Skill Supply, Firm Size, and Economic Development

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Abstract

This paper harmonizes individual-level data on labor supply for 54 countries to document how firm size and the skill intensity of employment by firm size vary across countries. First, it finds that the share of employment in large firms in high-income countries is more than three times larger than in low-income countries. Second, it shows that across countries, employees of large firms are more skilled than those of small firms. Third, it documents that lower skill endowments in low-income countries affect employment in firms of different sizes asymmetrically: the skill intensity of employment is much lower in small firms in low-income countries than in high-income countries, but only slightly lower in large firms. This evidence suggests that large firms rely particularly strongly on employing high-skill workers, so that the low skill endowment of low-income countries limits the size of firms in these countries.

Keywords: Firm Size, Economic Growth, Human Capital

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Introduction

Two characteristics that differ dramatically across high-income and low-income countries are the size of firms and the skill composition of the workforce. It is well known that firms are larger and workers have more skills in higher-income countries. This paper explores the importance of the low skill endowments in low-income countries for the small size of firms and low aggregate productivity. To do so, this study builds a novel data set that harmonizes labor force and household surveys for 54 countries at all stages of development. It exploits this micro data set to document novel facts about the joint distribution of skills and firm size, particularly concerning the skill intensity of firms of different sizes across countries at different income levels. It then combines this new evidence with a model of heterogeneous firms of endogenous size to study how skill endowments affect the size distribution of firms and aggregate productivity.

The study starts with the natural hypothesis that running large firms requires skilled workers and that, therefore, low skill endowments might limit the size of firms.[1] The existing literature comparing firm size distributions across countries has not been able to speak to this issue because the data sources used by these authors, by their nature, are silent on workforce skills.

The data set used in this study has several advantages. First, all surveys used are nationally representative. Second, they all provide information about respondents' demographics, education, employment, and the employer's firm size. This information, which is not available when firm sizes are measured based on firm register data, is essential to this study. Third, unlike surveys conducted at the firm level, these surveys provide detailed information about workers' skills across firms of all types and sizes, including informal firms, which account for a large share of firms and a sizeable share of employment in most low-income countries. This approach avoids the problem of representativeness confronted by many enterprise-level surveys, which often only survey large or formally registered firms.[2]

The data in this study confirm that firms are smaller in lower-income countries. In high-income countries, 51 percent of all employees work in firms with more than 50 employees, while only 15 percent do so in low-income countries. The data here allow the analysis to go beyond this and measure skill by firm size class. The study finds that in high-income countries, the share of workers with at least a secondary school degree is about 86 percent in large firms and about 79 percent in small firms. Large firms, thus, are more skill-intensive. In low-income countries, both shares are lower, and the gap is larger: the share of workers with at least a high school degree is about 50 percent in large firms and about 22 percent in small firms.

Given the greater skill intensity of large firms everywhere, these facts suggest that low skill endowments in low-income countries may contribute to the low number of large firms there. More precisely, the facts on skill intensity by size documented in this study are consistent with a world where (1) skills are scarce in low-income countries; (2) large firms use more skill-intensive technologies; and (3) large firms find it more difficult to substitute low-skill for high-skill workers. Fact (2) implies that large firms use more skilled workers around the globe. Fact (3) implies that when skilled workers are scarce, large firms reduce their employment of these workers less than small firms do. In such a world, it is particularly difficult or costly to run large firms when skills are scarce. Skill scarcity will thus limit firm size.

[1] This hypothesis is in line with work on managers and the structure of firms building on the seminal contribution of Garicano (2000), like Akcigit, Harun, and Peters (2021), Grobovšek (2020), and Hjort, Malmberg, and Schoellmann (2022), but goes beyond managers. Essentially, running an organization of more than minimal size requires record keeping and written communication, which requires some amount of skill from many workers, not just managers.

[2] For instance, the World Bank Enterprise Surveys focus only on formal (registered) companies with five or more employees. See https://www.enterprisesurveys.org/en/methodology.

To better understand the data and the importance of skills, this study builds a new heterogeneous firm macro model of skills and size. The model is in the tradition of Hopenhayn (1992). It features two sectors that differ not only in optimal scale [as in Buera, Kaboski, and Shin (2011)] but also in factor intensity and the elasticity of substitution [as in the representative firm models of Acemoglu and Guerrieri (2008) and Alvarez-Cuadrado, Long, and Poschke (2017)]. Firms in the model produce with both low- and high-skill workers and choose between a large-scale technology and a small-scale technology. In line with the data patterns, the technologies differ in optimal scale, skill intensity, and input substitutability. The optimal choice of technology depends on a firm's productivity and input prices. In this setting, a lower skill endowment has two effects. First, it raises the price of skills and makes all firms use fewer skilled workers. This directly reduces aggregate output. A second effect goes beyond this: a greater skill premium makes fewer firms use the large-scale technology, further reducing output.

To quantify the strength of these effects, this study follows a standard approach in the macroeconomic literature on cross-country productivity differences. The analysis proposes to calibrate the model to data from the United States and then vary skill endowments to determine their effect on firm size and productivity. The most challenging part of the calibration is that currently, only the aggregate elasticity of substitution between high- and low-skill workers is known. The study then calibrates this elasticity separately by firm size class.

Our future work will use the model to simulate the effect of scarcer skill endowments on the skill composition of different firms, relative wages by firm size, the size distribution of firms, and aggregate productivity. Also, it will conduct counterfactual exercises to isolate the direct effect of scarcer skills from the indirect effect via firm size. The analysis will then be able to contrast our findings, which rely on observables, with those of a large literature attributing the smaller relative size of large firms in low-income countries to unobservable "size-dependent distortions" (Guner, Ventura, and Xu 2008; Restuccia and Rogerson 2008).

The paper is structured as follows. The second section reviews the literature. The third section describes the data and discusses firm size and skill measurement. The fourth section presents cross-country evidence. It replicates established stylized facts and then provides new ones. Motivated by these new facts, it then outlines a new heterogeneous firm model, which is described in the Appendix. The final section concludes. Appendices present background information about the surveys and data.

Literature

The theoretical literature aiming to explain differences in firm size across countries generally builds on the heterogeneous firm models of Hopenhayn (1992). A large literature has explored the effects of specific distortions on the efficiency of resource allocation and aggregate productivity: in particular, entry costs (Moscoso Boedo and Mukoyama 2012; Poschke 2010); labor market regulation (Hopenhayn and Rogerson 1993; Poschke 2009; Ulyssea 2010); and financial frictions (Buera, Kaboski, and Shin 2011; Midrigan and Xu 2014). A parallel literature has diagnosed the existence of generic wedges or distortions that reduce aggregate productivity, in particular for large firms (Bartelsman, Haltiwanger, and Scarpetta 2013; Hsieh and Klenow 2009; Restuccia and Rogerson 2008). Bento and Restuccia (2017, 2021) also link such distortions to the smaller size of firms in low-income countries, whereas Poschke (2018) focuses on technological factors.

At the same time, a recent literature has revisited the importance of human capital for cross-country income differences, but without taking the analysis to the firm level (Caselli and Ciccone 2013; Hendricks and Schoellman 2023; Jones 2014). To the best of our knowledge, only Hjort, Malmberg, and Schoellmann (2022) analyze the effect of skill costs on firm sizes and aggregate productivity, focusing specifically on middle managers. It remains to be shown how skills more broadly differ across firm size and how skill scarcity affects the size distribution and aggregate productivity.

Data and measurement

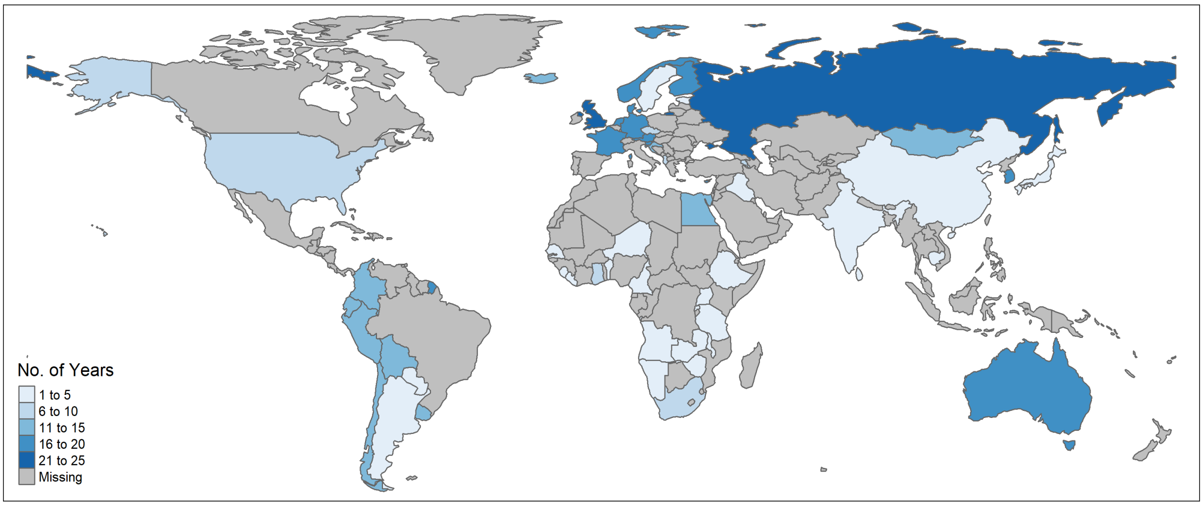
This section discusses the data sources used for the empirical analysis. The first main contribution is to provide a data set that allows the study of the human capital intensity by firm size in many countries across the income distribution. The discussion that follows describes the criteria for selecting these surveys and explains how the study measures skills and firm size.

Data sources

This study built a harmonized data set that provides information on the firm size distribution across a large set of countries. It draws from secondary data sources, particularly nationally representative surveys that provide information on individual characteristics (age and sex); years of schooling; and firm size of the employer.

The data set consists of 467 country-year surveys across 54 countries. It encompasses harmonized cross-country data sets, the European Union Statistics on Income and Living Conditions (SILC) survey, the IPUMS-International (Integrated Public Use Microdata Series, International), and the EU-LFS (European Union Labor Force Survey); the analysis sources and harmonizes all remaining surveys. The sample covers individuals across all continents in countries that span the income per capita distribution from $US871 (Rwanda, 2000) to $US62,313 (Norway, 2012) in terms of purchasing power parity (PPP). For many countries, there are multiple time observations, so the data set is an unbalanced panel at the country year level. Map 1 shows the number of year-observations for each country. Table A.1 in Appendix A lists the countries, years, and surveys used.

Map 1. Country and time coverage of data



Source: Original calculations for the *World Development Report 2024.*
Note: This map reports the geographic sample coverage. Darker shades of blue mean that there are more year observations for that particular country.

Measurement

The analysis is restricted to working-age individuals aged between 15 and 65. The three main variables of interest are firm size, worker demographics and job characteristics. The discussion that follows explains how the three variables are measured.

Firm size. The survey selection criterion for the harmonized data set is the availability of a survey question on the size of the establishment in which the respondent works. In particular, all surveys used contain the following question asked to wage workers: *"How many employees work in your place of work (establishment/work site)?"*. The analysis harmonizes answers to this question into three consistent categories: small, medium, and large. Small firms are defined as having fewer than

10 employees; medium firms have 10 to 50 employees; and large firms have more than 50 employees. This is the most common way labor force and household surveys collect information on employer firm size. If a survey provides more bins, the analysis assigns individuals to either of these three categories, provided the bins are consistent with the described thresholds.[3]

Worker characteristics. The data set contains information about a worker's demographics and education. The analysis uses data on the completed degree and years of education to determine whether a worker is skilled or not. It defines individuals with nine or fewer years of formal education as "unskilled" and those with more than nine years as "skilled." In most countries, this coincides with completing lower secondary education as defined by the International Standard Classification of Education (ISCED category 2), the transition point in the education system from a generalist classification to subject-oriented instruction.

Job characteristics. The data set also provides information on the individual's main job type and sector of employment. A job type can be either wage or self-employment. Within the self-employment category, the study distinguishes between unpaid work, own-account work, and employers. Moreover, the survey data contain information on the worker's sector of employment.

Cross-country evidence

This section documents facts on how firm size and skill intensity of employment by firm size vary across countries. It first provides new facts on the composition of employment by job type and firm size. It then studies the skill intensity of employment by firm size and how it evolves across country income levels. Finally, it leverages the data on employment by firm size to estimate average firm size by sector for all countries in our sample.

Employment by job type and firm size

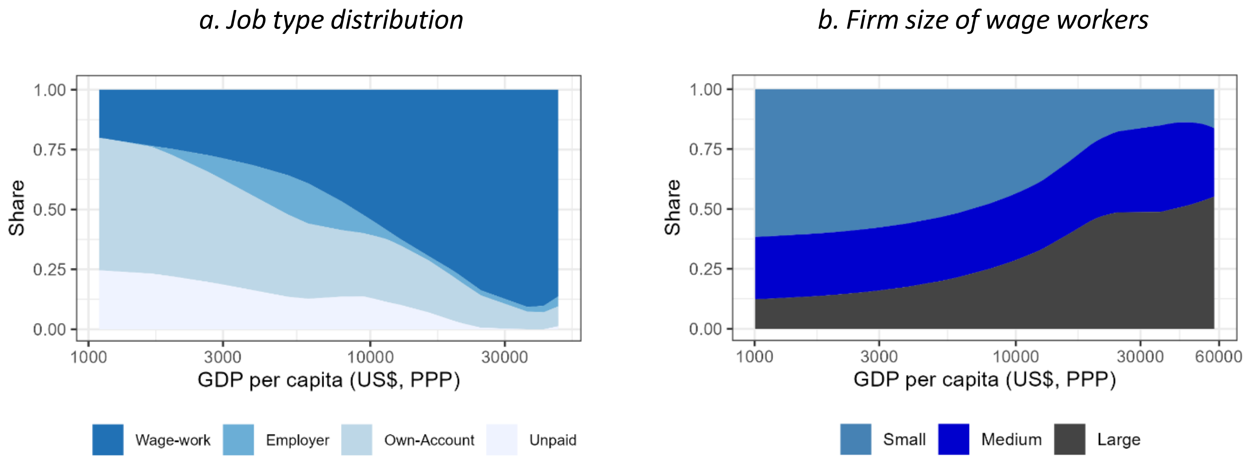
The following discussion provides descriptive evidence on the cross-country distribution of employment by job type and firm size.

Figure 1, panel a shows that the share of wage employment increases with GDP per capita while the share of self-employment declines. This pattern is in line with the findings reported by Gollin (2008) and others. The figure also reveals that the drop in the share of unpaid and own-account workers drives the decline in self-employment.

The data in the study provide information on the number of employees at their establishment for all wage workers. There is information on whether they work in small firms (less than 10 employees), medium firms (between 10 and 50 employees), or large firms (more than 50 employees). Figure 1, panel b displays the share of wage workers who work in these three firm size categories. In low-income countries, 60 percent of employees work in small firms, while only about 15 percent work in large firms. That share increases with GDP per capita until, in high-income countries, the share of employees in large firms reaches 51 percent (see table 1). When comparing low-income to high-income countries, the share of wage workers working in large firms increases by a factor of 3.4.

[3] Some surveys offer the possibility for respondents to report firm size in a different way in case the respondent is unsure. For instance, if respondents do not know whether the establishment falls into either of the three categories, they are asked whether the firm is above or below a single threshold—for example, 10 employees—instead of two thresholds. For such responses, the analysis is unable to assign individuals to a medium or large firm. It uses only those surveys for which these responses make up at most 1 percent of responses, and codes them as missing.

Figure 1. Employment by job type and firm size across countries



Source: Original calculations for the *World Development Report 2024.*
Note: Panel a shows the share of wage workers, employers, own-account workers, and unpaid workers based on the most recent year for each country in the sample and their corresponding GDP per capita (PPP, real). Panel b shows the share of wage workers that work in establishments with less than 10 employees (small), between 10 and 50 employees (medium), and more than 50 employees (large). In both panels, the lines correspond to the best local fit using a separate locally estimated scatterplot smoothing (LOESS) regression for each category-specific share. The category-fitted shares have been normalized to sum up to one and stacked. In both panels, these shares are plotted against GDP per capita in US dollars as provided by Feenstra, Inklaar, and Timmer (2015).

Table 1. Employment shares by firm size across countries

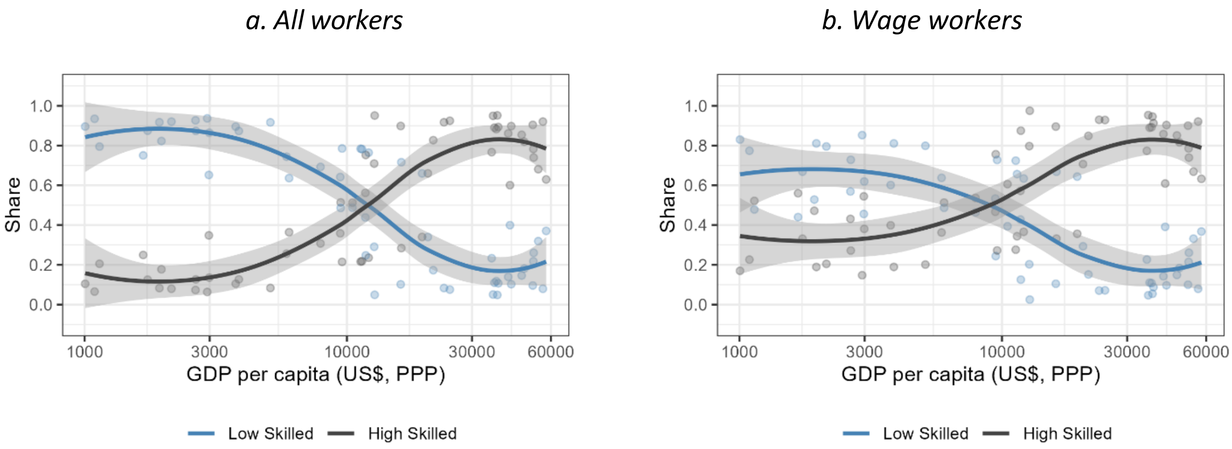
	Country income group			
Firm size category	**Low**	**Lower-middle**	**Upper-middle**	**High**
Large	0.15	0.19	0.40	0.51
Medium	0.25	0.34	0.30	0.34
Small	0.60	0.52	0.32	0.16
Number of countries	13	9	15	17

Source: Original calculations for the *World Development Report 2024.*
Note: This table reports the average employment share of wage workers in each firm size category. The averages are taken as the arithmetic average over each country's most recent observed year that falls in each income group. The income brackets we use to classify countries into income groups are [$0, $3,000], [$3,000, $10,000], [$10,000, $30,000], [$30,000, ∞], which this study refers to, respectively as low-income, lower-middle income, upper-middle-income, and high-income.

Skills across countries

Figure 2 panel a shows the share of skilled and unskilled workers for each country in the data set against GDP per capita (PPP), while figure 2 panel b reports the corresponding shares for wage workers only. In low-income countries, only about 10 percent of the workforce is skilled, compared to about 25 percent of wage workers. These shares increase with GDP per capita. At income levels of about $10,000 per capita, the share of low-skill and high-skill workers is at parity. In high-income countries, about 80 percent of the workforce and wage workers are skilled. This evidence implies that in low-income countries, wage workers are more skilled than self-employed workers, while this is not the case in high-income countries.

Figure 2. Distribution of skills across countries



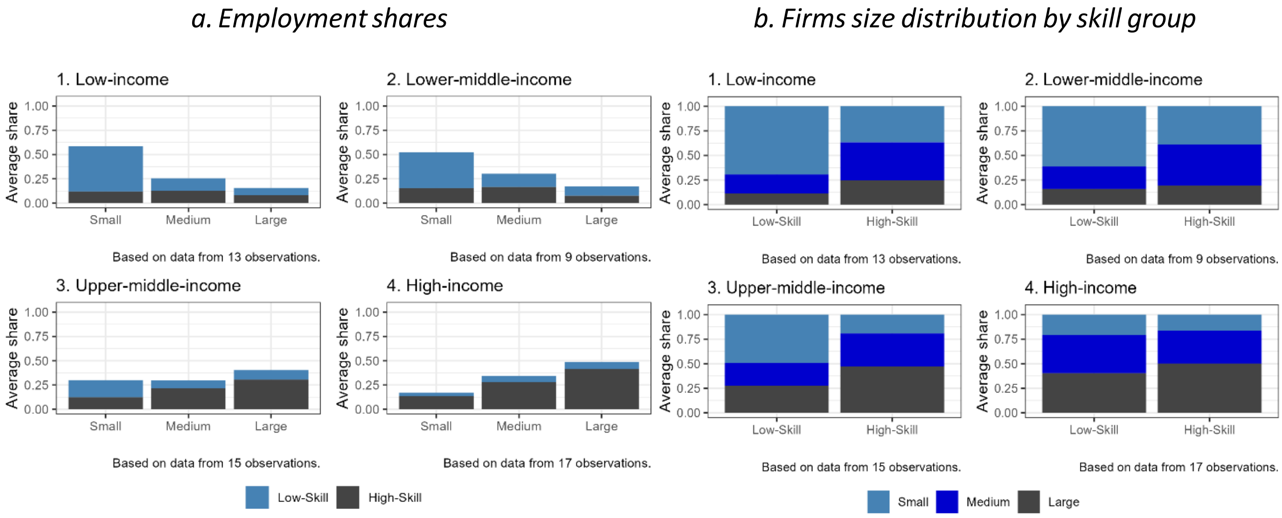
Source: Original calculations for the *World Development Report 2024.*
Note: This figure reports the share of skilled and unskilled workers, whereby an individual is considered skilled if s/he has more than nine years of schooling for the most recent observation of each country in the sample. Panel a reports these shares for the overall population of workers aged between 15 and 65, while panel b reports them for wage workers only. The lines show the best local fit using a locally estimated scatterplot smoothing (LOESS) regression. In both panels, these shares are plotted against GDP per capita in US dollars, as provided by Feenstra, Inklaar, and Timmer (2015). PPP = purchasing power parity.

Skill intensity by firm size

The discussion now comes to the main new empirical findings. Figure 3 panel a documents the skill distribution of workers by employer firm size. In the cross-section of countries, the study finds that in low-income countries, the majority of employees are unskilled and work in small firms (panel a). In all low- and middle-income country groups, small firms have a substantially lower skill intensity than large firms, or than small firms in higher-income countries. Figure 4 clearly shows that the share of skilled workers in large firms increases with per capita income.

Figure 3, panel b reports the employment shares in each firm size group for skilled and unskilled workers. Skilled workers are, in general, always more likely to work in medium and large firms than unskilled workers. In relative terms, this difference is particularly salient in low-income countries, where high-skill workers are about twice as likely to work in large firms as low-skill workers.

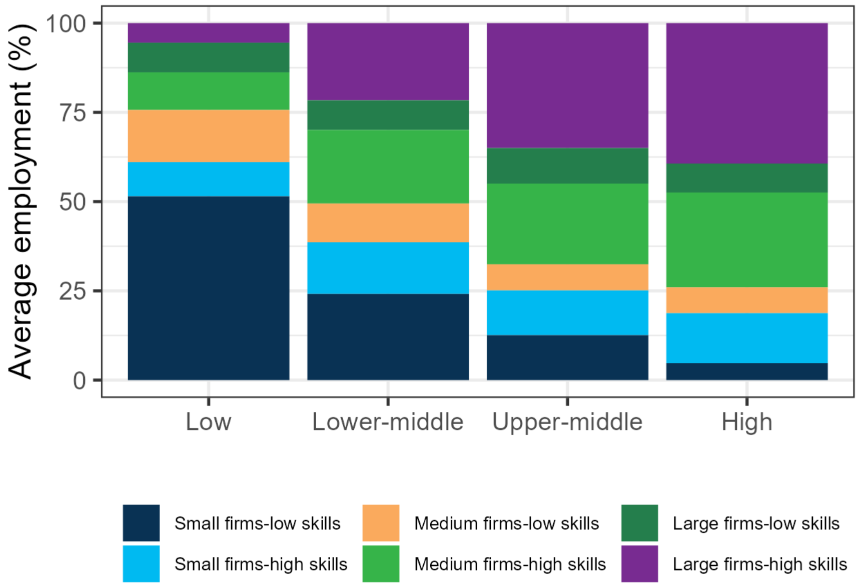
Figure 3. Skill distribution by employer firm size



Source: Original calculations for the *World Development Report 2024.*
Note: Panel a reports employment shares of skilled and unskilled workers in each firm category. The average

share is computed over the shares for the most recent country-year observations that fall in each income group. Panel b reports the employment shares in each firm size category for skilled and unskilled workers. The income groups correspond to low- [$0, $3,000], lower-middle- [$3,000, $10,000], upper-middle- [$10,000, $30,000], and high- [$30,000, ∞] income categories.

Figure 4. Composition of employment by skill and firm size



Source: Original calculations for the *World Development Report 2024.*
Note: This figure shows the share of low-skill and high-skill workers who are employed in small, medium, and large firms across four country income groups. The average share is computed over the shares for the most recent country-year observations that fall in each income group. The income groups correspond to low- [$0, $3,000], lower-middle- [$3,000, $10,000], upper-middle- [$10,000, $30,000], and high- [$30,000, ∞] income categories.

Table 2. Skill distribution by firm size

Firm size category		Country income group: Low	Lower-middle	Upper-middle	High
Large	Skilled	0.50	0.48	0.72	0.86
	Unskilled	0.50	0.52	0.28	0.14
Medium	Skilled	0.50	0.53	0.67	0.82
	Unskilled	0.50	0.47	0.33	0.18
Small	Skilled	0.22	0.30	0.51	0.79
	Unskilled	0.78	0.70	0.49	0.21
Number of countries		13	9	15	17

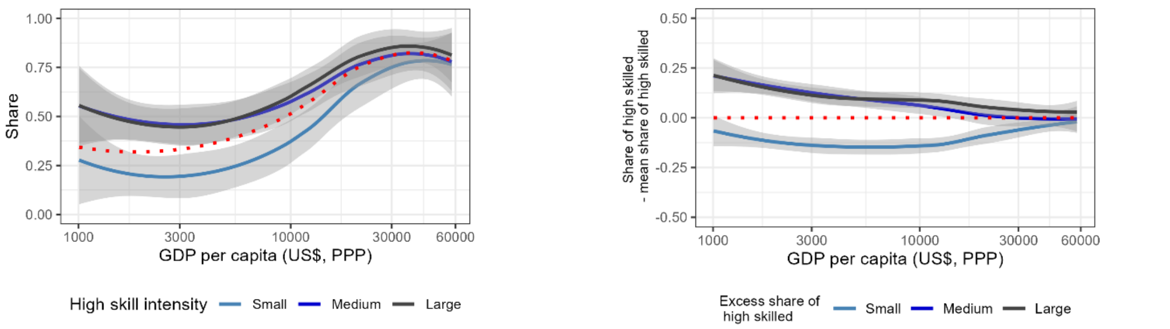
Source: Original calculations for the *World Development Report 2024.*
Note: This table is the equivalent of figure 4, panel a. It reports the share of skilled and unskilled workers in each firm category. The average share is computed over the shares for the most recent country-year observations that fall in each income group. The income groups correspond to low- [$0,$3,000], lower-middle [$3,000, $10,000], upper-middle [$10,000, $30,000], and high- [$30,000, ∞] income categories.

The discussion now documents the skill intensity of employment: that is, the share of skilled employment in each firm size. Figure 5, panel a reports the skill intensity in the population (dotted red line) and by firm size category.[4] Three patterns stand out. First, across all firm size categories, the skill intensity correlates positively with GDP per capita, in line with higher skill endowments in higher-income countries. Second, the skill intensity of employment is generally higher in larger firms. Finally, while the skill intensity of employment in low-income countries is generally lower, the gap compared to high-income countries is particularly large for small firms. The skill intensity of large firms in low-income countries is about 60 percent of that in high-income countries (0.5 compared to 0.86; see table 2), whereas the ratio is about 30 percent for small firms (0.22 compared to 0.79). In low-income countries, half the workers in large firms are skilled, compared to less than one-quarter of the workers in small firms. In high-income countries, in contrast, the share of skilled workers is about 86 percent in large firms and about 79 percent in small firms.

That is, large and medium firms are more skill-intensive everywhere. But their skill intensity varies less with country income, and thus skill endowments, than that of small firms, suggesting that large firms are less flexible in adjusting to the scarcity of skilled workers in low-income countries.

Figure 5. Skill intensity by firm size across countries

a. Skill intensity for each firm size category *b. Deviation from the share of skilled workers*



Source: Original calculations for the *World Development Report 2024.*
Note: This figure shows the share of high-skill workers conditional on firm size across the GDP per capita spectrum. The underlying data are for the most recent observation for each country. The three lines correspond to the best local fit using a separate locally estimated scatterplot smoothing (LOESS) regression for each category-specific share. PPP = purchasing power parity.

Estimating and comparing firm size

The analysis now exploits the fact that the distribution of wage workers by firm size is informative about the unobserved underlying firm size distribution. It uses these data to estimate average firm size for each country survey in the sample and for each sector. This allows this study to relate its estimates to earlier work in this literature (particularly Bento and Restuccia 2021).

Bento and Restuccia (2021) directly measure the distribution of firm size using firm-level data, and focus on mean employment across firms. Comparing our measures to theirs requires a few steps because this present study does not directly observe the distribution of firm size; instead, this study measures the distribution of employment by firm size.

To carry out the comparison, suppose that firm size follows a Pareto distribution with probability density function

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

[4] The skill intensity is higher for all firm size categories than for the population because the population also encompasses self-employed workers who, in general, have lower educational outcomes than wage workers.

following Luttmer (2007) and others. α is the shape parameter of the distribution. Because this study's data also includes the smallest firms, the scale parameter x_m, which corresponds to minimum employment, can be set equal to one.

This study does not directly observe *f(x)*, but instead measures the distribution of employment by firm size. This is closely linked to the firm size distribution. Its probability density function, g(x), is given by

$$g(x) = (\alpha - 1)x^{-\alpha},$$

and the corresponding cumulative distribution function is

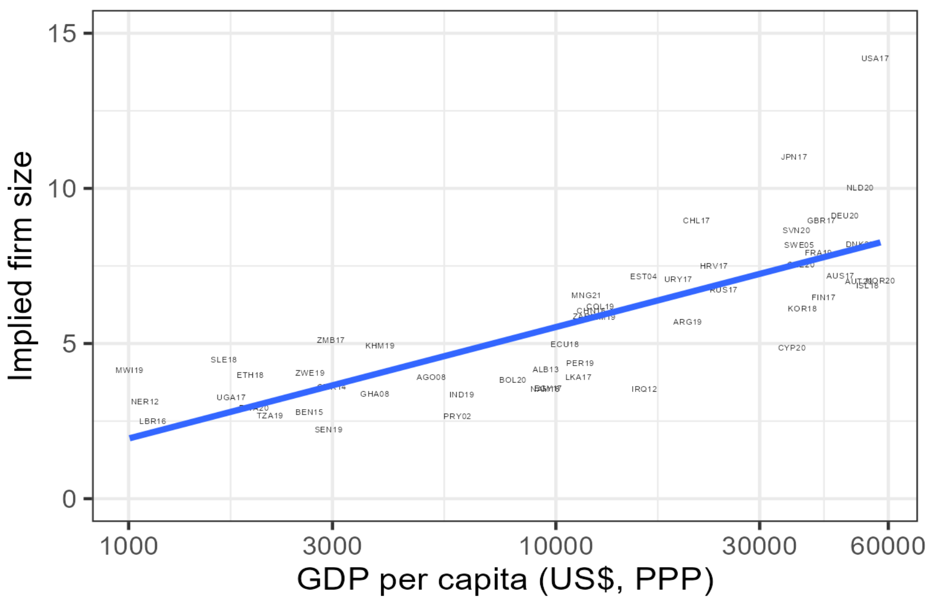
$$G(x) = \int_1^x (\alpha - 1)t^{-\alpha}dt = 1 - x^{1-\alpha}.$$

Because this study measures the share of employment in small firms [G(10)], the share of workers in medium firms [G(50) − G(10)], and that in large firms [G(50)] in each survey, these shares can easily be used to infer the shape parameter of the underlying Pareto distribution. From that, mean firm size follows by the properties of the Pareto distribution as

$$E(X) = \frac{\alpha}{\alpha - 1}.$$

The estimated shape parameters are reported in figure B.1 in appendix B. The implied average firm size for all surveys in the data set is reported in figure 6. The average firm has three employees in low-income countries and about eight workers in high-income countries. Average employment increases linearly in the log of GDP per capita, and the semi-elasticity is 0.28. This elasticity measure is consistent with other papers in the literature that find an elasticity of average size with respect to GDP per capita between 0.3 and 0.4 (Bento and Restuccia 2021).

Figure 6. Average firm size and GDP per capita

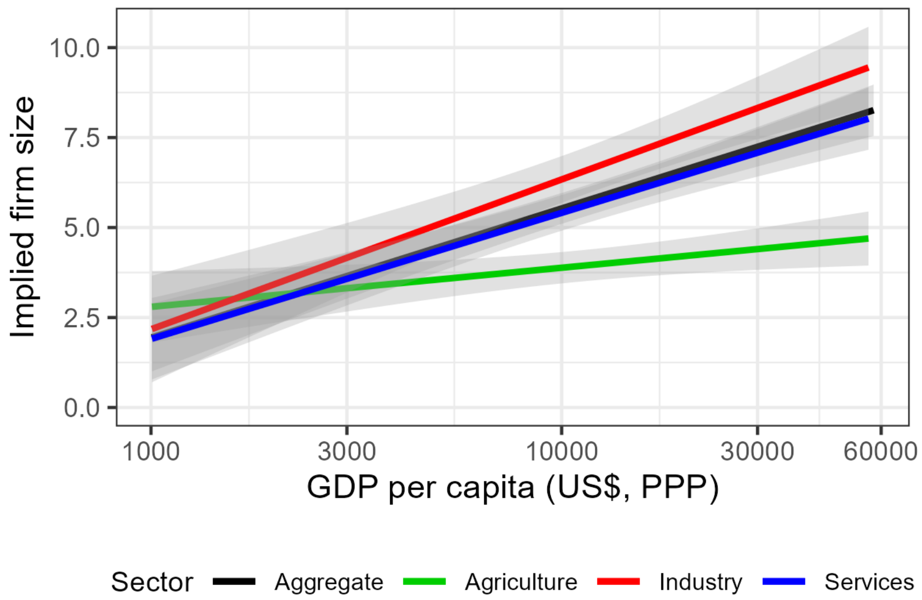


Source: Original calculations for the *World Development Report 2024.*
Note: This plot shows the implied average firm size against the GDP per capita (log-transformed) for the most recent country year. The average firm size is constructed from the shares of workers reporting to work either in small or medium firms [G(50)], as described in the fourth section. Data labels use International Organization for Standardization (ISO) country codes and average firm size in terms of number of employees. PPP = purchasing power parity.

How does the average firm size implied by the employment shares relate to the existing literature? The analysis uses the same procedure to infer the average firm size for each sector (see figure B.2) and compares these to the average firm size data for manufacturing and service firms from Bento and Restuccia (2021). The correlation coefficient between both series is 0.53 for the average firm size in the manufacturing sector and 0.47 for the service sector (see figure B.3).

Figure 7 plots the line of best fit of the implied average firm size with GDP per capita for each sector. It shows that firm size increases for all sectors with country income levels. However, there are large sectoral differences. The gradient of firm size with GDP per capita is much weaker in agriculture than in the other two sectors. In high-income countries, firms in the agricultural sector have only 1 more employee than in low-income countries. (In this context, an agriculture firm employs wage workers and, therefore, does not encompass household farms that characterize subsistence agriculture). In contrast, there is a strong gradient of average firm size with country income levels in industry and service sectors. Across the development spectrum, firm size in both of these sectors increases by a factor of 2.3.

Figure 7. Average firm size across countries for each sector



Source: Original calculations for the *World Development Report 2024.*
Note: This plot shows the average implied firm size by sector (on a log scale) against the GDP per capita (log-transformed). It measures the implied average firm size using employment shares by small, medium, and large firms in each sector, as described in the third section. The underlying data are for the most recent country-year. The lines show the linear fit of a regression. PPP = purchasing power parity.

Table 3. Average firm size by sector

	Country income group				All countries
Sector	**Low-**	**Lower-middle**	**Upper-middle**	**High-**	**Semi-elasticity**
Aggregate	3.45	3.71	6.03	8.20	0.28
Agriculture	3.41	2.77	4.54	4.35	0.15
Industry	4.05	4.19	7.20	9.24	0.29
Services	3.56	3.61	5.88	8.08	0.27
Number of countries	13	9	15	17	

Source: Original calculations for the *World Development Report 2024.*
Note: This table reports the average implied firm size for each country income group, presented for the aggregate economy and for each sector. The last column reports the semi-elasticity of implied firm size with GDP per capita in purchasing power parity (PPP) terms.

Conclusion

This paper presents three main findings about the relationship between firm size, skill distribution, and economic development. First, it shows that the share of employment in large firms in high-income countries is more than three times larger than in low-income countries. Second, it shows that across countries, employees of large firms are more skilled than those of small firms. Third, it shows that in low-income countries, employment in small firms is much less skilled than in large firms, while in high-income countries, skilled workers are distributed similarly across all firm sizes. This evidence suggests that higher levels of education are associated with larger firm sizes and that high-skill workers in large firms generate higher incomes. In future work, the authors plan to use a new heterogeneous firm macro model of skills and size discussed in the Appendix of this paper to disentangle the impact of barriers to firm growth and skill supply on economic development, shedding light on the complex interplay between these factors.

Appendix A. Data sources

Table A.1. Household and Labor Force Surveys

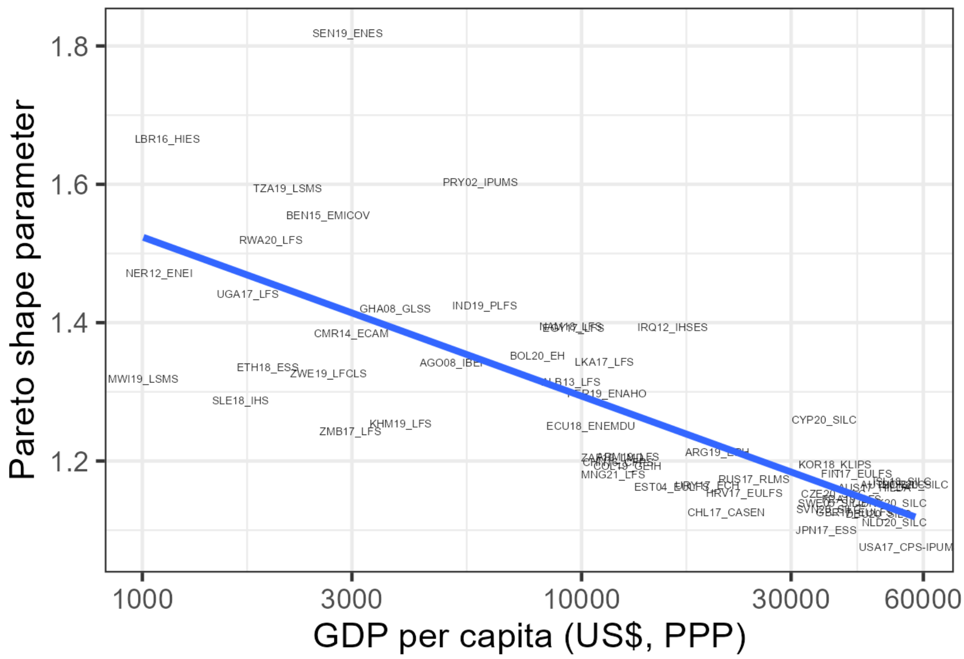
Country	Earliest year	Latest year	Survey name
Albania	2007	2013	Labour Force Survey
Angola	2008	2008	Inquerito Integrado sobre o Bem-Estar da Populacao
Argentina	2019	2019	Encuesta Permanente de Hogares
Armenia	2009	2013	Integrated Living Conditions Survey
Armenia	2016	2019	Labour Force Survey
Australia	2001	2017	Household, Income and Labour Dynamics in Australia
Austria	2002	2003	European Labor Force Survey
Austria	2004	2020	European Union Statistics on Income and Living Conditions
Benin	2010	2015	Enquête Modulaire Intégrée sur les Conditions de Vie des ménages
Bolivia	2015	2018	Encuesta Continua de Empleo
Bolivia	2005	2020	Encuesta de Hogares
Cambodia	2012	2019	Cambodia Labor Force Survey
Cambodia	2012	2019	Cambodia Labor Force and Child Labor Survey
Cambodia	2012	2019	Labor Force Survey
Cameroon	2014	2014	Fourth Cameroon Household Survey
Chile	1990	2017	Encuesta de Caracterización Socioeconómica Nacional
China	2014	2016	Family Panel Studies
Colombia	2007	2019	Gran Encuesta Integrada de Hogares
Croatia	2006	2017	European Labor Force Survey
Cyprus	2005	2020	European Union Statistics on Income and Living Conditions
Czechia	2011	2020	European Union Statistics on Income and Living Conditions
Denmark	2004	2020	European Union Statistics on Income and Living Conditions
Ecuador	2007	2018	Encuesta Nacional de Empleo, Desempleo y Subempleo
Ecuador	2005	2005	Encuesta de Condiciones de Vida
Egypt, Arab Rep.	2007	2016	Harmonized Labor Force Survey
Egypt, Arab Rep.	2017	2017	Labor Force Survey
Egypt, Arab Rep.	2006	2006	Labor Market Panel Survey
Estonia	2001	2004	European Labor Force Survey
Ethiopia	2018	2018	Ethiopia Socioeconomic Survey
Ethiopia	2018	2018	Socioeconomic Survey
Finland	2001	2017	European Labor Force Survey
Finland	2005	2006	European Union Statistics on Income and Living Conditions
France	2003	2019	Enquête emploi annuelle
France	2003	2019	Enquête emploi en continu
France	2012	2015	European Union Statistics on Income and Living Conditions
Germany	2020	2020	European Union Statistics on Income and Living Conditions
Germany	2005	2019	Socio-economic Panel
Ghana	1987	2008	Ghana Living Standard Survey
Ghana	1987	2008	Living Standard Survey
Iceland	2003	2003	European Labor Force Survey
Iceland	2004	2018	European Union Statistics on Income and Living Conditions
India	2018	2019	Periodic Labor Force Survey
Iraq	2007	2012	Household Socio-Economic Survey
Japan	1997	2017	Employment Status Survey
Korea, Rep.	2003	2018	Korean Labor and Income Panel Study
Liberia	2014	2016	Household Income and Expenditure Survey
Malawi	2019	2019	Integrated Household Survey
Mongolia	2007	2021	Labor Force Survey
Namibia	2012	2018	Labor Force Survey
Netherlands	2003	2004	European Labor Force Survey
Netherlands	2005	2020	European Union Statistics on Income and Living Conditions
Niger	2012	2012	ENQUETE NATIONALE SUR L'EMPLOI ET LE SECTEUR INFORMEL
Niger	2011	2011	National Survey on Household Living Conditions and Agriculture
Norway	2004	2020	European Union Statistics on Income and Living Conditions

Country	Earliest year	Latest year	Survey name
Paraguay	2002	2002	Integrated Public Use Microdata Series - International
Peru	2007	2019	Encuesta Nacional de Hogares
Russia	1994	2017	Russia Longitudinal Monitoring Survey
Rwanda	2000	2000	Enquête Intégrale sur les Conditions de Vie des Ménages
Rwanda	2017	2020	Labor Force Survey
Senegal	2017	2019	Enquête nationale sur l'Emploi au Sénégal
Sierra Leone	2018	2018	Integrated Household Survey
Slovenia	2001	2004	European Labor Force Survey
Slovenia	2005	2020	European Union Statistics on Income and Living Conditions
South Africa	2010	2019	Labor Market Dynamics
Sri Lanka	2017	2017	Labor Force Survey
Sweden	2004	2005	European Union Statistics on Income and Living Conditions
Tanzania	2008	2019	Living Standards Measurement Survey
Tanzania	2008	2019	National Panel Survey
Uganda	2017	2017	Labor Force Survey
United Kingdom	1991	2008	British Household Panel Survey
United Kingdom	2012	2017	European Labor Force Survey
United States	2010	2017	Current Population Survey
Uruguay	2006	2017	Encuesta Continua de Hogares
Zambia	2017	2017	Labour Force Survey
Zimbabwe	2014	2019	Labour Force and Child Labour Survey

Appendix B. Firm size distribution

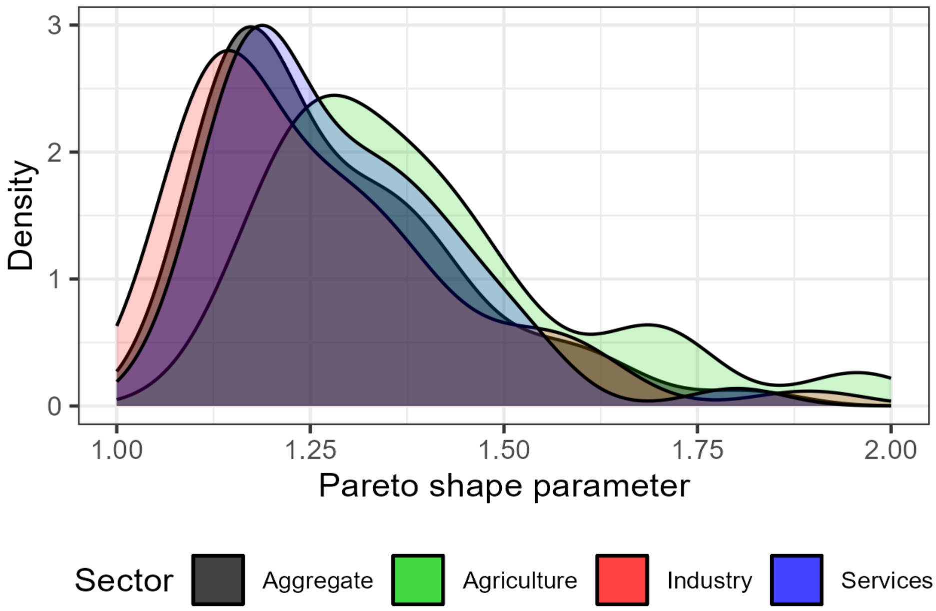
Figure B.1 plots the estimates of the shape parameter for the most recent country observations in our sample. Figure B.2 reports the distribution of the shape parameters we estimate for the aggregate economy and for each sector. A higher shape parameter implies a lower average firm size.

Figure B.1. Estimates of the shape parameter for each country



Source: Original calculations for the *World Development Report 2024*.
Note: This figure shows the estimates of the shape parameter of the firm size distribution against GDP per capita. Labels use International Organization for Standardization (ISO) country codes and the survey name abbreviation. PPP = purchasing power parity.

Figure B.2. Distribution of the estimates for the shape parameter (α)



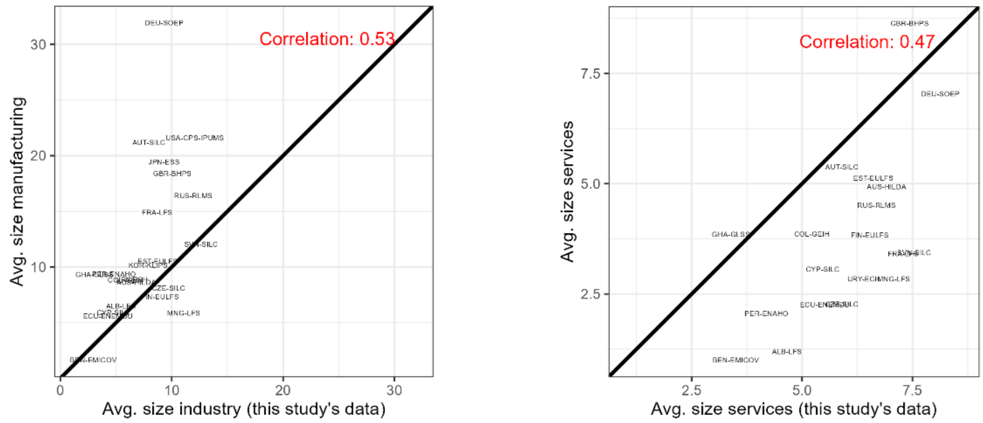
Source: Original calculations for the *World Development Report 2024*.
Note: This figure shows the distribution of estimated shape parameters for the underlying firm distribution for our data. A higher shape parameter implies a smaller average firm size and a more right-skewed Pareto distribution.

Comparison to Literature

Figure B.3 plots the data by Bento and Restuccia (2021) against this study's implied firm size measures for the industry and service sectors. Bento and Restuccia have indicated that they chose their data sources to be as close to 2007 as possible. This analysis, therefore, compares their numbers for each country-year that is closest to 2007.

Figure B.3. Comparison of this study's mean firm size measure with that of Bento and Restuccia (2021)

a. Industry *b. Services*



Source: Original calculations for the *World Development Report 2024.*
Note: Labels use International Organization for Standardization (ISO) country codes and the survey name abbreviation.

Appendix C. Summary tables

Table C.1. Job type Statistics

Income group	Job type	Mean	Median	Min	Max
Low-income	Employer	0.022	0.019	0.008	0.043
Low-income	Own-Account	0.496	0.566	0.104	0.730
Low-income	Unpaid	0.222	0.149	0.045	0.749
Low-income	Wage-work	0.260	0.216	0.108	0.677
Lower-middle-income	Employer	0.130	0.039	0.018	0.699
Lower-middle-income	Own-Account	0.305	0.302	0.017	0.579
Lower-middle-income	Unpaid	0.137	0.124	0.000	0.330
Lower-middle-income	Wage-work	0.429	0.426	0.156	0.741
Upper-middle-income	Employer	0.037	0.032	0.010	0.081
Upper-middle-income	Own-Account	0.234	0.207	0.078	0.436
Upper-middle-income	Unpaid	0.075	0.030	0.000	0.383
Upper-middle-income	Wage-work	0.654	0.659	0.450	0.908
High-income	Employer	0.026	0.016	0.009	0.054
High-income	Own-Account	0.073	0.077	0.041	0.101
High-income	Unpaid	0.003	0.002	0.000	0.007
High-income	Wage-work	0.898	0.884	0.867	0.943

Source: Original calculations for the *World Development Report 2024.*

Table C.2. Skill Statistics (Working-Age Population)

Income group	Education	Mean	Median	Min	Max
Low-income	High-skill	0.132	0.111	0.052	0.238
Low-income	Low-skill	0.868	0.889	0.762	0.948
Lower-middle-income	High-skill	0.229	0.210	0.070	0.465
Lower-middle-income	Low-skill	0.771	0.790	0.535	0.930
Upper-middle-income	High-skill	0.544	0.586	0.189	0.900
Upper-middle-income	Low-skill	0.456	0.414	0.100	0.811
High-income	High-skill	0.755	0.791	0.542	0.895
High-income	Low-skill	0.245	0.209	0.105	0.458

Source: Original calculations for the *World Development Report 2024.*

Table C3. Skill Statistics (Wage Workers)

Income group	Education WW	Mean	Median	Min	Max
Low-income	High-skill WW	0.342	0.331	0.147	0.560
Low-income	Low-skill WW	0.658	0.669	0.440	0.853
Lower-middle-income	High-skill WW	0.411	0.399	0.189	0.756
Lower-middle-income	Low-skill WW	0.589	0.601	0.244	0.811
Upper-middle-income	High-skill WW	0.654	0.707	0.276	0.975
Upper-middle-income	Low-skill WW	0.346	0.293	0.025	0.724
High-income	High-skill WW	0.827	0.858	0.609	0.953
High-income	Low-skill WW	0.173	0.142	0.047	0.391

Source: Original calculations for the *World Development Report 2024.*
Note: WW = wage worker.

Appendix D. Model

This appendix explains the model proposed to study the role of skill supply for the firm size distribution and aggregate productivity.

Households. The representative household derives utility from the consumption of a final good. The representative household consists of workers who are heterogeneous in terms of their skill level (education). This is denoted by the subscripts *l*(ow-skill) and *h*(igh-skill). Both worker types supply labor inelastically.

Production technology. Two types of firms exist (small and large). These are referred to using superscripts *s*(mall) and *b*(ig) to avoid letter clashes, with generic superscript *i*.

Firms differ in their productivity z. Each firm produces a final good using skilled and unskilled labor, L_h and L_l. These are combined in a constant elasticity of substitution (CES) production function with weight μ^i on the unskilled and elasticity of substitution ρ^i. These two parameters differ between small and large firms. Production has decreasing returns to scale, with parameter $\gamma^s < \gamma^b < 1$.

The model abstracts from physical capital. It also allows for an output tax τ, which may vary with a firm's productivity and can capture distortions à la Restuccia and Rogerson (2008) and others.

Output of a firm of size i with productivity z then is given by

$$Y^i(z) = z\left[\mu^i L_l^{i\,\frac{\rho^i-1}{\rho^i}} + (1-\mu^i)L_h^{i\,\frac{\rho^i-1}{\rho^i}}\right]^{\frac{\rho^i}{\rho^i-1}\gamma^i}.$$

The firm chooses skilled and unskilled labor inputs to maximize profits. Dropping firm-type superscripts i for conciseness, the problem is to maximize

$$\pi(z) \quad = \quad \max_{L_l,L_h}(1-\tau(z))z\left[\mu L_l^{\frac{\rho-1}{\rho}} + (1-\mu)L_h^{\frac{\rho-1}{\rho}}\right]^{\frac{\rho}{\rho-1}\gamma} - w_l L_l - w_h L_h$$

The first-order conditions for this problem are

$$\begin{aligned}(1-\tau(z))\gamma\mu z\left(\frac{Y(z)}{z}\right)^{1-\frac{\rho-1}{\rho\gamma}} L_l^{-\frac{1}{\rho}} &= w_l\\ (1-\tau(z))\gamma(1-\mu) z\left(\frac{Y(z)}{z}\right)^{1-\frac{\rho-1}{\rho\gamma}} L_h^{-\frac{1}{\rho}} &= w_h.\end{aligned}$$

The optimal ratio of skilled to unskilled workers is thus common for all firms of a given type, and is given by

$$\left(\frac{L_l}{L_h}\right)^i = \left(\frac{1-\mu^i}{\mu^i}\frac{w_l}{w_h}\right)^{-\rho^i}.$$

Denote this by Ω. This implies $L_l = \Omega L_h$, and

$$Y(z) = zL_h^{\gamma}\underbrace{\left[\mu\Omega^{\frac{\rho-1}{\rho}} + 1 - \mu\right]^{\frac{\rho}{\rho-1}\gamma}}_{\equiv\Theta}.$$

From this, the first order condition for L_h is

$$(1-\tau(z))z\gamma\Theta L_h^{\gamma-1} = w_h\underbrace{\left(1+\frac{w_l}{w_h}\Omega\right)}_{\tilde{\Omega}}.$$

It follows that optimal demand for skilled labor is

$$L_h(z) = \left(\frac{(1-\tau(z))z\Theta\gamma}{\tilde{\Omega}w_h}\right)^{\frac{1}{1-\gamma}}.$$

From this, it follows that the profits of a firm with productivity z are

$$\begin{aligned}
\pi(z) &= ((1-\tau(z))z\Theta)^{\frac{1}{1-\gamma}}\left[\left(\frac{\gamma}{\tilde{\Omega}w_h}\right)^{\frac{\gamma}{1-\gamma}} - (w_l\Omega + w_h)\left(\frac{\gamma}{\tilde{\Omega}w_h}\right)^{\frac{1}{1-\gamma}}\right] \\
&= ((1-\tau(z))z\Theta)^{\frac{1}{1-\gamma}}\left(\tilde{\Omega}w_h\right)^{-\frac{\gamma}{1-\gamma}}\left[\gamma^{\frac{\gamma}{1-\gamma}} - \gamma^{\frac{1}{1-\gamma}}\right] \\
&\equiv \Pi((1-\tau(z))z)^{\frac{1}{1-\gamma}}w_h^{-\frac{\gamma}{1-\gamma}},
\end{aligned}$$

where

$$\Pi = \Theta^{\frac{1}{1-\gamma}}\tilde{\Omega}^{-\frac{\gamma}{1-\gamma}}\left[\gamma^{\frac{\gamma}{1-\gamma}} - \gamma^{\frac{1}{1-\gamma}}\right].$$

Profits increase monotonically in z, from 0 for z of 0 to infinity as z goes to infinity. Note that both Π and γ differ by firm type.

Because $\gamma^b > \gamma^s$, $\pi^b(z)$ is less than $\pi^s(z)$ for small z, and is larger for large z. Hence, low- productivity firms prefer the small-firm technology, and high-productivity firms prefer the large-firm technology. Denote the cutoff where $\pi^s(z) = \pi^b(z)$ by z^*.

Size-dependent distortions. Following Buera and Fattal-Jaef (2018) and others, the output tax τ is modelled as

$$1-\tau(z) = z^{-\nu}.$$

This implies that for $\nu = 0$, $1-\tau = 1$ for all values of z, and there is no tax. For $\nu > 0$, after-tax revenue falls with productivity, so there are size-dependent distortions (SDD).

With this functional form assumption, the profit function for type i is

$$\pi(z) = \Pi w_h^{-\frac{\gamma}{1-\gamma}} z^{\frac{1}{1-\gamma}-\nu}.$$

Entry. There is a large number of potential entrants. To enter the market, an entrant pays an entry cost $c_e \cdot w_h$,[5] and then draws a productivity z from a distribution with a cumulative distribution function $G(z)$. It is assumed that G is a Pareto distribution with parameter α, so its cumulative distribution function is $1 - (z_m/z)^\alpha$.

Because entrants with $z \geq (<) z^*$ choose the large (small-) firm technology, the measure of large relative to small firms is

$$\frac{M^b}{M^s} = \frac{1 - G(z^*)}{G(z^*)} = \frac{(z_m/z^*)^\alpha}{1 - (z_m/z^*)^\alpha}$$

The share of large firms is

$$m^b = 1 - G(z^*) = (z_m/z^*)^\alpha.$$

Firms enter until the expected value of entry equals the entry cost. This implies

$$\begin{aligned} c_e &= \int_{z_m}^{z^*} \pi^s(z)\mathrm{d}G(z) + \int_{z^*}^{\infty} \pi^b(z)\mathrm{d}G(z) \\ &= \Pi^s w_h^{-\frac{\gamma^s}{1-\gamma^s}} \alpha z_m^\alpha \int_{z}^{z^*} z^{\frac{1}{1-\gamma^s}-\nu-\alpha-1}\mathrm{d}z + \Pi^b w_h^{-\frac{\gamma^b}{1-\gamma^b}} \alpha z_m^\alpha \int_{z^*}^{\infty} z^{\frac{1}{1-\gamma^b}-\nu-\alpha-1}\mathrm{d}z. \end{aligned}$$

Mean *z*. Define

$$\bar{z}^s \equiv \alpha z_m^\alpha \int_{z_m}^{z^*} z^{\frac{1}{1-\gamma^s}-\nu-\alpha-1}\mathrm{d}z \quad \text{and} \quad \bar{z}^b \equiv \alpha z_m^\alpha \int_{z^*}^{\infty} z^{\frac{1}{1-\gamma^b}-\nu-\alpha-1}\mathrm{d}z.$$

With Pareto distributed z, these are

$$\bar{z}^b = \frac{\alpha z_m^\alpha z^{*\frac{1}{1-\gamma^b}-\nu-\alpha}}{\alpha - \frac{1}{1-\gamma^s} + \nu}$$

And

$$\bar{z}^s = \alpha z_m^\alpha \frac{z_m^{\frac{1}{1-\gamma^s}-\nu-\alpha} - z^{*\frac{1}{1-\gamma^s}-\nu-\alpha}}{\alpha - \frac{1}{1-\gamma^s} + \nu}$$

With this definition, the free entry condition becomes

$$c_e = \Pi^s w_h^{-\frac{\gamma^s}{1-\gamma^s}} \bar{z}^s + \Pi^b w_h^{-\frac{\gamma^b}{1-\gamma^b}} \bar{z}^b.$$

[5] The idea is that skilled work is required to set up a firm. This is in line with Bollard, Klenow, and Li (2014).

Labor market clearing. For high-skill workers,

$$L_h = M^s \int_{z_m}^{z^*} L_h^s(z)\mathrm{d}G(z) + M^b \int_{z^*}^{\infty} L_h^b(z)\mathrm{d}G(z)$$
$$= M^s \left(\frac{\Theta^s \gamma^s}{\tilde{\Omega} w_h}\right)^{\frac{1}{1-\gamma^s}} \bar{z}^s + M^b \left(\frac{\Theta^b \gamma^b}{\tilde{\Omega} w_h}\right)^{\frac{1}{1-\gamma^b}} \bar{z}^b.$$

For low-skill workers,

$$L_l = M^s \Omega^s \left(\frac{\Theta^s \gamma^s}{\tilde{\Omega} w_h}\right)^{\frac{1}{1-\gamma^s}} \bar{z}^s + M^b \Omega^b \left(\frac{\Theta^b \gamma^b}{\tilde{\Omega} w_h}\right)^{\frac{1}{1-\gamma^b}} \bar{z}^b.$$

Equilibrium. Equilibrium variables: $w_h, w_l, L_h^s, L_l^s, L_h^b, L_l^b, M^s, M^b, z^*, \bar{z}^b, \bar{z}^s$ s.t.

1. Skill mix, for each firm type:

$$\left(\frac{L_l}{L_h}\right)^i = \left(\frac{1-\mu^i}{\mu^i}\frac{w_l}{w_h}\right)^{-\rho^i}.$$

2. Labor demand, for each firm type:

$$L_h(z) = \left(\frac{(1-\tau(z))z\Theta\gamma}{w_h}\right)^{\frac{1}{1-\gamma}}.$$

3. Labor market clearing, for each worker type *j*:

$$L_j = M^s \int_{z_m}^{z^*} L_j^s(z)\mathrm{d}G(z) + M^b \int_{z^*}^{\infty} L_j^b(z)\mathrm{d}G(z).$$

4. Free entry:

$$c_e = \Pi^s w_h^{-\frac{\gamma^s}{1-\gamma^s}} \bar{z}^s + \Pi^b w_h^{-\frac{\gamma^b}{1-\gamma^b}} \bar{z}^b.$$

5. $\bar{z}$:

$$\bar{z}^b = \frac{\alpha z_m^\alpha z^{*\frac{1}{1-\gamma^b}-\nu-\alpha}}{\alpha - \frac{1}{1-\gamma^b} + \nu}$$
$$\bar{z}^s = \alpha z_m^\alpha \frac{z_m^{\frac{1}{1-\gamma^s}-\nu-\alpha} - z^{*\frac{1}{1-\gamma^s}-\nu-\alpha}}{\alpha - \frac{1}{1-\gamma^s} + \nu}$$

6. Firm size choice:

$$\pi^s(z^*) = \pi^b(z^*)$$

7. Relative measure of firms:

$$\frac{M^b}{M^s} = \frac{1 - G(z^*)}{G(z^*)} = \frac{(z_m/z^*)^\alpha}{1 - (z_m/z^*)^\alpha}$$

Note that the auxiliary parameters Ω, Θ, and Π all depend on the wage ratio w_l/w_h and vary by firm type.

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