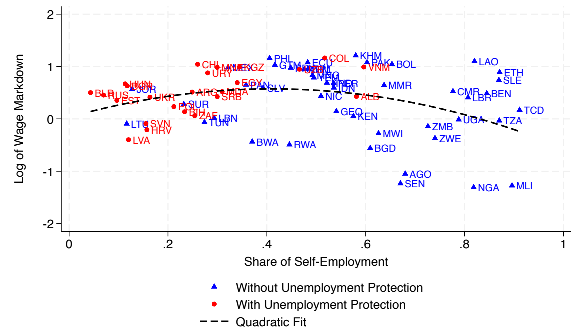


Notes. The figure in panel (a) plots the median wage markdown against the share of self-employed workers across countries. The figure in panel (b) plots the 25th percentile of wage markdown in each country against the share of self-employment. The figure in panel (c) plots the 75th percentile of wage markdown in each country against the share of self-employment. The figure in panel (d) plots the log of median wage markdown against the share of self-employment across countries with at least 50 establishment-level observations in our sample. The figure in panel (e) plots the log of median wage markdown against the share of self-employment across countries with at least 100 establishment-level observations in our sample. All figures also show the quadratic fit and highlight countries depending on the availability of unemployment protection after one year of job tenure according to national employment regulations.

Figure A.3: Robustness – Revenue Production Function Estimation Method

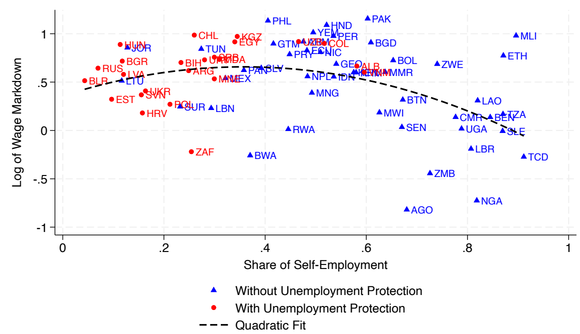
(a) Cobb-Douglas VA – ACF – Cut-off at 100 Obs.

(b) Translog – ACF – Cut-off at 100 Obs.

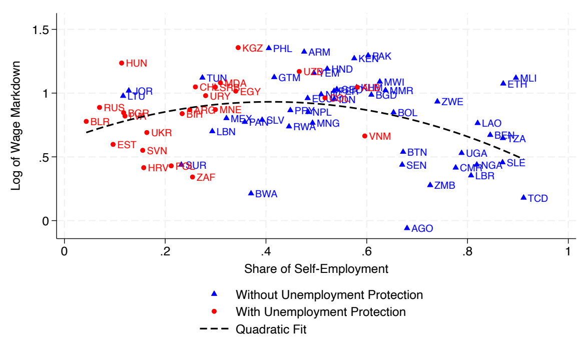


(c) Cobb-Douglas – LP – Cut-off at 100 Obs.

(d) Cobb-Douglas – LP – Cut-off at 50 Obs.

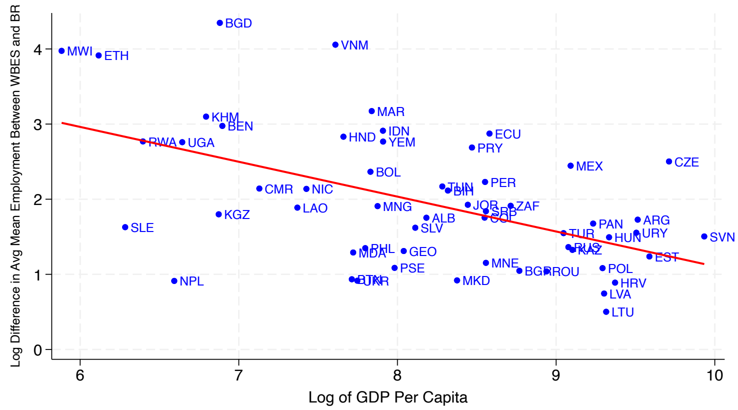


(e) Cobb-Douglas – ACF – Cut-off at 50 Obs.



Notes. All figures plot the log of median wage markdown against the share of self-employed workers across countries, but differ in the revenue production function estimation method used to estimate markdowns as well as the number of observations per industry × country or cut-off used to determine the level of production function aggregation – see Section 3.

Figure A.4: Average Firm Size Across Countries in Sample vs. Bento and Restuccia (2017)



Notes. The figures plot the log difference in average establishment size (employment) between the WBES sample for which we estimate wage markdowns and the average manufacturing establishment size as measured by Bento and Restuccia (2017) against the log of GDP per capita (top panel) and the share of self-employment (bottom panel) across countries in our sample together with a linear fit.

B Data Appendix

This Section complements Section 2 by providing additional information on all the variables used in the empirical analysis. Additionally, Table B.1 provides a detailed list of the countries and waves included in the final firm-level dataset.

B.1 Firm-level Data

We construct our initial sample starting from the Global Panel component of the World Bank Enterprise Survey. The following explains the different variables we build and use from the original survey.

- *employment*, variable `l1` capturing the number of permanent, full-time employees at the end of the last fiscal year;
- *wage bill*, variable `n2a` capturing total labor costs such as wages, salaries, and bonuses in the last fiscal year;
- *average wage*, obtained by dividing *wage bill* by *employment*;
- *sales*, variable `d2` capturing total sales in the previous fiscal year; we use nominal exchange rate data and US CPI data to transform all values to 2002 US dollars; we further trim the top and bottom 1% of the distribution;
- *sales per worker*, obtained by dividing *sales* by *employment*; we further trim the top and bottom 2% of the distribution;
- *age*, obtained by subtracting from the year of the survey wave the value of the variable `b5` capturing the year in which the establishment began operations;
- *foreign owned*, variable `car7` indicating whether the firm has at least 10% of foreign ownership;
- *state owned*, variable `car8` indicating whether the firm has at least 10% of state ownership;
- *sector*, variable `d1a2` providing ISIC Rev. 3.1 4-digit sector information, of which we take the first two digits;

- *share of wage employment*, we calculate the weighted (using weights `wt_rs`) sum of employment across firms, and then divide *employment* at the firm by this total; to get nationwide employment shares, we use as denominator the sum of employment across all manufacturing firms in each country and survey wave; to get local shares of wage employment, we use as denominator the sum of employment across all manufacturing firms in each local labor market (see below) and survey wave.

To define *local labor markets*, we use either level 1 or level 2 sub-national administrative units and make this decision on a country-by-country basis depending on the available information. We then assign each firm to a local labor market by spatially merging its geo-localization with the map of sub-national administrative boundaries.

B.2 Country-level Data

Data on real *GDP per capita* across countries and over time come from the World Bank. The data are in constant 2015 USD. Out of the whole series, we focus on the year 2010 to make comparisons across countries.

From the International Labor Organization (ILO), we derive information on all the following variables. In all cases, and to maximize coverage, we take the average for each country across all the available years between 2008 and 2023 and in most cases between 2010 and 2020.

- *share of self-employment*, 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, wherein earnings directly depends upon the (actual or potential) profits derived from the goods and services produced. Self employment encompasses a wide range of occupations and industries, including employers, own-account workers, members of producer cooperatives, and contributing family workers (as per the International Classification by Status in Employment, ICSE-93). For more information, refer to the Labour Force Statistics (LFS and STLFS) database description;

- *agricultural and manufacturing employment share*, obtained by dividing the number of workers employed in agriculture or manufacturing by the number of employed workers.

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 that 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;

- *unemployment rate*, conveys the number of persons who are unemployed as a percent of the labour force (i.e., the employed plus the unemployed). The unemployed comprise all persons of working age who were: a) without work during the reference period, i.e. were not in paid employment or self-employment; b) currently available for work, i.e. were available for paid employment or self-employment during the reference period; and c) seeking work, i.e. had taken specific steps in a specified recent period to seek paid employment or self-employment. For more information, refer to the Labour Market-related SDG Indicators (ILOSDG) database description;

For systematic information on labor market institutions and regulations across countries, including the availability of *unemployment protection*, we rely on the World Bank Employing Workers (WBEW) project dataset, which collects comparable information across 191 economies between 2004 and 2020. The Data is collected by the World Bank through multiple rounds of communication with local lawyers and government officials, complemented by a review of the main national laws concerning employment, social insurance, unemployment security acts, and other relevant regulations.

Table B.1: Sample Composition

Country	Waves	Firms	Obs.	Country	Waves	Firms	Obs.
Afghanistan	08-14	37	74	Lithuania	09-13-19	106	226
Albania	13-19	152	304	Malawi	09-14	87	174
Angola	06-10	183	366	Mali	07-10-16	193	442
Argentina	06-10-17	629	1438	Mexico	06-10	210	420
Armenia	09-13-20	225	506	Moldova	09-13-19	247	572
Azerbaijan	09-13-19	127	269	Mongolia	09-13-19	219	522
Bangladesh	07-13	120	242	Montenegro	09-13-19	101	226
Belarus	08-13-18	216	495	Morocco	13-19	139	278
Benin	09-16	62	124	Myanmar	14-16	278	556
Bhutan	09-15	113	226	Nepal	09-13	232	464
Bolivia	06-10-17	265	612	Nicaragua	06-10-16	217	481
Bosnia and Herzegovina	09-13-19	216	482	Niger	09-17	57	114
Botswana	06-10	119	238	Nigeria	07-14	364	728
Bulgaria	07-09-13-19	141	309	North Macedonia	09-13-19	241	538
Cambodia	13-16	131	262	Pakistan	07-13	76	152
Cameroon	09-16	160	320	Panama	06-10	124	248
Chad	09-18	70	140	Paraguay	06-10-17	208	479
Chile	06-10	430	860	Peru	06-10-17	540	1228
Colombia	06-10-17	500	1110	Philippines	09-15	375	750
Cote d'Ivoire	09-16	145	290	Poland	09-13-19	203	414
Croatia	13-19	71	142	Romania	09-13-19	196	419
Czech Republic	09-13-19	68	142	Russia	09-12-19	597	1222
DRC	06-10-13	167	364	Rwanda	06-11-19	138	307
Dominican Republic	10-16	103	206	Senegal	07-14	238	476
Ecuador	06-10-17	214	477	Serbia	09-13-19	212	477
Egypt	13-16-20	1291	2974	Slovak Republic	09-13-19	46	94
El Salvador	06-10-16	273	612	Slovenia	09-13-19	143	317
Estonia	09-13-19	121	257	SouthAfrica	07-20	139	278
Ethiopia	11-15	372	744	Suriname	10-18	55	110
Georgia	08-13-19	158	349	Tajikistan	08-13-19	143	293
Ghana	07-13	31	62	Tanzania	06-13	115	230
Guatemala	06-10-17	331	745	Timor-Leste	09-15-21	109	267
Honduras	06-10-16	162	352	Togo	09-16	60	120
Hungary	09-13-19	121	265	Tunisia	13-20	228	456
Indonesia	09-15	491	982	Turkey	08-13-19	694	1441
Jordan	13-19	193	386	Uganda	06-13	209	418
Kazakhstan	09-13-19	197	420	Ukraine	08-13-19	328	688
Kenya	07-13-18	384	828	Uruguay	06-10-17	338	737
Kosovo	09-13-19	87	176	Uzbekistan	08-13-19	246	556
Kyrgyz Republic	09-13-19	159	340	Venezuela	06-10	149	298
Lao PDR	09-12-16-18	195	422	Vietnam	09-15	294	588
Latvia	09-13-19	150	332	West Bank And Gaza	13-19	182	364
Lebanon	13-19	219	438	Yemen	10-13	139	278
Lesotho	09-16	61	122	Zambia	07-13-19	368	792
Liberia	09-17	81	162	Zimbabwe	11-16	302	604

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.