Skill Supply, Firm Size, and Economic Development

Charles Gottlieb [*] Markus Poschke [†] Michael Tueting [‡]

Abstract

Across countries, the organisation of production differs widely, and firms are substantially smaller in low-income countries. How are these differences related to a country's skill endowment? In this paper, we study the interplay between skill endowment and firm size along the development path. Empirically, we measure the skill intensity of employment by firm size for 57 countries and document four facts. First, we show that the share of employment in large firms is about four times as high in high-income countries as in to low-income countries. Second, we find that across countries, employees of large firms are more skilled than those of small firms. Third, whereas small firms in rich countries are almost as skill intensive as large firms, small firms employ much fewer skilled workers in poor countries. Fourth, whereas small firms are almost as skill intensive as large firms when the skill premium is low, they are much less skill intensive when the skill premium is high. This evidence suggests that small firms can easily substitute low-skill for high skill workers when high skill workers are scarce and expensive, but large firms are less flexible. As a result, the low skill endowment of low-income countries limits the size of firms in these countries. We then use a span-of-control model with worker skill heterogeneity and two technologies (large and small scale) to analyze the effect of skill endowments on the firm size distribution and economic development. Calibrated to the US and varying only skill endowments, our model closely replicates skill intensity by firm size across countries. It implies that, to a large extent, it is the lower skill endowments of poor countries that lie behind the four facts we document. Our findings also imply that greater skill levels benefit production not only directly, but also through a shift to more large scale production units. Finally, we illustrate how our work relates to the literature on misallocation.

1 Introduction

The organisation of production differs widely across countries. For example, in the United States, more than 80% of employment is in firms with 10 or more employees. This number is only 15% in low-income economies. It is often argued that a lack of employment in large firms contributes to lower overall wage employment and productivity in poor countries.

In this paper, we argue that running large firms requires skilled workers, and explore how the low skill endowments of poor countries affect employment patterns and productivity. While this argument appears natural, studying it has hitherto been impossible due to a lack of comparable cross-country data on employment by skill and firm size. Existing data allow measuring countries' skill endowments and provide some information on employment by firm size, but do not allow measuring the skill intensity of firms of different sizes. To overcome this knowledge gap, we build a new dataset on the skill composition of employment in small and large firms, harmonizing information from nationally representative labor force surveys and household surveys from 57 countries at all stages of development.

Using this new data set, we establish four facts. First, we show that the share of employment in large firms is about four times as high in high-income countries as in low-income countries. This finding dovetails with earlier findings in the literature that firms are larger in rich countries.

Our second to fourth facts exploit the novel intersection of skill and firm size of our data, which allow us to document the skill intensity of firms of different sizes. So, second, we find that across

[*] Aix-Marseille School of Economics, Université Aix-Marseille; charles.gottlieb@univ-amu.fr

[†] Department of Economics, McGill University; markus.poschke@mcgill.ca

[‡] Department of Economics, University of St.Gallen; michael.tueting@unisg.ch

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countries, employees of large firms are more skilled than those of small firms. Third, whereas small firms in rich countries are almost as skill intensive as large firms, small firms employ much fewer skilled workers in poor countries.

Our data thus show that large firms are generally more skill intensive, but that the gap varies significantly with income per capita. Whereas in the US, the share of workers in large firms who are skilled exceeds its counterpart in small firms by only four percentage points, the gap is around twenty percentage points in middle income countries, and more than thirty percentage points in poorer countries. Stated differently, although there are few large firms in poor countries and only a small fraction of low-skill workers work in a large firm, most skilled workers work in a large firm. In rich countries, again, the gap is small.

Fourth and finally, we find that whereas small firms are almost as skill intensive as large firms when the skill premium is low, they are much less skill intensive when the skill premium is high. Concretely, small and large firms have similar skill intensities when the skill premium is around 50%. But small firms employ much fewer skilled workers than large firms when the skill premium is higher.

Overall, the cross-country dataset we built strongly indicates that large firms rely much more on skilled workers than small firms do. This is particularly salient in poor countries, where skilled workers are scarce and, as we also document, the skill premium is high. These facts are consistent with a world where (1) skills are scarce in poor 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 in poor countries.

To better understand the data and the role of skill supply for firm growth and the organization of production more broadly, we build 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 et al. [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 substitutability. The optimal choice of technology depends on a firm's productivity and on input prices. In this setting, a lower skill endowment has two effects. First, it raises the price of skill and makes all firms use fewer skilled workers. A second effect goes beyond this: a greater skill premium makes fewer firms use the large scale technology.

To quantify the strength of these effects, we follow a standard approach in the macroeconomic literature on cross-country productivity differences. We calibrate the model to US data and then study the effect of varying skill endowments in the model on firms' demand for skill, the firm size distribution and productivity.

Our first finding is that as greater skill scarcity raises the skill premium, small firms strongly substitute towards low-skill workers. Large firms reduce their employment of skilled workers much less. As a result, skill intensity varies little with firm size in rich countries, but strongly in poor countries. Although the model has been calibrated only to US data and we only vary the aggregate skill endowment, the skill intensity of large vs small firms predicted by the model comes close to the facts we see in cross-country data. Second, a greater cost of skill makes running the large scale technology less attractive. As a result, there are fewer large firms in poor countries. The share of employment in large firms drops from around 80% in rich to around 10% in poor countries. Again, this contrast is very close to the data patterns, and only driven by the change in the skill endowment.

Clearly, changes in technology have implications for output and productivity. We ask: how much would US output decline if firms chose the smaller-scale technologies operated in poorer countries? We find that, without any change in aggregate productivity or skill endowments, US output would decline by 8% simply due to the use of smaller-scale technologies. This number corresponds to 18% of the total difference in net output between low income economies and the US in our model.

Before concluding, we relate our work to the literature on misallocation. Many scholars have attributed differences in firm sizes across countries to size- or productivity-dependent distortions [Guner et al., 2008, Restuccia and Rogerson, 2008]. Similarly, it is common to interpret dispersion in labor productivity across firms in a country as evidence of distortions. Yet, in our model, such differences arise endogenously, since firms operating different technologies optimally choose different levels of labor productivity. We show that when skills are scarce and expensive, the optimal size of large scale firms is reduced more, raising their relative labor productivity. This greater gap is entirely due to optimal choices. We also show that introducing productivity-dependent distortions into our model has a similar effect to reducing skill endowments.

The remainder of the paper is structured as follows. In section 2, we relate our contribution to the literature. We describe the data in section 3 and discuss firm size and skill measurement. In section 4, we document cross-country patterns of employment by skill and firm size and wage premia. Section 5 introduces a new model of heterogeneous firms. In section 6 we lay out our calibration strategy. In section 7, we report results from our counterfactual analysis. Section 8 relates our findings to the literature on misallocation. Section 9 concludes.

2 Related literature

Our work is motivated by a literature showing that the production structure in poor countries is different, with high levels of self-employment [Gollin, 2008] and smaller firms [Bento and Restuccia, 2017, 2021, Poschke, 2018]. Policy makers consider a lack of "good jobs" in large firms a development challenge, as evidenced by the World Bank's Development Report on Jobs.

By their nature, the data sources used by these authors are either silent on workforce skills or not nationally representative. In contrast, all labor force and household surveys we use are nationally representative and provide information on individuals' characteristics, educational attainment, employment type, and the employer's firm size. This information is not available when firm sizes are measured using firm register data. While firm-level surveys occasionally include information on work force skills, they generally do not include informal firms. These account for a large share of firms and of employment in most poor countries.[1]

The literature aiming to understand the sources of these differences in production structure has either attributed these differences to a set of frictions or distortions, or has seen them as an optimal reaction to a different environment [Davis et al., 2023]. A large literature 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], financial frictions [Buera et al., 2011, Midrigan and Xu, 2014], or delegation frictions [Akcigit et al., 2021, Grobovšek, 2020, Guner et al., 2018]. A parallel literature diagnosed the existence of generic wedges or distortions that reduce aggregate productivity, in particular for large firms [Bartelsman et al., 2013, Hsieh and Klenow, 2009, Restuccia and Rogerson, 2008]. At the same time, others have argued that small firm sizes may be an optimal reaction to a different environment, for example in terms of the level of capital [Gollin, 2008] or of technology [Poschke, 2018]. To our knowledge, none of this work has addressed the effect of differences in skills on the production structure across countries.

Our work also close relates to a recent literature that has revisited the importance of human capital for cross-country income differences [Bils et al., 2024, Caselli and Ciccone, 2013, Hendricks and Schoellman, 2023, Jones, 2014]. This literature mostly has taken an aggregate perspective, and not taken the analysis to the firm level. To the best of our knowledge, only Hjort et al. [2023] analyze the effect of skill costs on firm sizes and aggregate productivity, focusing specifically on middle managers, and exploiting evidence from a single global firm.

In related work, Engbom et al. [2024] and Gottlieb et al. [2024] study how skill supply shapes the occupational composition of employment and aggregate productivity across countries. Our work differs from these studies both in the facts we document and in the theoretical and quatitative analysis.

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

3 Data and measurement

This section lays out the data sources we use for our empirical analysis as well as the choices we make to measure skills, firm size and wages.

3.1 Data Sources

We build a harmonized data set that provides information on the firm size distribution and the composition of employment for a large set of countries. The harmonized dataset draws on nationally representative household and labor force surveys. All the surveys we use provide information on (i) individual characteristics (age and sex), (ii) education level, and (iii) firm size of the employer. Overall, our dataset consists of 483 country-year surveys across 57 countries. It encompasses on other existing harmonized cross-country datasets, such as the EU-Survey Income and Living Conditions (SILC) survey and IPUMS-International. We expand by this by identifying many additional surveys with the required information, which we then source and harmonize.

Ultimately, our sample covers individuals in countries that span the income per capita distribution, ranging from USD PPP 871 (Rwanda 2000) to 66059 (Switzerland 2019). Table 5 lists the countries, years and survey names we use.

3.2 Measurement

We restrict our analysis to the working-age population (age 15-65). Our two main variables of interest are firm size and worker characteristics, foremost education.

Worker Skill. We use data on the completed degree and years of education to determine whether a worker is skilled or not. We define 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). This typically corresponds to the transition point in the education system from a generalist education to subject-oriented instruction.[2]

Establishment size. All surveys we draw from ask wage workers the following question: "*How many employees work in your place of work (establishment/work site)?*" The answers provided to this question are generally in bins. We harmonize answers to this question into two consistent categories: small and large. Small firms are defined as having fewer than ten employees, and large firms as having at least ten employees. This is the most common way labor force and household surveys collect information on employer firm size. If a survey provides more bins, we assign individuals to either of these two categories, provided the bins are consistent with the above thresholds.[3]

Job characteristics. Our dataset also provides information on the job type and sector of employment of an individual's main job. Thus, we can distinguish wage employment from self-employment, and further between unpaid work, own-account work, and employers. We also observe whether individuals work in agriculture, manufacturing, or services.

[2] An alternative would be to consider only college-educated individuals as skilled. This is a common convention in the analysis of labor markets in rich countries. Our choice of cutoff responds to the fact that in poor countries, only a very small share of the population is college educated. Moreover, our initial argument focusses on the importance of skill for participating productively in a large organization. Plausibly, the most important skills for this dimension are sufficiently advanced literacy and numeracy, for which our cutoff is a natural choice. In ongoing work, we explore robustness of our quantitative findings to the precise cutoff.

[3] As a result, we can also consistently capture employment in medium-sized firms of 10-49 employees for a subset of countries. These data reveal that the main variation with country income per capita is in the share of employment in small (<10) and large (≥ 50) employees. The share of employment in medium-sized firms varies little with GDP per capita, and the skill intensity of medium-sized firms is similar to that of large firms. This implies that the facts we show in the next Section are not sensitive to the precise choice of cutoff in the range of 10 to 50.

4 Cross-country evidence

In this section, we document how the organization of production differs across countries with income per capita. We first measure the composition of employment by job types (wage, self-employed and unpaid) and by firm size. We then show novel facts on the skill intensity of employment for these different job types, with a particular emphasis on the skill content of employment in small and large firms.

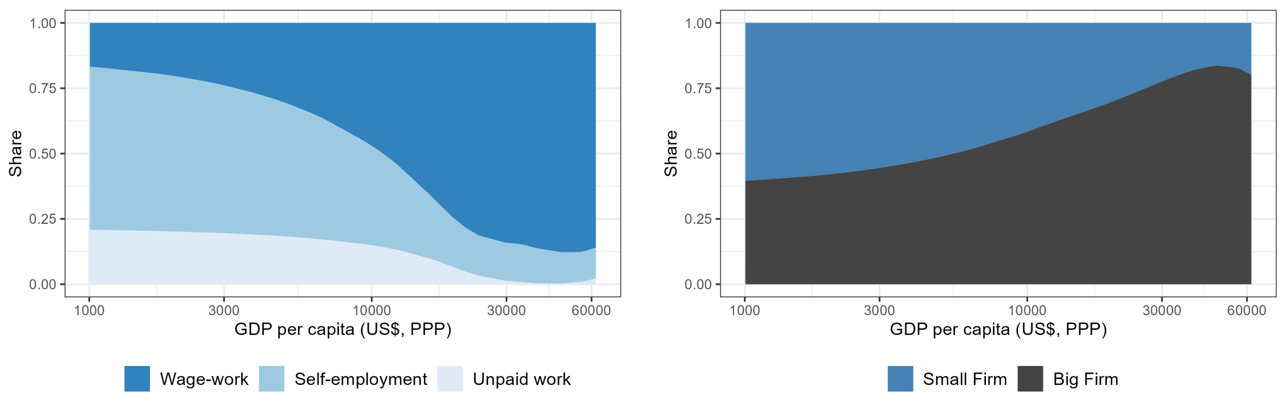
4.1 Job types and firm sizes across countries

Figure 1a shows that, across countries, the share of wage employment increases with GDP per capita, while the share of self-employment declines. In the typical rich country, more than 80% of employment is wage employment, while this share is only 20-30% in the poorest countries. This pattern is in line with the findings reported by Gollin [2008], Poschke [2025], and others.

Our data further allow us to distinguish various types of self-employment, namely unpaid work, own-account work, and being an employer. Unpaid workers are those who contribute to the production of goods and market services without earning a wage or deriving income, typically on a family farm. Figure 1a shows that unpaid work represents a quarter of total employment in low-income countries, while it is virtually absent in high-income countries. The lower levels of self-employment in rich countries reflect both less unpaid work and less own-account work, as also shown in Poschke [2025].

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

(a) Job type distribution. (b) Firm size of wage workers.



Notes. The figure in panel (a) shows the share of wage, self-employed (employers / own-account workers), and unpaid workers based on surveys conducted around 2015 for each country in our sample and their corresponding GDP per capita (PPP, real). The figure in panel (b) shows the share of wage workers that work in establishments with less than 10 employees (small), and more than ten employees (large). In both panels, the lines correspond to the best local fit using a separate LOESS regression for each category-specific share. The category-fitted shares have been normalized to sum up to one and stacked. In both panels, we plot these shares against GDP per capita as provided by Feenstra et al. [2015].

We now set the focus on the employed population that works for a wage. Figure 1b displays the share of wage workers who work in small (< 10) and large (≥ 10) firms across countries.

It is clear that in low-income countries, the majority of employees – 57% – work in small firms. This share is much lower in high-income countries, at only 18%. In ongoing work, we show that these differences are not due to differences in the sectoral composition of countries, but also appear within sectors.

This pattern is in line with the findings of Poschke [2018] and Bento and Restuccia [2017, 2021], who have shown that the average size of firms is greater in rich countries.

Summarizing, in high income countries, most employment is wage employment in large firms, whereas in poor countries, self-employment dominates, followed by employment in small firms. Large firms account for only a small share of employment.

4.2 Skill endowments across countries

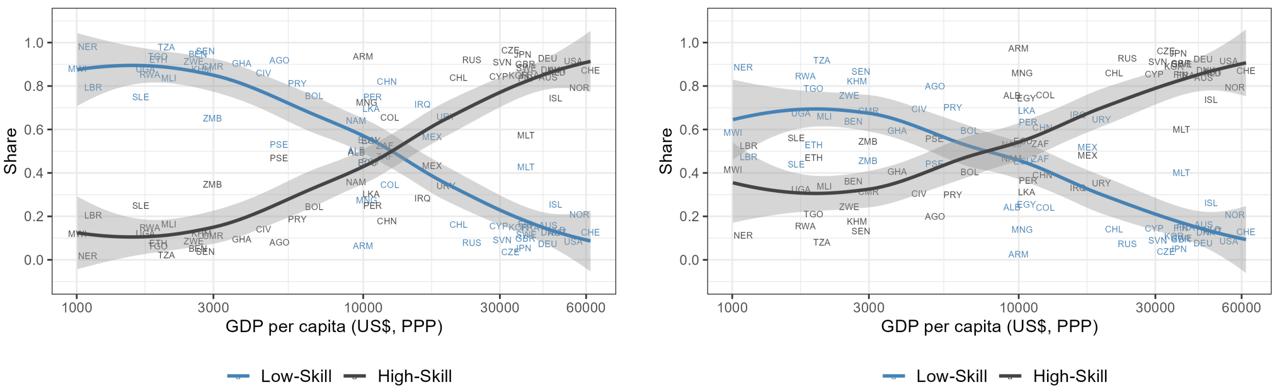
Figure 2a shows the share of skilled and unskilled workers for each country in our dataset against GDP per capita (PPP). Figure 2b reports the corresponding shares for wage workers only. In low-income countries, only around 15% of the labor force, or about 30% of wage workers, are skilled. The difference reflects the fact that in these countries, only 10% of the self-employed are skilled.

The shares of skilled workers increase strongly with GDP per capita. At income levels of around 10,000$ per capita, the share of low and high-skilled workers is at parity. In high-income countries, around 85% of the labor force are skilled. The figure is similar for wage workers and for the self-employed. Overall, the share of skilled workers in the labor force of rich countries is 5-6 times that in poor countries.

These figures show not only that the population of poor countries has lower levels of educational attainment – as is well known – but also that in lower income countries, wage workers are much more skilled than the self-employed. This gap gradually closes with income per capita.

Figure 2: Skill supply across countries.

(a) All workers (b) Wage-Workers



Notes: This figure reports the share of skilled and unskilled workers, whereby an individual is skilled if he has more than nine years of schooling for the most recent observation of each country in our sample. Panel A reports these shares for the population of workers aged between 15 and 65 and Panel B for wage workers only. The lines show the best local fit using a LOESS regression. In both panels, we plot these shares against GDP per capita as provided by Feenstra et al. [2015].

4.3 Skill supply in small and large firms

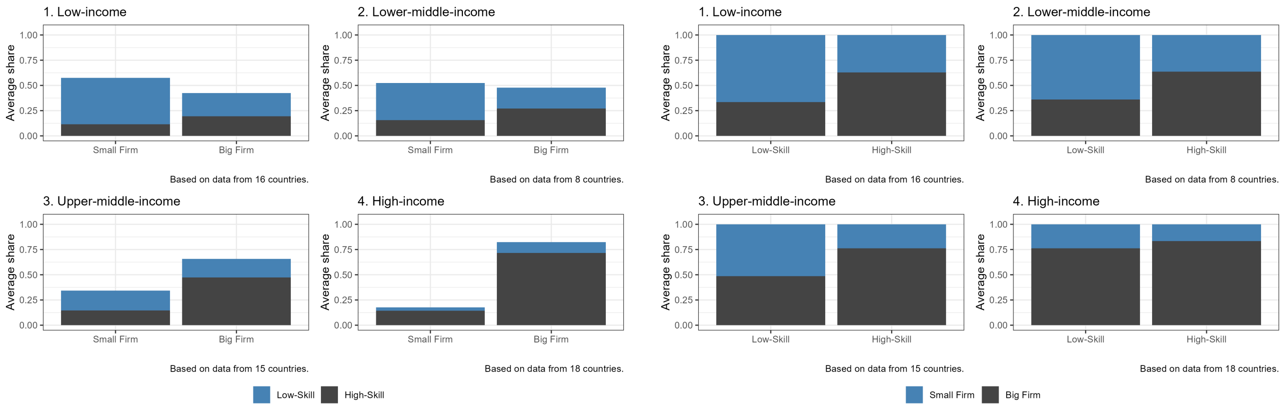
Finally, we turn to our novel empirical findings. Figure 3a documents the skill distribution of wage workers by employer firm size for different country income groups. Table 1 shows the same information as a table, and Figure 4 shows the skill intensity of large and small firms against a continuous measure of GDP per capita.

All these exhibits show that large firms are more skill intensive, with a gap that is much larger in poor countries. Consider rich countries first. Here, the share of skilled workers in large firms, at 87%, slightly exceeds that of 82% found in small firms.

Figure 3: Skill distribution by employer firm size.

(a) Skill composition of employment in small and large firms

(b) Employer size of skilled and unskilled employees.



Notes. Figure 3a reports employment shares of skilled and unskilled workers in each firm category. We compute the average over the shares for the most recent country observations that fall in each income group. Figure 3b 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.

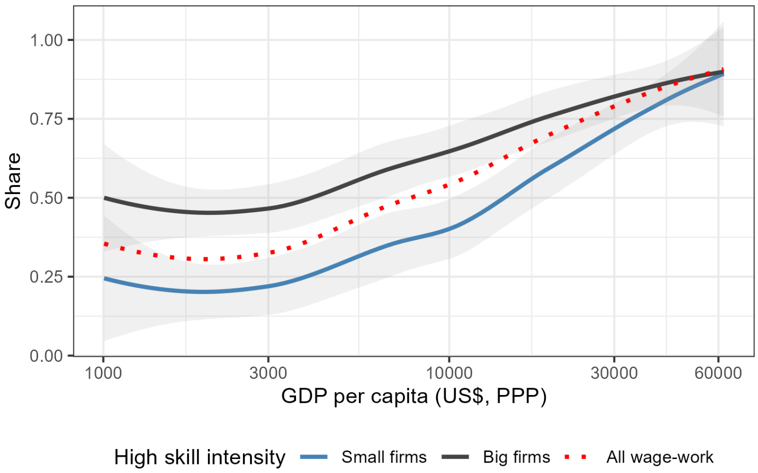
Table 1: Skill intensity of employment in small and large firms

		Country Income Group			
Firm size category		Low	Lower-middle	Upper-middle	High
Big firm	High skill	0.45	0.55	0.70	0.87
	Low skill	0.55	0.45	0.30	0.13
Small firm	High skill	0.21	0.31	0.49	0.82
	Low skill	0.79	0.69	0.51	0.18
Number of countries		16	8	15	18

Notes. This table is the equivalent of Figure 3a. We report the share of skilled and unskilled workers in small and large firms. We compute the average over the shares for countries that fall in an 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.

In poorer countries, both of these figures are lower, reflecting their lower skill endowments (recall that the share of skilled workers in rich countries is 5-6 times higher than in poor countries). The share of skilled workers in large firms in poor countries is about half that in rich countries, at 45%. This gap is much larger in small firms: in poor countries, only 20% of workers in small firms are skilled; about a quarter of the share in rich countries. Among the self-employed in poor countries, the share of skilled individuals self-employed is a mere tenth of that in rich countries. Figure 4 shows that the gap in skill intensity between large and small firms closes smoothly as we move up the GDP per capita distribution, but is generally statistically significant for low- and middle-income countries.

Figure 4: Skill intensity by firm size across countries.



Notes. This figure shows the share of high-skilled workers conditional on firm size across the GDP per capita spectrum. The three lines correspond to the best local fit using a separate LOESS regression for each category-specific share.

Figure 3b takes the reverse perspective, and reports where skilled and unskilled workers work in different countries. In general, skilled workers are always more likely to work in large firms than low-skill workers are. However, this difference is tiny in rich countries. In poor countries, in contrast, a majority of around 60% of skilled wage employees work in a large firm, compared to only 30% of unskilled wage workers.

Summarizing, large 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 they are less flexible in adjusting to the scarcity of skilled workers in poor countries.

4.4 Skill Premia

Our dataset also contains information on hourly wages. We use these data to compute the average hourly wage for workers in each firm size category and by skill for all countries in our sample.

Table 2 reports the average skill premium across countries in each country income group. The skill premium is much higher in low-income countries.

Table 2: Relative wages of high vs. low skilled wage workers (w^h/w^l)

	Country Income Group			
	Low	Lower-middle	Upper-middle	High
Skill premium (w_h/w_l)	2.54	2.30	1.50	1.53
Number of countries	10	5	11	8

Notes. This table reports the raw, relative wages of high to low-skilled wage workers by country income group and (1) all employees, (2) employees in big firms, and (3) employees in small firms.

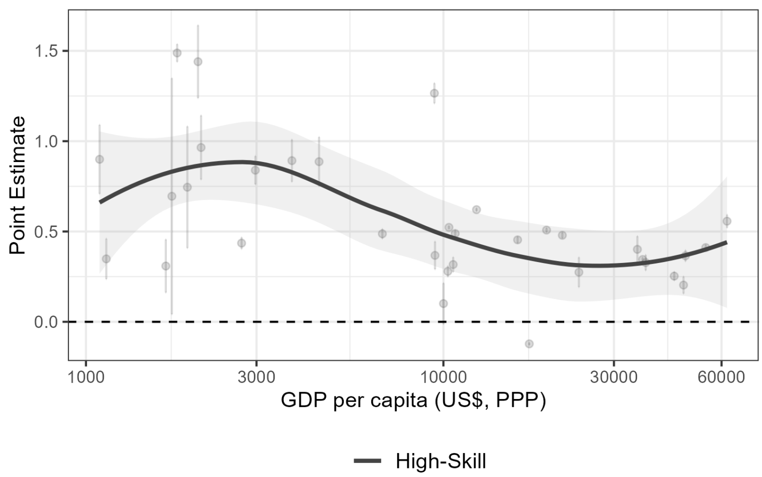
We now exploit the micro data to account for the fact that the composition of employment varies along other dimensions. To account for these compositional differences, we estimate the skill premium controlling for worker characteristics, in particular age, gender and marital status, and run the following Mincer regression:

$$\log w_{ict} = \beta \mathbb{1}\{\text{high-skill}\}_i + X_i \gamma_i + \varepsilon_{ict} \tag{1}$$

where w_{ict} is the hourly wage of individual i in country-survey c at time t. $\mathbb{1}\{\text{high-skill}\}_i$ is a dummy variable that takes the value one if the individual i is high-skilled, and zero otherwise, X_i are individual characteristics (sex, age, age-squared, marital status). ε_{ict} is the error term.

Figure 5 reports the point estimate of the skill dummy for each country in our sample. The patterns that we find in Table 2 hold when we control for worker characteristics. The conditional skill premium is higher in low-income countries, with points estimates around 0.80, suggesting that in these countries a skilled workers has an hourly wage that more than 100% higher. In high-income countries, the corresponding number is around 0.3 log points, or 35%, in line with evidence in the literature.

Figure 5: Skill Premium conditional on worker characteristics.



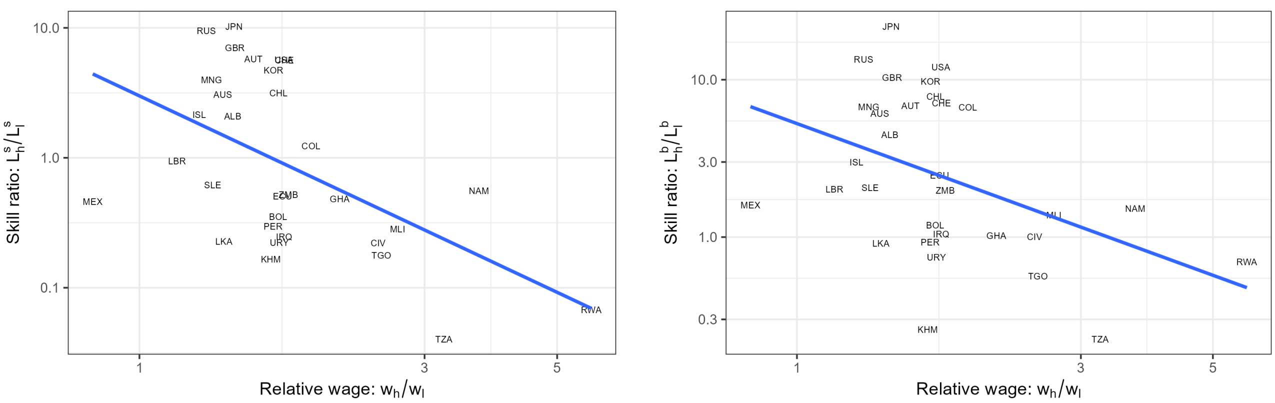
Notes. This figure reports the country × survey × year-specific point estimates of the skill premium from Mincer regressions. We then plot the point estimate and 95% confidence interval against GDP per capita (PPP). The fitted line shows the best local fit through the point estimate cloud. We weight each country × survey × year observation by the total number of observations by country.

4.5 The skill premium and firm skill intensity

Finally, we explore how the skill premium in a country is related to the skill intensity of its firms. Figure 6 plots employment of high skilled relative to low skilled workers against the skill premium, for large and small firms separately. The relationship is strongly negative, as expected.

Figure 6: Skill intensity by employer firm size versus the skill premium.

(a) Small firms (b) Large firms



More importantly, the figure reveals that small firms' skill intensity responds much more to the skill premium than that of large firms. In countries with low skill premia, around 1.5, small firms are almost as skill intensive as large firms. (Note that these countries are mostly rich countries, with high skill levels.) In countries with high skill premia, say between 1.7 and 3, in contrast, small firms employ much fewer high-skill than low-skill workers, whereas large firms employ about equal numbers of the two.

Correspondingly, in a regression of the ratio of high- to low-skill workers against the skill premium, the coefficient is -1.38 for large firms, but -2.16 for small firms. This suggests that small firms can adjust their employment more easily to changes in skill prices – a key feature of the model we develop in the next section.

5 Model

In this section, we propose a simple model to study the role of skill supply for the firm size distribution and aggregate productivity. In the next Sections, we calibrate the model, and use it to infer to what extent the differences in the size and skill intensity of firms across countries documented in the previous Section may be due to differences in countries' skill endowments.

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). We refer to these using subscript l(ow-skill) and h(igh-skill). Both worker types supply labor inelastically.

Production technology Two types of firms exist (small and large). We refer to these using superscript s(mall) and b(ig) to avoid letter clashes, with generic superscript i.[4]

Firms differ in their productivity z. We abstract from physical capital. Each firm produces a final good using skilled and unskilled labor, L_h and L_l. These are combined in a 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. Technology may be skill-biased. We denote the relative productivity of high skilled workers by A. Production has decreasing returns to scale, with parameter $0 < \gamma^s < \gamma^b < 1$.

We also allow 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

$$y^i(z) = z\left[\mu^i {L_l^i}^{\frac{\rho^i-1}{\rho^i}} + (1-\mu^i)(AL_h^i)^{\frac{\rho^i-1}{\rho^i}}\right]^{\frac{\rho^i}{\rho^i-1}\gamma^i}. \tag{2}$$

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

$$\pi(z) = \max_{L_l,L_h}(1-\tau(z))z\left[\mu L_l^{\frac{\rho-1}{\rho}} + (1-\mu)(AL_h)^{\frac{\rho-1}{\rho}}\right]^{\frac{\rho}{\rho-1}\gamma} - w_l L_l - w_h L_h \tag{3}$$

The first-order conditions for this problem are

$$(1-\tau(z))\gamma\mu z\left(\frac{y(z)}{z}\right)^{1-\frac{\rho-1}{\rho\gamma}} L_l^{-\frac{1}{\rho}} = w_l \tag{4}$$

$$(1-\tau(z))\gamma(1-\mu)A^{\frac{\rho-1}{\rho}} z\left(\frac{y(z)}{z}\right)^{1-\frac{\rho-1}{\rho\gamma}} L_h^{-\frac{1}{\rho}} = w_h. \tag{5}$$

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

$$\left(\frac{L_l}{L_h}\right)^i = \left(A^{\frac{\rho-1}{\rho}}\frac{1-\mu^i}{\mu^i}\frac{w_l}{w_h}\right)^{-\rho^i}. \tag{6}$$

[4] Note that whereas in the empirical analysis above, large (small) referred to firms with at least (less than) ten employees, here large and small refer to technology choices. These will correlate with firm size, but the size threshold need not be at ten. In our quantitative analysis below, we compute model statistics both by size (as in the empirical analysis) and by technology type (the model object).

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

$$y(z) = zL_h^{\gamma} \underbrace{\left[\mu\Omega^{\frac{\rho-1}{\rho}} + (1-\mu)A^{\frac{\rho-1}{\rho}}\right]^{\frac{\rho}{\rho-1}\gamma}}_{\equiv\Theta}. \tag{7}$$

From this, the first order condition for L_h is

$$(1-\tau(z))z\gamma\Theta L_h^{\gamma-1} = w_h \underbrace{\left(1 + \frac{w_l}{w_h}\Omega\right)}_{\tilde{\Omega}}. \tag{8}$$

It follows that optimal demand for skilled labor is

$$L_h(z) = \left(\frac{(1-\tau(z))z\Theta\gamma}{\tilde{\Omega}w_h}\right)^{\frac{1}{1-\gamma}}. \tag{9}$$

Optimal overall employment in the firm is

$$L(z) = L_h(z) + L_l(z) = (1+\Omega)\left(\frac{(1-\tau(z))z\Theta\gamma}{\tilde{\Omega}w_h}\right)^{\frac{1}{1-\gamma}}. \tag{10}$$

Optimal output (net of distortions) is

$$y^i(z) = (1-\tau(z))z\left[\left(\frac{(1-\tau(z))z\Theta\gamma}{\tilde{\Omega}w_h}\right)^{\frac{1}{1-\gamma}}\right]^{\gamma} \underbrace{\left[\mu\Omega^{\frac{\rho-1}{\rho}} + (1-\mu)A^{\frac{\rho-1}{\rho}}\right]^{\frac{\rho}{\rho-1}\gamma}}_{\equiv\Theta} \tag{11}$$

$$= ((1-\tau(z))z\Theta)^{\frac{1}{1-\gamma}}\left(\frac{\gamma}{\tilde{\Omega}w_h}\right)^{\frac{\gamma}{1-\gamma}}. \tag{12}$$

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

$$\begin{aligned}
\pi(z) &= ((1-\tau(z))z\Theta)^{\frac{1}{1-\gamma}}\left[\left(\frac{\gamma}{\tilde{\Omega}w_h}\right)^{\frac{\gamma}{1-\gamma}} - (w_l\Omega + w_h)\left(\frac{\gamma}{\tilde{\Omega}w_h}\right)^{\frac{1}{1-\gamma}}\right] \\
&= ((1-\tau(z))z\Theta)^{\frac{1}{1-\gamma}}\left(\tilde{\Omega}w_h\right)^{-\frac{\gamma}{1-\gamma}}\left[\gamma^{\frac{\gamma}{1-\gamma}} - \gamma^{\frac{1}{1-\gamma}}\right] \\
&\equiv \Pi((1-\tau(z))z)^{\frac{1}{1-\gamma}} w_h^{-\frac{\gamma}{1-\gamma}}, \qquad (13)
\end{aligned}$$

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.

Size-dependent distortions. Following Buera and Fattal-Jaef [2018] and others, we model the output tax τ as

$$1 - \tau(z) = z^{-\nu}. \tag{14}$$

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 productivity-dependent distortions. With this functional form assumption, the profit function for type i is

$$\pi(z) = \Pi w_h^{-\frac{\gamma}{1-\gamma}} z^{\frac{1-\nu}{1-\gamma}}. \tag{15}$$

Technology choice 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 the large-firm technology. Denote the cutoff where $\pi_j^s(z) = \pi_j^b(z)$ by z_j^*. At this value,

$$\pi_j^s(z_j^*) = \pi_j^b(z_j^*) \tag{16}$$

This implies

$$\Pi^s(z^*)^{\frac{1-\nu}{1-\gamma^s}} w_h^{-\frac{\gamma^s}{1-\gamma^s}} = \Pi^b(z^*)^{\frac{1-\nu}{1-\gamma^b}} w_h^{-\frac{\gamma^b}{1-\gamma^b}} \tag{17}$$

Hence,

$$z^* = w_h^{\frac{1}{1-\nu}} \left(\frac{\Pi^s}{\Pi^b}\right)^{\frac{1}{1-\nu}/\left(\frac{1}{1-\gamma^b} - \frac{1}{1-\gamma^s}\right)} \tag{18}$$

Because large firms are more skill intensive, the optimal cutoff for being large, z^*, increases in the wage of skilled workers.

Entry and operational choice. There is an unlimited mass of potential entrants. To start a firm, an entrant pays an entry cost $c_j^e \cdot \Lambda w_h$, and then draws a productivity z from a distribution with *cdf* $G(z)$. We assume that G is a Pareto distribution with parameter α, so its *cdf* is $1 - (z_m/z)^\alpha$. Active firms pay a fixed operating cost $c^f \Lambda w_h$.

Both entry costs and fixed costs are in units of labor, as in Bollard et al. [2016]. Given the difference in the skill composition of the population, we assume $\Lambda = w_l/w_h L_l + L_h$, which implies that these costs scale with the aggregate wage bill.

Due to the presence of fixed costs, not all firms are profitable. That is, a firm that drew a productivity z only operates if this yields positive profits. This occurs if productivity exceeds a threshold $\hat{z}_j$ at which

$$\max(\pi_j^s(\hat{z}_j), \pi_j^b(\hat{z}_j)) = 0. \tag{19}$$

Suppose for here that at $\hat{z}_j$, it is optimal to run a small firm, so that we will observe firms of both sizes run by entrepreneurs of both skill types in equilibrium. This implies

$$\Pi^s(\hat{z})^{\frac{1-\nu}{1-\gamma^s}} w_h^{-\frac{\gamma^s}{1-\gamma^s}} = c^f \Lambda w_h. \tag{20}$$

As a consequence,

$$\hat{z} = \left(\frac{c^f \Lambda}{\Pi^s}\right)^{\frac{1-\gamma^s}{1-\nu}} w_h^{\frac{1}{1-\nu}}. \tag{21}$$

If there are no productivity-dependent distortions ($\nu = 0$), the threshold is proportional to the high skilled wage. It is lower when firm profitability is higher, and higher when fixed costs are higher. If fixed costs are low enough, equation (21) may imply values of $\hat{z}$ below the lowest level of productivity, z_m. In that case, $\hat{z} = z_m$.

Note that although the "natural case" is that $\hat{z} < z^*$, so that entrepreneurs choose to run both large and small firms, it is also possible that $\hat{z} > z^*$. Then z^* is not relevant, and the conditions for $\hat{z}$ feature γ^b and Π^b instead of γ^s and Π^s.

In the "natural case", entrants who draw $z < \hat{z}_j$ do not operate, those with $z > z_j^*$ operate a large firm, and those with $z \in (\hat{z}_j, z_j^*)$ operate a small firm.

Comparing thresholds The ratio of thresholds is

$$\frac{z^*}{\hat{z}} = \left(\frac{\Pi^s}{\Pi^b}\right)^{\frac{1}{1-\nu}/\left(\frac{1}{1-\gamma^b}-\frac{1}{1-\gamma^s}\right)} \left(\frac{\Pi^s}{c^f}\right)^{\frac{1-\gamma_s}{1-\nu}}. \tag{22}$$

if the constraint $\hat{z} \geq z_m$ is not binding.

Since entrants with $z \geq (<) z^*$ choose the large (small-) firm technology, the share of large firms is

$$m^b \equiv \frac{M^b}{M} = \frac{1-G(z^*)}{1-G(\hat{z})} = (\hat{z}/z^*)^\alpha = \left(\frac{\Pi^b}{\Pi^s}\right)^{\frac{\alpha}{1-\nu}/\left(\frac{1}{1-\gamma^b}-\frac{1}{1-\gamma^s}\right)} \left(\frac{c^f}{\Pi^s}\right)^{\alpha\frac{1-\gamma_s}{1-\nu}}, \tag{23}$$

if $z^* > \hat{z}$, and 1 otherwise.

Free entry. Firms enter until the expected value of entry, net of the entry cost, is zero. This implies

$$\begin{aligned} c^e \Lambda w_h &= \int_{\hat{z}}^{z^*} \pi^s(z) \mathrm{d}G(z) + \int_{z^*}^{\infty} \pi^b(z) \mathrm{d}G(z) \\ &= \Pi^s w_h^{-\frac{\gamma^s}{1-\gamma^s}} \alpha z_m^\alpha \int_{\hat{z}}^{z^*} z^{\frac{1-\nu}{1-\gamma^s}-\alpha-1} \mathrm{d}z \\ &\quad + \Pi^b w_h^{-\frac{\gamma^b}{1-\gamma^b}} \alpha z_m^\alpha \int_{z^*}^{\infty} z^{\frac{1-\nu}{1-\gamma^b}-\alpha-1} \mathrm{d}z - \left(\frac{z_m}{\hat{z}}\right)^\alpha c^f \Lambda w_h. \end{aligned} \tag{24}$$

$\bar{z}$. Define

$$\bar{z}^s \equiv \alpha z_m^\alpha \int_{\hat{z}}^{z^*} z^{\frac{1-\nu}{1-\gamma^s}-\alpha-1} \mathrm{d}z \quad \text{and} \quad \bar{z}^b \equiv \alpha z_m^\alpha \int_{z^*}^{\infty} z^{\frac{1-\nu}{1-\gamma^b}-\alpha-1} \mathrm{d}z. \tag{25}$$

With Pareto distributed z, these are

$$\bar{z}^b = \frac{\alpha z_m^\alpha z^{*\frac{1-\nu}{1-\gamma^b}-\alpha}}{\alpha - \frac{1-\nu}{1-\gamma^b}} \tag{26}$$

and

$$\bar{z}^s = \alpha z_m^\alpha \frac{\hat{z}^{\frac{1-\nu}{1-\gamma^s}-\alpha} - z^{*\frac{1-\nu}{1-\gamma^s}-\alpha}}{\alpha - \frac{1-\nu}{1-\gamma^s}} \tag{27}$$

With this definition, the free entry condition becomes

$$c^e \Lambda w_h = \Pi^s w_h^{-\frac{\gamma^s}{1-\gamma^s}} \bar{z}^s + \Pi^b w_h^{-\frac{\gamma^b}{1-\gamma^b}} \bar{z}^b - \left(\frac{z_m}{\hat{z}}\right)^\alpha c^f \Lambda w_h. \tag{28}$$

Using the expressions for z_j^* obtained above, the thresholds become

$$\bar{z}^b = \frac{\alpha z_m^\alpha}{\alpha - \frac{1-\nu}{1-\gamma^b}} w_h^{\frac{1}{1-\gamma^b}-\frac{\alpha}{1-\nu}} \left[\left(\frac{\Pi^s}{\Pi^b}\right)^{\frac{1}{1-\nu}/\left(\frac{1}{1-\gamma^b}-\frac{1}{1-\gamma^s}\right)}\right]^{\frac{1-\nu}{1-\gamma^b}-\alpha} \tag{29}$$

and

$$\bar{z}^s = \frac{\alpha z_m^\alpha}{\alpha - \frac{1-\nu}{1-\gamma^s}} w_h^{\frac{1}{1-\gamma^s}-\frac{\alpha}{1-\nu}} \left\{\left(\frac{c^f}{\Pi^s}\right)^{1-\alpha\frac{1-\gamma^s}{1-\nu}} - \left(\frac{\Pi^s}{\Pi^b}\right)^{\left(\frac{1}{1-\gamma^s}-\frac{\alpha}{1-\nu}\right)/\left(\frac{1}{1-\gamma^b}-\frac{1}{1-\gamma^s}\right)}\right\} \tag{30}$$

if $\hat{z} > z_m$. Let

$$\Pi_1 \equiv \left[\left(\frac{\Pi^s}{\Pi^b} \right)^{\frac{1}{1-\nu} / \left(\frac{1}{1-\gamma^b} - \frac{1}{1-\gamma^s} \right)} \right]^{\frac{1-\nu}{1-\gamma^b} - \alpha} \tag{31}$$

$$\Pi_2 \equiv \left(\frac{c^f}{\Pi^s} \right)^{1-\alpha \frac{1-\gamma^s}{1-\nu}} - \left(\frac{\Pi^s}{\Pi^b} \right)^{\left(\frac{1}{1-\gamma^s} - \frac{\alpha}{1-\nu} \right) / \left(\frac{1}{1-\gamma^b} - \frac{1}{1-\gamma^s} \right)}, \tag{32}$$

and

$$A^i \equiv \frac{\alpha z_m^\alpha}{\alpha - \frac{1-\nu}{1-\gamma^i}}, \tag{33}$$

so that

$$\bar{z}^b = A^b w_h^{\frac{1}{1-\gamma^b} - \frac{\alpha}{1-\nu}} \Pi_1 \tag{34}$$

$$\bar{z}^s = A^s w_h^{\frac{1}{1-\gamma^s} - \frac{\alpha}{1-\nu}} \Pi_2. \tag{35}$$

As a result, the free entry condition becomes

$$c^e \Lambda w_h + z_m^\alpha c^f \Lambda \left(\frac{c^f \Lambda}{\Pi^s} \right)^{-\alpha \frac{1-\gamma^s}{1-\nu}} w_h^{1-\frac{\alpha}{1-\nu}} = w_h^{1-\frac{\alpha}{1-\nu}} \left(A^s \Pi^s \Pi_2 + A^b \Pi^b \Pi_1 \right) \tag{36}$$

This can be solved for

$$w_h = \left(\frac{1}{c^e \Lambda} \right)^{\frac{1-\nu}{\alpha}} \left[A^s \Pi^s \Pi_2 + A^b \Pi^b \Pi_1 - z_m^\alpha c^f \Lambda \left(\frac{c^f \Lambda}{\Pi^s} \right)^{-\alpha \frac{1-\gamma^s}{1-\nu}} \right]^{\frac{1-\nu}{\alpha}} \tag{37}$$

The wage increases in the firm profitability terms. The effect of c^f is more complicated because of selection.

Instead, if $\hat{z} = z_m$,

$$\bar{z}^s \bar{z}^s = A^s \left\{ z_m^{\frac{1-\nu}{1-\gamma^s} - \alpha} - w_h^{\frac{1}{1-\gamma_s} - \frac{\alpha}{1-\nu}} \Pi_1 \right\}. \tag{38}$$

Here, the free entry condition becomes

$$c^e \Lambda w_h = A^s \Pi^s w_h^{-\frac{\gamma^s}{1-\gamma^s}} z_m^{\frac{1-\nu}{1-\gamma^s} - \alpha} + \Pi_1 (A^b \Pi^b - A^s \Pi^s) w_h^{1-\frac{\alpha}{1-\nu}} - c^f \Lambda w_h. \tag{39}$$

This is a non-linear equation that determines w_h.

Labor market clearing. First note that the number of firms M and the number of entrants M^e are related by

$$M = (1 - G(\hat{z})) M^e. \tag{40}$$

Then, for high-skilled workers,

$$L_h = M^e \left[\int_{\hat{z}}^{z^*} L_h^s(z) \mathrm{d}G(z) + \int_{z^*}^{\infty} L_h^b(z) \mathrm{d}G(z) \right] \tag{41}$$

$$= \frac{M}{1 - G(\hat{z})} \left[\left(\frac{\Theta^s \gamma^s}{\tilde{\Omega} w_h} \right)^{\frac{1}{1-\gamma^s}} \bar{z}^s + \left(\frac{\Theta^b \gamma^b}{\tilde{\Omega} w_h} \right)^{\frac{1}{1-\gamma^b}} \bar{z}^b. \right] \tag{42}$$

This pins down M. It increases in the number of workers, and decreases in $\bar{z}$. Note that $\bar{z}^s$ and $\bar{z}^b$ already contain the relative proportions of large and small firms. When $\hat{z} > z_m$, we can further use the expressions for $\bar{z}$ and $\hat{z}$ to obtain

$$L_h = M z_m^{-\alpha} \left(\frac{c^f}{\Pi^s}\right)^{\alpha \frac{1-\gamma^s}{1-\nu}} \left[\left(\frac{\Theta^s \gamma^s}{\tilde{\Omega}^s}\right)^{\frac{1}{1-\gamma^s}} A^s \Pi_2 + \left(\frac{\Theta^b \gamma^b}{\tilde{\Omega}^b}\right)^{\frac{1}{1-\gamma^b}} A^b \Pi_1.\right] \tag{43}$$

For low-skilled workers,

$$L_l = \frac{M}{1-G(\hat{z})} \left[\Omega^s \left(\frac{\Theta^s \gamma^s}{\tilde{\Omega} w_h}\right)^{\frac{1}{1-\gamma^s}} \bar{z}^s + \Omega^b \left(\frac{\Theta^b \gamma^b}{\tilde{\Omega} w_h}\right)^{\frac{1}{1-\gamma^b}} \bar{z}^b\right]. \tag{44}$$

This pins down w_l (which, as w_l/w_h, enters Ω^i, and thus Θ^i and $\tilde{\Omega}^i$, and thus Π^i in the equation). In computation of the equilibrium, it serves to verify the initial guess of w_l/w_h. When $\hat{z} > z_m$, we can again use the expressions for $\bar{z}$ and $\hat{z}$ to obtain

$$L_l = M z_m^{-\alpha} \left(\frac{c^f}{\Pi^s}\right)^{\alpha \frac{1-\gamma^s}{1-\nu}} \left[\Omega^s \left(\frac{\Theta^s \gamma^s}{\tilde{\Omega}^s}\right)^{\frac{1}{1-\gamma^s}} A^s \Pi_2 + \Omega^b \left(\frac{\Theta^b \gamma^b}{\tilde{\Omega}^b}\right)^{\frac{1}{1-\gamma^b}} A^b \Pi_1.\right] \tag{45}$$

Average firm size equals $(L_l + L_h)/M$.

Aggregate output. Aggregate output net of distortions is:

$$Y = \frac{M}{1-G(\hat{z})} \left[\int_{\hat{z}}^{z^*} y^s(z) \mathrm{d}G(z) + \int_{z^*}^{\infty} y^b(z) \mathrm{d}G(z)\right] \tag{46}$$

$$= \frac{M}{1-G(\hat{z})} \left[(\Theta^s)^{\frac{1}{1-\gamma^s}} \left(\frac{\gamma^s}{\tilde{\Omega}^s w_h}\right)^{\frac{\gamma^s}{1-\gamma^s}} \bar{z}^s + (\Theta^b)^{\frac{1}{1-\gamma^b}} \left(\frac{\gamma^b}{\tilde{\Omega}^b w_h}\right)^{\frac{\gamma^b}{1-\gamma^b}} \bar{z}^b\right]. \tag{47}$$

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

1. Skill mix, for each firm type:

$$\left(\frac{L_l}{L_h}\right)^i = \left(A^{\frac{\rho-1}{\rho}} \frac{1-\mu^i}{\mu^i} \frac{w_l}{w_h}\right)^{-\rho^i}. \tag{6}$$

2. Labor demand, for each firm type:

$$L_h^i(z) = \left(\frac{z^{1-\nu} \Theta^i \gamma^i}{\tilde{\Omega}^i w_h}\right)^{\frac{1}{1-\gamma^i}}. \tag{9}$$

3. Labor market clearing, high skill:

$$L_h = \frac{M}{1-G(\hat{z})} \left[\left(\frac{\Theta^s \gamma^s}{\tilde{\Omega} w_h}\right)^{\frac{1}{1-\gamma^s}} \bar{z}^s + \left(\frac{\Theta^b \gamma^b}{\tilde{\Omega} w_h}\right)^{\frac{1}{1-\gamma^b}} \bar{z}^b.\right] \tag{42}$$

4. Labor market clearing, low skill:

$$L_l = \frac{M}{1-G(\hat{z})} \left[\Omega^s \left(\frac{\Theta^s \gamma^s}{\tilde{\Omega} w_h}\right)^{\frac{1}{1-\gamma^s}} \bar{z}^s + \Omega^b \left(\frac{\Theta^b \gamma^b}{\tilde{\Omega} w_h}\right)^{\frac{1}{1-\gamma^b}} \bar{z}^b\right] \tag{44}$$

5. Free entry:

$$w_h = \left(\frac{1}{c^e\Lambda}\right)^{\frac{1-\nu}{\alpha}} \left[A^s\Pi^s\Pi_2 + A^b\Pi^b\Pi_1 - z_m^\alpha c^f\Lambda \left(\frac{c^f\Lambda}{\Pi^s}\right)^{-\alpha\frac{1-\gamma^s}{1-\nu}} \right]^{\frac{1-\nu}{\alpha}} \tag{37}$$

if $\hat{z} > z_m$, and

$$c^e\Lambda w_h = A^s\Pi^s w_h^{-\frac{\gamma^s}{1-\gamma^s}} z_m^{\frac{1-\nu}{1-\gamma^s}-\alpha} + \Pi_1(A^b\Pi^b - A^s\Pi^s){w_h}^{1-\frac{\alpha}{1-\nu}} - c^f\Lambda w_h. \tag{39}$$

otherwise

6. Optimal continuation:

$$\pi(\hat{z}) = 0 \Leftrightarrow \hat{z} = \max\left(z_m, \left(\frac{c^f\Lambda}{\Pi^s}\right)^{\frac{1-\gamma^s}{1-\nu}} w_h^{\frac{1}{1-\nu}} \right). \tag{21}$$

7. Firm size choice:

$$\pi^s(z^*) = \pi^b(z^*) \Leftrightarrow z^* = {w_h}^{\frac{1}{1-\nu}} \left(\frac{\Pi^s}{\Pi^b}\right)^{\frac{1}{1-\nu}/\left(\frac{1}{1-\gamma^b}-\frac{1}{1-\gamma^s}\right)} \tag{18}$$

Other definitions and useful objects:

- $\bar{z}$:

$$\bar{z}^b = A^b {w_h}^{\frac{1}{1-\gamma^b}-\frac{\alpha}{1-\nu}}\Pi_1$$
$$\bar{z}^s = A^s w_h^{\frac{1}{1-\gamma^s}-\frac{\alpha}{1-\nu}}\Pi_2.$$

  if $\hat{z} > z_m$ or

$$\bar{z}^s = A^s \left\{ z_m^{\frac{1-\nu}{1-\gamma^s}-\alpha} - {w_h}^{\frac{1}{1-\gamma_s}-\frac{\alpha}{1-\nu}}\Pi_1 \right\}$$

  otherwise.

- Share large firms:

$$m^b \equiv \frac{M^b}{M} = \frac{1-G(z^*)}{1-G(\hat{z})} = (\hat{z}/z^*)^\alpha = \left(\frac{\Pi^b}{\Pi^s}\right)^{\frac{\alpha}{1-\nu}/\left(\frac{1}{1-\gamma^b}-\frac{1}{1-\gamma^s}\right)} \left(\frac{c^f}{\Pi^s}\right)^{\alpha\frac{1-\gamma_s}{1-\nu}},$$

  if $\hat{z} > z_m$.

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

6 Calibration

For the benchmark economy, we need to calibrate 6 production parameters $(\mu^i, \rho^i, \gamma^i)$, entry and fixed cost (c^e, c^f), the productivity distribution (α and z_m) and distortions (ν). We take skill aggregate endowments directly from the data. As typical in the literature, we calibrate some parameters to aggregate statistics and measures from the literature, and others to data counterparts of model moments.

We set the elasticity of substitution and returns to scale in large firms, ρ^b and γ^b, to typical estimated values in the literature, 1.67 and 0.85 [Atkeson and Kehoe, 2007, Katz and Murphy, 1992].

Moment	Data	Model
Skill premium (w_h/w_l)	1.75	1.75
Share workers in large firms with high skills (%)	92	92
Share of employment in large firms (%)	81	81
Share of firms with at least 10 employees (%)	4.8	4.8
Mean firm employment	5	5
Tail index of firm size distribution	1.13	1.134

Table 3: Model and data moments

Parameter	Value	Parameter	Value
Production:		*Productivity distribution:*	
μ^b	0.117	z_m	1
μ^s	0.248	α	7.56
		Costs:	
ρ^b	1.67	c^e	0.01
ρ^s	2.5	c^f	0.392
γ^b	0.85	*Distortions:*	
γ^s	0.436	ν	0

Table 4: Parameters for the benchmark economy (calibration to US)

We normalize z_m to 1, and assume that there are no distortions in the benchmark economy (ν=0). This leaves 7 parameters to calibrate: $\mu^i, \rho^s, \gamma^s, c^e, c^f$ and α. We calibrate these internally to match the following moments: the skill premium, the share of employment in large firms, the skill intensity of large firms, the share of large firms, mean firm size, and the tail index of the firm size distribution. We set them so the model moments match their data counterparts in the United States.

From our data, the former is 1.75, and the second 81%. The share workers in large firms with high skills is 92%. (That in small firms is 88%, and the share of high-skilled workers in the labor force is 91%.) Including the self-employed, combining data from the US Census Business Dynamics Statistics (BDS) and Non-employer Statistics, the share of firms with at least 10 employees is 4.8%, and mean employment is 5. The BDS data imply a tail index of employment of 1.13.

These model moments are closely related to and informative about the parameters we are calibrating. Concretely, the skill intensity of large firms, given the skill premium, directly implies a value for μ^b. The share of employment in large firms then implies the skill intensity of small firms, and thus μ^s. Given γ^b, the tail index of the firm size distribution directly implies the value of α. Given the function for optimal employment, α equals the empirical tail index divided by $1-\gamma^b$. The fixed cost closely affects the share of large firms, as a lower fixed cost implies a lower entry threshold and more small firms. The entry cost c^e affects mean firm size. Finally, γ^s also affects employment in large versus small firms. Because large firms are more skill intensive, this directly affects the skill premium.

Finally, the elasticity of substitution in small firms, ρ^s, is not identified from data for a single country. We set it to 2.5, significantly higher than ρ^b, and explore sensitivity to this choice. It turns out that for reasonable values of ρ^s, results do not change much.

Table 3 shows model and data moments. The model matches the data almost exactly. Table 4 shows the calibrated parameter values. Some parameters are worth noting. First, the tail index of the Pareto productivity distribution is directly implied by the firm size data. Second, $\mu^b < \mu^s$, reflecting that large firms are more skill intensive. Third, we calibrate a greater elasticity of substitution between skill types in small firms. As we show below, this will be key in capturing the greater variability in their skill composition with development. Fourth, the calibration implies significantly lower returns to scale for small firms, with γ^s barely more than half as large as γ^b. The large gap reflects the difference

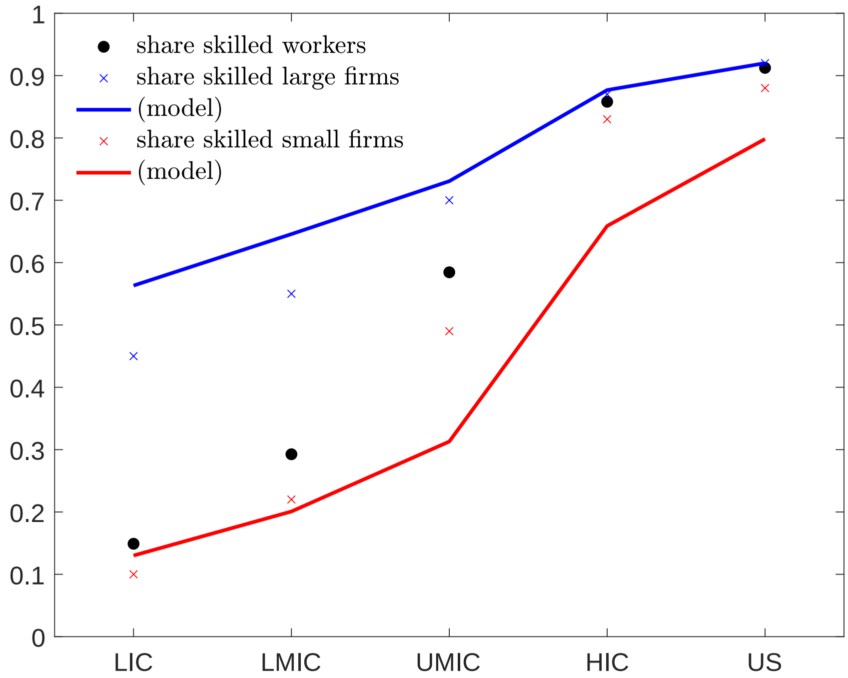


Figure 7: Skill intensity by firm size, model and data

in size and skill composition between large and small firms, as well as their implications for the skill premium.

The model also implies that in the benchmark economy, 16% of firms choose the large technology. These firms on average hire 25 workers. The smallest "large" firm has 3.4 workers, and above that, their size distribution is Pareto with tail index 1.134. On average, small firms thus are much smaller than large firms.

7 Skill endowments, the firm size distribution, and aggregate output

In Section 4, we have shown very large differences in the skill composition of economies at different stages of development. In this section, we explore how the model economy reacts to changes in the aggregate skill endowment. Figure 2a showed that the average high-income economy has a slightly lower fraction (86%) of high-skill workers than the US (91%), upper middle income economies have around 60%, and lower-middle income and low income economies have 29 and 15%, respectively. These numbers are represented by black dots in Figure 7.

Skill composition by firm size. Greater scarcity of high skills implies a larger skill premium, as we also observe in the data. As a result, all firms hire fewer skilled workers. Because of their greater ability to adjust, this difference is much larger for small firms. Thus, whereas in the US, small firms are only slightly less skill intensive than large firms, this gap is much larger in countries with fewer skilled workers. In the US, the workforce of small firms consists to 80% of skilled workers, compared to 92% for large firms. In a middle-income country, with only 58% skilled workers, the workers at large firms are to 73% high skilled, but those at small firms only to 31%. The ratio is even greater in countries with fewer skilled workers. In low-income countries, with their very few (15%) skilled workers, small firms hire hardly any skilled workers. At large firms, in contrast, slightly more than half the workers are still high skilled. Figure 7 shows that these model-generated patterns are very similar to the skill intensity by firm sized observed in the data.

Technology choice. A higher skill premium also makes running the large technology more costly, since it is more intensive in high skills and cannot substitute away from them as easily as the small scale technology. As a result, the productivity threshold for the large technology, z^*, rises. Whereas

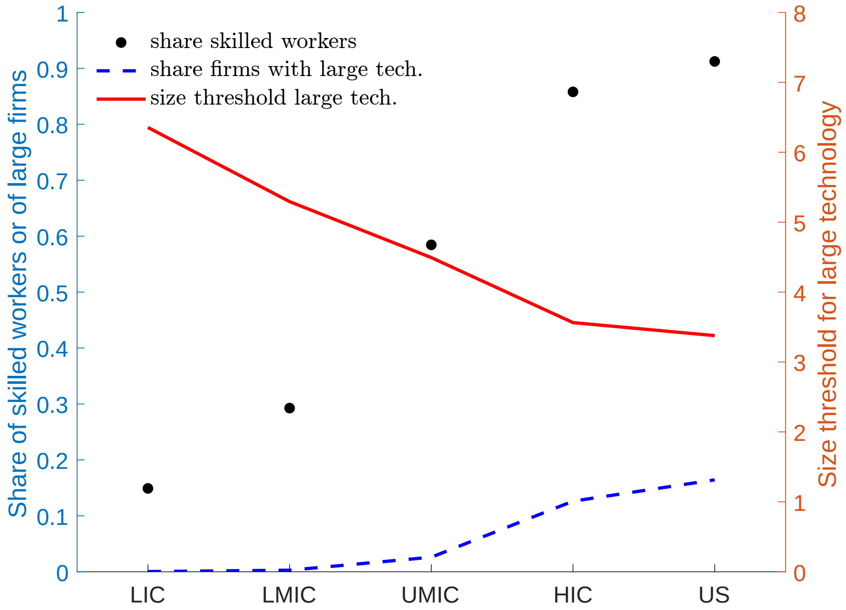


Figure 8: Technology choice

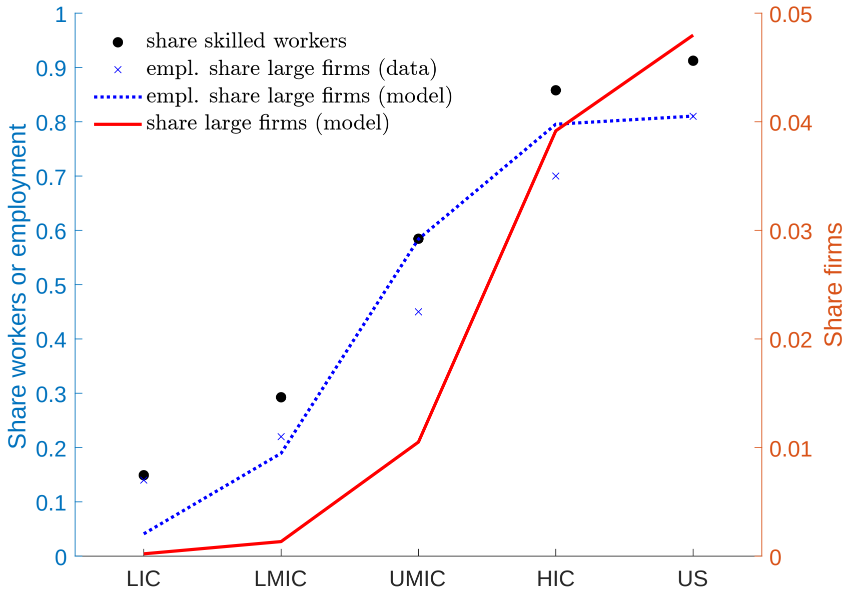


Figure 9: Employment in large firms ($L \geq 10$)

in the US, the large technology is optimal for firms with more than 3.4 employees, this size threshold is greater than 6 in a low-income economy. As a result, very few firms adopt the large technology when the skill premium is high. Figure 8 illustrates these patterns.

With fewer firms using the large technology, there very few firms with at least 10 employees in poor countries. Whereas in the US and in high-income economies, around 80% of employment is in firms with at least 10 employees, the model predicts that this fraction is about half in upper middle income countries, and even lower in countries with fewer skilled workers. As shown in Figure 9, these patterns are quite close to those observed in the data.

Overall, although no cross-country data were used in the calibration, the model comes very close to differences in firm size patterns across countries, varying only the skill endowment.

Output. These changes in the size distribution also affect output. Overall, of course, in adjusting their technology choices, firms react optimally to different skill prices, and so differences in thresholds and technology choices across economies in our model are efficient. Nevertheless, we can evaluate the impact of differences in technology choices across countries by evaluating their effect on output keeping skill endowments fixed.

In doing so, we find that imposing the technology and entry choices of a low income economy in the US implies a reduction in output net of fixed and entry costs of 8.2%. That is, changes in technology account for 18% of the difference in net output between low income economies and the US in our model.[5]

The reaction of technology choices to the skill endowment also implies that increasing work force skills has benefits beyond simply those of having more skilled workers for a given production structure. Skill accumulation allows for greater use of large-scale technology.

8 Endowments, firm sizes, and distortions

In this section, we briefly relate our results to those of a rich literature on misallocation. This literature often interprets average product dispersion and differences in the firm size distribution as evidence of distortions.

8.1 Average and marginal products

In work on misallocation, it is common to use labor productivity or a firm's average product as a proxy of its marginal product, since the two are proportional with Cobb-Douglas production functions. Then, dispersion in measured labor productivity across firms is often taken to indicate marginal product dispersion, and interpreted as evidence of the presence of distortions. Such an approach often suggests greater distortions to large firms. It is well known that such size- or productivity-dependent distortions induce misallocation, and have the potential to significantly reduce an economy's output.

With CES production functions, average and marginal products are not uniformly proportional. As a result, in the competitive equilibrium of the model analyzed here, labor productivity is not equated across firms using different technologies, even in the absence of distortions. Hence, in the present context, dispersion in labor productivity does not necessarily indicate the presence of distortions.

To see this, consider optimal labor productivity of each type of firm. At optimal employment, given wages, average output of a firm of technology i is

$$\left(\frac{y}{L}\right)^i = \frac{w_h}{\gamma^i}\frac{1+\left(\frac{1-\mu^i}{\mu^i}\right)^{-\rho^i}\left(\frac{w_l}{w_h}\right)^{1-\rho^i}}{1+\left(\frac{1-\mu^i}{\mu^i}\right)^{-\rho^i}\left(\frac{w_l}{w_h}\right)^{-\rho^i}}. \tag{48}$$

Clearly, optimal labor productivity varies with a firm's technology, as well as with factor prices in an economy.

First, the average products of large and small firms differ because of differences in returns to scale, γ. Greater returns to scale imply a slower decline of the marginal product with firm size, thus greater optimal size for any z and input prices, and thus a lower optimal average product. This channel, captured in the equation via γ^i, affects the optimal average product of large vs small firms in the same way in all economies, regardless of input prices.

Second, if firms differ in factor intensity, optimal average products depend on relative input prices. An increase in the skill premium increases the unit cost of large relative to small firms, reducing their relative size, and thus increases their optimal labor productivity.

This implies that in economies where skills are more scarce, generating a greater skill premium, the average product of large firms relative to small firms is greater – simply because a high price of skill curtails the size of large firms, and without any size- or productivity-dependent distortions.

How large is this effect? Across our country groups, labor productivity in large relative to small firms, $(y/L)^b/(y/L)^s$, is more than 50% greater in a middle income country compared to the US, and more than twice as large in a low-income country compared to the US.

[5] In computing this, we impose z^* and $\hat{z}$ from other economies in the US economy. To ensure labor market clearing, we let the number of firms M and the skill premium adjust. This implies a lower skill premium in poor economies, since their technology choices imply a lower value of skill.

8.2 Productivity- or size-dependent distortions

In the model, a lower skill endowment strongly affects the firm size distribution. How do these effects compare to those of the productivity- or size-dependent distortions that have frequently been analyzed in the literature?

To illustrate, consider increasing the parameter ν, which controls productivity-dependent distortions, from its benchmark value of zero to 0.25. This implies an elasticity of the net of tax rate on revenue with respect to z of 0.25.

Because this distortion primarily hits large firms, it makes running the large technology less attractive, and raises the threshold z^*, relative to the continuation threshold $\hat{z}$. As a result, the share of large firms declines by 40%, and the share of firms with at least ten workers by more than half. The share of employment in large firm falls by about half.

In addition, because large firms intensively employ skilled workers, distortions also reduce the skill premium. Conditional on technology choice, this implies a greater skill intensity of all firms – but of course this is balanced by the smaller share of large firms.

These effects are comparable to those in similar studies in the literature. More importantly, they are roughly comparable in magnitude to those of reducing the skill endowment from that in the US to that in a typical middle-income country.

This brief analysis illustrates that differences in the firm size distribution per se do not necessarily indicate the presence of productivity-dependent distortions. These can instead stem from differences in skill endowments, which have a powerful effect on the firm size distribution. Nor does variation in average product dispersion across countries necessarily indicate the presence of distortions, given that it can be the direct consequence of differences in skill prices when firms differ in skill intensity. Plausibly, differences in the firm size distribution across countries reflect both differences in skill endowments and in distortions.

9 Conclusion

This paper provides three facts on the relationship between firm size, skill distribution, and economic development. First, we show that the share of employment in large firms in high-income countries is more than three times larger than in low-income countries. Second, we show that across countries, employees of large firms are more skilled than those of small firms. Third, we show 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 similarly distributed across all firm sizes. This evidence suggests that higher levels of education are associated with larger firm sizes and that high-skilled workers in large firms generate higher incomes. In future work, we use a new heterogeneous firm macro model of skills and size that we outline in section 5 to disentangle the impact of barriers to firm growth and skill supply on economic development, shedding light on the complex interplay between these factors.

A Data sources

Table 5: 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
Armenia	2009	2013	Integrated Living Conditions Survey
Armenia	2016	2019	Labour Force Survey
Australia	2001	2017	Household, Income and Labour Dynamics in Australia
Austria	2004	2020	European Union Statistics on Income and Living Conditions
Benin	2010	2015	Enquête Modulaire Intégrée sur les Conditions de Vie des ménages
Benin	2018	2018	INTEGRATED REGIONAL SURVEY ON EMPLOYMENT AND THE INFORMAL SECTOR IN MEMBER STATES OF UEMOA (ERI -ESI)
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
Cyprus	2005	2020	European Union Statistics on Income and Living Conditions
Czechia	2011	2020	European Union Statistics on Income and Living Conditions
Côte d'Ivoire	2018	2018	INTEGRATED REGIONAL SURVEY ON EMPLOYMENT AND THE INFORMAL SECTOR IN MEMBER STATES OF UEMOA (ERI -ESI)
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	2007	2017	Harmonized Labor Force Survey
Egypt	2017	2017	Labor Force Survey
Egypt	2006	2006	Labor Market Panel Survey
Ethiopia	2018	2018	Ethiopia Socioeconomic Survey
Ethiopia	2018	2018	Socioeconomic 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	2004	2019	European Union Statistics on Income and Living Conditions
Germany	2005	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	2004	2018	European Union Statistics on Income and Living Conditions
Iraq	2007	2012	Household Socio-Economic Survey
Japan	1997	2017	Employment Status Survey
Liberia	2014	2016	Household Income and Expenditure Survey
Malawi	2019	2019	Integrated Household Survey
Mali	2018	2018	INTEGRATED REGIONAL SURVEY ON EMPLOYMENT AND THE INFORMAL SECTOR IN MEMBER STATES OF UEMOA (ERI -ESI)
Malta	2008	2018	European Union Statistics on Income and Living Conditions
Mexico	2005	2019	Encuesta Nacional de Ocupación y Empleo
Mongolia	2007	2021	Labor Force Survey
Namibia	2012	2018	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
Palestinian Territories	2009	2014	Harmonized Labor Force Survey
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	2005	2020	European Union Statistics on Income and Living Conditions
South Africa	2010	2019	Labor Market Dynamics
South Africa	2008	2022	Quarterly Labor Force Survey
South Korea	2003	2018	Korean Labor and Income Panel Study
Sri Lanka	2011	2022	Labor Force Survey
Sweden	2004	2005	European Union Statistics on Income and Living Conditions
Switzerland	2009	2020	European Union Statistics on Income and Living Conditions
Tanzania	2008	2019	Living Standards Measurement Survey
Tanzania	2008	2019	National Panel Survey
Togo	2018	2018	INTEGRATED REGIONAL SURVEY ON EMPLOYMENT AND THE INFORMAL SECTOR IN MEMBER STATES OF UEMOA (ERI -ESI)
Uganda	2017	2017	Labor Force Survey
United Kingdom	1991	2008	British Household Panel Survey
United Kingdom	2008	2011	European Union Statistics on Income and Living Conditions
United States	2010	2017	Current Population Survey
Uruguay	2006	2017	Encuesta Continua de Hogares
Uruguay	2006	2006	Integrated Public Use Microdata Series - International
Zambia	2017	2017	Labour Force Survey
Zimbabwe	2014	2019	Labour Force and Child Labour Survey

B Summary tables

Table 6: Employment by jobtype

	Country Income Group			
Jobtype	Low	Lower-middle	Upper-middle	High
Wage-work	0.21	0.34	0.60	0.84
Self-employment	0.56	0.52	0.28	0.15
Unpaid work	0.24	0.14	0.12	0.01
Number of countries	16	8	15	18

Table 7: Skill Statistics (Laborforce).

	Country Income Group			
Skill category	Low	Lower-middle	Upper-middle	High
High skill	0.12	0.26	0.55	0.86
Low skill	0.88	0.74	0.45	0.14
Number of countries	16	8	15	18

Table 8: Skill Statistics (Wage-Workers).

	Country Income Group			
Skill category	Low	Lower-middle	Upper-middle	High
High skill	0.31	0.42	0.62	0.86
Low skill	0.69	0.58	0.38	0.14
Number of countries	16	8	15	18

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