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On Productivity and Distortions across Countries
Diego Restuccia
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ABSTRACT

I examine the empirical properties of firm-level productivity and distortions across countries using the newly released World Bank Enterprise Surveys (WBES). Using a standard framework of production heterogeneity, I show that the gap in productivity and distortions between high and low productivity firms is larger in developing countries, generating large aggregate productivity losses from misallocation. A key empirical property of distortions in developing countries is that they systematically weaken the relationship between firm size and firm productivity. I exploit a unique feature of the WBES data to document which specific aspects of the economic environment faced by firms, such as financial constraints, regulation, corruption, and weak infrastructure, are consistent with the empirical pattern of distortions across countries.

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1 Introduction

Aggregate productivity is at the core of differences in income per capita across countries (Klenow and Rodriguez-Clare, 1997; Prescott, 1998; Jones, 2016). As a result, a key question in the literature on macroeconomic growth and development is what are the fundamental determinants of aggregate productivity differences across countries? There are several useful perspectives explored in the literature. In this paper, I focus on resource misallocation across firms. I assess the extent of misallocation across countries using the newly released and expanded World Bank Enterprise Survey (WBES). Using a standard framework of heterogeneous firms, I measure firm-level productivity and the implied firm-level distortions in each country in the dataset. A main finding is that both firm-level productivity and distortions are more dispersed across firms in developing countries, consistent with evidence for specific countries in the literature. But the key empirical property I highlight is that distortions are more highly correlated with firm productivity in developing countries, implying that distortions weaken the systematic relationship between firm size and productivity expected in economies with no distortions. I then exploit a unique feature of the WBES data to assess the specific obstacles facing firms in their economic environment that are consistent with the empirical pattern of distortions.

To derive insights from the cross-country data, I consider a standard framework of production heterogeneity following Hopenhayn (1992). Production of a homogeneous good takes places in establishments. Establishments are characterized by a production function that features decreasing returns to scale to variable inputs such as labor, and differ in their total factor productivity. Markets are competitive but prices of individual producers may be distorted (Restuccia and Rogerson, 2008). This simple framework of production heterogeneity with distortions is a well-established theory of firm size and permits comparative analysis of actual data of individual producers with a benchmark efficient allocation of resources. The cost associated with the misallocation of resources across producers is summarized by the aggregate productivity gain from an efficient reallocation or alternatively its inverse,

allocative efficiency.

I use WBES data (World Bank, 2025) to assess misallocation within sectors and across countries. The highlights of the WBES dataset are that is a common survey conducted in many countries (103 countries), spanning the entire range of cross-country income distribution and that has an opinion-based component that asks establishments about the barriers and constraints the firm faces. It is important to note some limitations as well, especially in qualifying some findings. First, it only includes establishments with five or more employees. Since average firm size increases systematically with income per capita across countries (Bento and Restuccia, 2021), this restriction impacts differentially across countries, potentially biasing some statistics. Second, sample sizes are relatively small, with sample sizes ranging between 79 and 2600 establishments, which restricts a more granular examination of the data; and third, it only includes non-farm enterprises. It is well known that for many developing countries, more than 60% of employment is engaged in family farms in the agricultural sector, which may face distinct barriers to their operation relative to those emphasized in WBES surveys.

Using the data and framework, I measure firm's output as sales and labor as full-time permanent employees, and construct measures of firm-level productivity and distortions. Distortions are indirectly inferred such that in equilibrium, firms choose the observed level of employment given their productivity. In this regard, distortions represent an indirect catchall of the barriers faced by firms that affect their operating size relative to their productivity. To minimize the potential influence of time and sectoral composition across countries, I residualize both firm-level productivity and distortions by removing country by sector by time fixed effects. I document three main empirical findings. First, the productivity gap between the most and least productive firms is larger in developing countries. Moreover, this larger dispersion in firm-level productivity in developing countries arises from the greater prevalence of lower productivity firms. Second, the gap in distortions between the most and least productive firms is also larger in developing countries, implying that distortions

hurt productive firms the most in developing countries. Indeed, the elasticity of firm size (employment) with respect to firm productivity is weakest in developing countries. Third, the overall aggregate productivity impact of distortions is largest in developing countries in each sector, with allocative efficiency less than half than that in advanced economies. These findings are consistent with evidence for specific countries in the literature, such as the seminal article by Hsieh and Klenow (2009) for the examination of China, India, and the United States, Cirera et al. (2020) for countries in Africa, Pagés (2010) for countries in Latin America, and Ayerst et al. (2024) for a cross-country sample using the Orbis dataset. Restuccia and Rogerson (2013), Hopenhayn (2014), and Restuccia and Rogerson (2017) offer more comprehensive surveys of the literature.

I conduct two more specific analyses with the data. First, I show that a simple parametric form of firm-level productivity and distortions can match the granular data across countries quite well, and use this parameterization to assess the importance of the restricted sample in WBES, which focuses on establishments with five or more employees, for the empirical findings. The analysis indicates that while the magnitudes of dispersion in productivity and distortions and their correlation across countries change somewhat, the main empirical findings emphasized with the WBES data hold in the population sample. Moreover, the most systematic effect across countries is the bias on measures of distortions, which indicate that the gap in distortions between developing and developed countries is greater than what is indicated by the WBES sample. This implies that for some countries, the difference in allocative efficiency is greater than indicated by the WBES sample.

Second, I examine which specific barriers reported in WBES data have the property of being most hurtful for the more productive firms in developing countries. I document the patterns from a few indicators of the economic environment of firms related to regulation, finance, infrastructure, and corruption. I emphasize that it is not only the difference in average distortion that matters, but how the distortions affect differentially firms across the productivity distribution. I find that aspects of regulations, corruption, and infrastructure

all feature higher negative impacts on more productive firms in developing countries, even for indicators that do not feature a systematic difference in the average across countries. This suggest policy reforms aimed at reducing distortions but specially reducing the idiosyncratic impact that affect the most productive firms in developing countries.

The paper proceeds as follows. In the next section, I describe the framework of production heterogeneity used to derive measures of firm-level productivity and distortions. Section 3 describes the data and presents the main empirical observations from the cross-country data, including an overall assessment of the aggregate productivity cost of misallocation across sectors and countries. In Section 4, I provide an analysis of the potential implications of the restricted sample in WBES data for key moments of firm-level productivity and distortion. I also document basic measures of the economic environment such as access to finance, corruption, infrastructure, and regulation, with regard to their empirical cross-country and within country patterns. I show some of these barriers to firm's operation in developing countries feature correlated patterns in that more productive firms are impacted the most by these country barriers. I conclude in Section 5.

2 Framework

I consider a model of producer heterogeneity and distortions following Hopenhayn (1992) and Restuccia and Rogerson (2008). To deliver some basic insights, I make several simplifications to focus on a static economy with a fixed set of producers and hence focus on a narrow notion of misallocation, whereby a constant amount of aggregate resources are allocated across a fixed set of producers. Restuccia and Rogerson (2017) provide a detailed description of research considering broader notions of misallocation.

Technology. Production of a homogeneous good takes place in M establishments with access to a decreasing returns to scale technology in variable inputs.[1] These establishments

[1] In what follows I refer to production units, establishments, or firms indistinguishably.

differ only on their total factor productivity. For simplicity, I consider employment as the only factor input but I discuss below the advantages and potential limitations of this assumption. I assume an establishment i production function is as follows:

$$y_i = z_i h_i^{\gamma}, \qquad \gamma \in (0,1), \tag{1}$$

where z_i is measured establishment TFP, h_i is total establishment employment, and γ represents the extent of decreasing returns to scale at the firm level. I rely on this specification of the production function to measure firm-level TFP as a residual from firm-level data on output and employment, i.e, $z_i = y_i/h_i^{\gamma}$.

Note that in order to accommodate that there may be differences in production technologies across industries s, countries c, and time t, following Ayerst et al. (2024) I residualize firm-level TFP by running a regression of log measured TFP ($\log z_{isct}$) on an interaction fixed effect term of sector, country, and time ($\log z_{sct}$) and retaining the residual as $\log z_i$. I use this residualized measure of firm TFP and the assumed production function with data on actual employment to compute the implied actual output that is devoid of industry, country, and time fixed effects.

Market structure and distortions. Output and labor markets are competitive but potentially subject to distortions, which for simplicity I model as implicit idiosyncratic taxes or subsidies to firm's revenue τ_i. Total employment in the economy is fixed equal to H. Denoting the real wage rate by w and normalizing the price of output to one, the profit maximization problem of firms is given by

$$\max_{h_i \geq 0} \{(1-\tau_i) z_i h_i^{\gamma} - w h_i\}. \tag{2}$$

Equilibrium. A competitive equilibrium in this static economy is a wage rate w and employment demand by firms $\{h_i\}$ such that: (i) Given w, firm's employment demand $\{h_i\}$ solves the profit maximization problem in equation (2) and (ii) the labor market clears:

$\sum_{i=1}^{M} h_i = H$.

Characterization. The first order condition for profit maximization implies,

$$(1-\tau_i)\gamma\frac{y_i}{h_i} = w. \tag{3}$$

An important implication of equation (3) is that absent idiosyncratic distortions, output per unit of factor input equalizes across firms to maximize the aggregate output this economy can produce given resources. By implication then, the measure of idiosyncratic distortions (or wedge) that I use is output per unit of employment:

$$\text{wedge}_i = \frac{y_i}{h_i} \propto \frac{1}{(1-\tau_i)}, \tag{4}$$

and this measure can be shown to be proportional to deviations in the marginal product of labor (since the technologies are assumed to be the same across producers) and proportional to the implicit tax.

The other implication which is worth highlighting is that distortions that are common across firms in this simple framework do not create misallocation, would only affect the factor input price in equilibrium that clears the factor input market. From equation (3) and solving for the demand for labor for each firm h_i, if τ_i is the same across all establishments, then the wage that clears the labor market would adjust to exactly undo the effect of the tax on the demand for labor of all the firms, that is, in this case the market clearing condition for employment is

$$\sum_i \left(\frac{(1-\tau)\gamma z_i}{w}\right)^{1/(1-\gamma)} = H,$$

and the equilibrium wage w would adjust proportionally to undo the effect of a common tax on the demand for labor of all the firms to clear the labor market. This suggests that, in this simple context, it is not the average size of the distortion that matters for misallocation but instead differences in distortions across producers. Hence, in characterizing specific

distortions from the data, I focus on cross-country variations in distortions that generate idiosyncratic effects across producers as the relevant metric, not necessarily the average distortion in the economy.

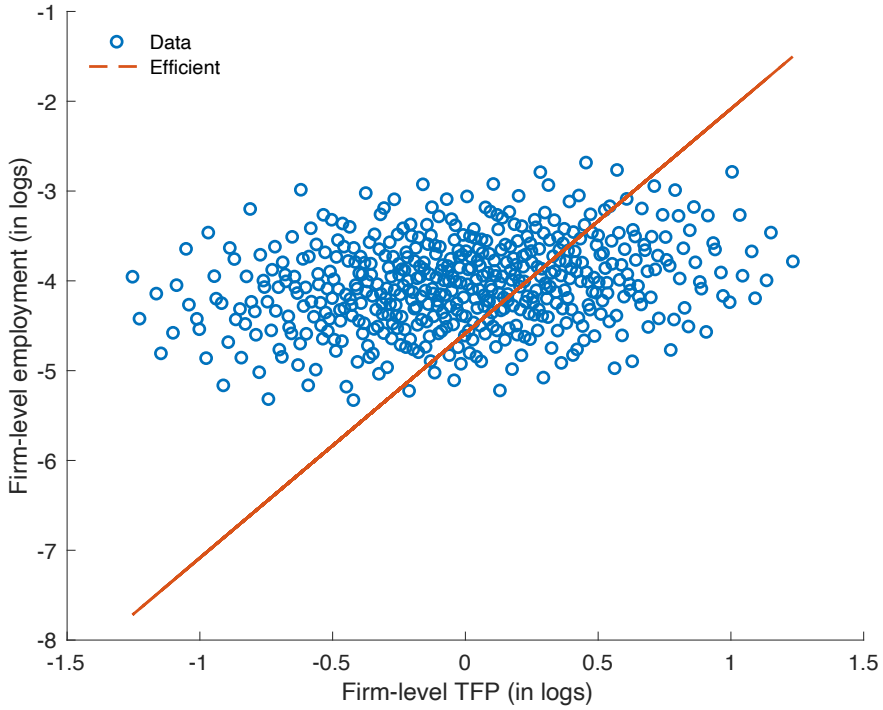
Stylized misallocation. To illustrate more precisely the role of distortions in generating the observed firm size given firm productivity in the data, the optimality condition in equation (3) generates the following firm's demand for employment:

$$\log h_i = \text{constant} + \frac{1}{(1-\gamma)} \left[\log(1-\tau_i) + \log z_i\right]. \tag{5}$$

In the absence of idiosyncratic distortions there is a tight positive relationship between firm productivity (z_i) and firm employment (h_i), a relationship that is highly non-linear but with a constant elasticity given by $1/(1-\gamma)$. In essence, in an economy without distortions, more productive firms operate a larger fraction of employment because this is what brings their marginal product of labor down to equalize with lower productivity firms that operate a smaller share of employment. Idiosyncratic distortions in this context capture any relationship between productivity and employment across firms observed in the data. Figure 1 presents hypothetical firm-level data on employment and TFP in (blue) circles and the employment allocation in the absence of distortions (efficient allocation) in (red) line.

As noted earlier, given differences in productivity across firms, in the absence of distortions, there would be a tight positive relationship between firm's employment and productivity, more productive firms operate larger shares of employment and firms with the same productivity operate the same size. Both of these properties are not satisfied in the hypothetical data in Figure 1: there is a fairly flat relationship between employment size and productivity across firms and there is dispersion in size across firms with the same productivity. Both of these deviations from undistorted (efficient) allocations imply a loss in aggregate productivity as marginal products of labor are not equalized in this hypothetical context. In what follows, I characterize employment allocations and the implied distortions

Figure 1: Stylized Misallocation



Notes: Hypothetical firm-level data on employment and TFP (both in logs) in blue circles, and the implied efficient allocation in red line from equation (5).

faced by firms in the data, in terms of their systematic relationship with respect to firm productivity and in terms of the overall dispersion. This is motivated by the fact that deviations in marginal products that are systematic across the firm productivity distribution tend to be more damaging in terms of aggregate productivity than other non-systematic deviations. And importantly, distinguishing between different patterns of distortions can be helpful in identifying specific distortions or separating from other sources of dispersion. Moreover, as I show below, the employment allocations in most developing countries feature the pattern illustrated by the hypothetical example so these deviations from efficient allocations are of practical importance.

I use the WBES data to first characterize the patterns of the implicit distortions affecting firm's choices. Conceptually, distortions represent the effective tax or subsidy that is required for a firm with a given productivity to choose in equilibrium the amount of employment observed in the data. For example, a relatively high tax would be required for a

high productivity firm to choose to operate a relatively low level of employment or a lower tax for a low productivity firm to operate a relatively large amount of employment. Then, in section 4, I use economic indicators from WBES data to examine what features of the economic environment across countries may be consistent with the documented pattern of distortions.

3 Data

I describe the basic features of the data and report a few observations across countries that arise from these data.

3.1 Description and Variables Construction

I use data from the World Bank Enterprise Surveys (WBES) (World Bank, 2025). WBES are nationally representative firm-level surveys with top managers and owners of businesses. I focus on the newer standardized global methodology surveys that cover over 100 economies. The surveys provide establishment-level information on many topics related to the business environment such as access to finance, infrastructure, performance, among others. Relative to other firm-level data that also provide information about output and inputs, the advantage of WBES data is the unique detailed information about aspects of the business environment in which these firms operate, providing novel insights not only about country level features of the economic environment, but also about how those conditions differ across establishments depending on their size or productivity. The comprehensive data under a common survey methodology and data collection enable comparisons across countries.

I construct measures of output y and employment h for each firm in each country survey. I measure output as the establishment's sales. I do not use value added because there are too many missing information for intermediate inputs. Employment is measured as the number of permanent full-time employees. The findings are robust to using other measures of

employment such as full-time equivalent employees and total employees including full-time, part-time, and seasonal. Similarly to intermediate inputs, I also do not use the available information on capital because there are too many missing information on the required variables to render the remaining sample representative. Nevertheless, other studies have shown that the main effect of distortions is on the overall size of the establishment, not on the input ratios across establishments (Hsieh and Klenow, 2009; Ayerst et al., 2024). In other words, as long as the capital to labor ratio or the intermediate input to labor ratio are roughly constant across firms withing a sector, country, and time, then all the characterization on productivity and distortions across firms with labor input would be the same than with all inputs.

I define firm-level TFP using the production function in equation (1) as a residual from measures of firm-level output and employment:

$$\text{TFP}_i = \frac{y_i}{h_i^{\gamma}}. \tag{6}$$

Firm-level distortions are measured using equation (4) using data on firm-level output and employment and assuming a decreasing returns to scale parameter $\gamma = 0.8$ as commonly used in the misallocation literature (Guner et al., 2008). Both firm-level TFP and distortions (or wedges) are residualized by removing country-sector-year fixed effects. All country moments are calculated using absolute weights provided in WBES data.

A restrictive issue with WBES data is the sample size in many countries which declines substantially when incorporating capital and intermediates as noted above. Hence, there is a trade off between constructing more comprehensive measure of firm-level TFP and having a more restricted (and potentially biased) sample. In the analysis that follows, I side with maintaining the sample of firms as large as possible noting previous studies where measuring TFP with capital and intermediates does not change the results substantially. Moreover, a key aspect in the analysis is that γ represents the decreasing returns to scale

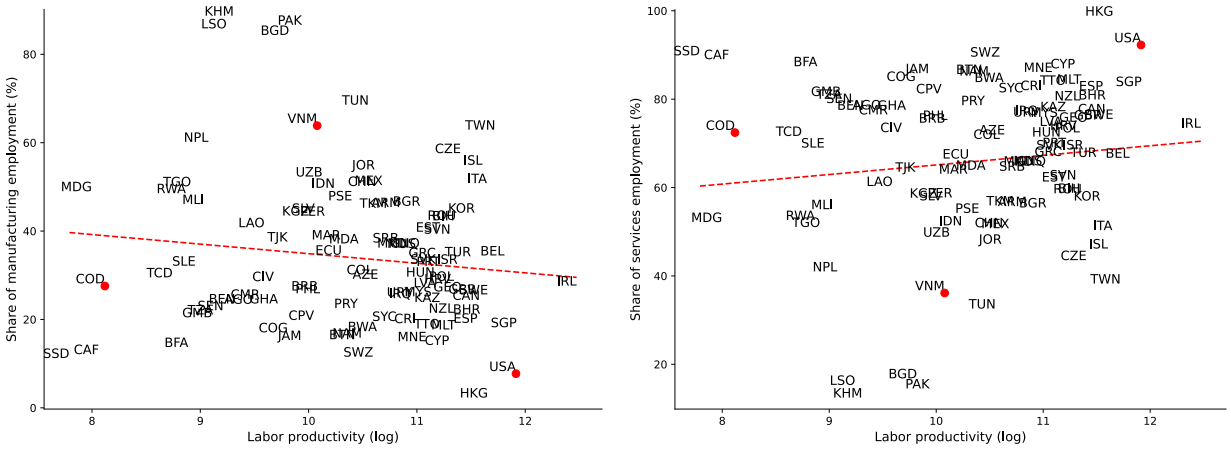
in establishment production, not the labor's income share. Hence, the analysis applies more broadly when input ratios (such as capital to labor or intermediates to labor) are constant across establishments within a sector, country, and time.

The WBES data offers a unique opportunity to assess firm-level information under a common survey questionnaire applied in 103 countries, spanning the entire range of the income per capita distribution. The surveys were conducted between 2022 and 2025. From the available data to construct our measures of firm productivity and wedge and after residualizing, we trim each variable by the top and bottom 1% as is common in studies of misallocation. After trimming, the sample size varies between 76 establishments in Seychelles to 2,631 establishments in the United States. The average number of establishments is 542 and the median 356.

A unique aspect of the data is the inclusion of opinion-base questions of the top manager regarding the economic environment the establishment operates in. At the same time, it is important to recognize some limitations of the WBES data, to keep in mind in interpreting the observations documented below. First, the WBES data only includes non-farm establishments. This is relevant in cross-country comparisons, and in particular comparing developed and developing countries since in developing countries the bulk of employment is engaged in the agricultural sector. As a result, findings regarding establishment-level observations from WBES can only indirectly address the situation of farms in less developed countries. Moreover, the share of non-farm employment between manufacturing and services, illustrated in Figure 2, differs quite substantially across countries, even though there is some systematic negative and positive relationship with aggregate labor productivity across countries.

Second, sample sizes differ quite substantially across countries as noted above. More importantly, sample sizes become too restrictive in some countries when disaggregating the data based on multiple characteristics of the firm. Third, it is also important to note in interpreting the observations documented below that the sample restrictions in WBES data affect cross-country comparisons, for example average establishment size by sector. The reason is that

Figure 2: Shares of Employment in Manufacturing and Services, WBES



(a) Manufacturing (b) Services

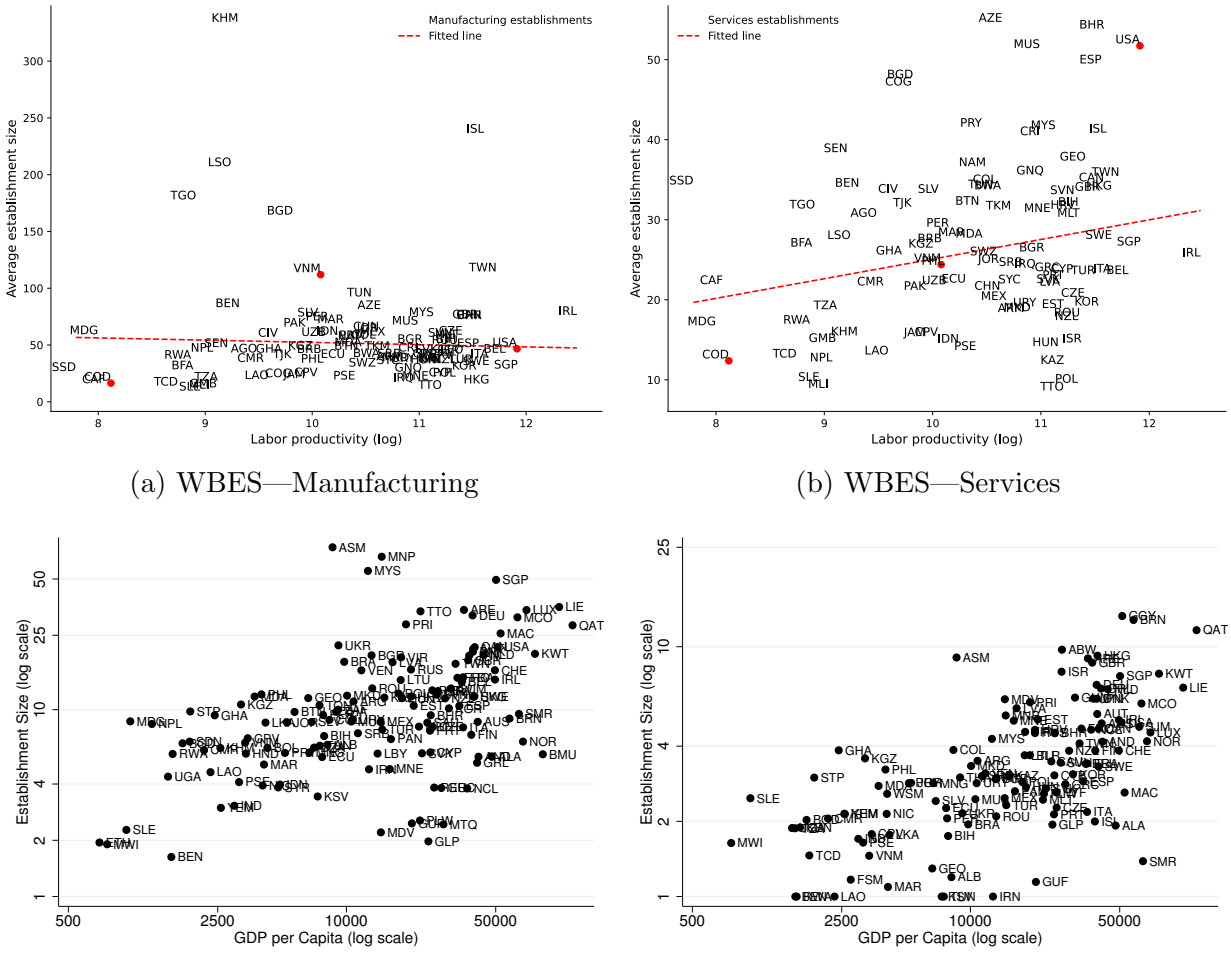
Notes: Shares of non-farm employment in manufacturing and services from WBES data. Aggregate labor productivity in logs for the year 2023 from the Penn World Table v11.0 (Feenstra et al., 2015).

the survey covers firms with five or more employees and to the extent that more developed countries feature larger average size establishments, then effectively the survey compares larger establishments in developing countries with most establishments in advanced countries. To illustrate this limitation of the data, Figure 3 reports the average establishment size in manufacturing and services in WBES data, in contrast to average establishment sizes from data that includes all establishments (Bento and Restuccia, 2017, 2021).

3.2 Main Empirical Observations

I characterize firm-level productivity across countries at different levels of development. To set the stage and illustrate the changes in firm-level productivity, I first focus on the comparison between firm-level productivity in Vietnam and the United States, two countries representative of the developing and developed countries categories. Figure 4 documents the percentile distribution of firm-level TFP in the United States and Vietnam from WBES data. For the comparison in this figure, I do not use the residualized TFP, instead the US dollar converted values to retain the level. I report 50 percentile points from percentile one (p1) to percentile 99 (p99) for each country.

Figure 3: Average Establishment Size in Each Sector



(a) WBES—Manufacturing

(b) WBES—Services

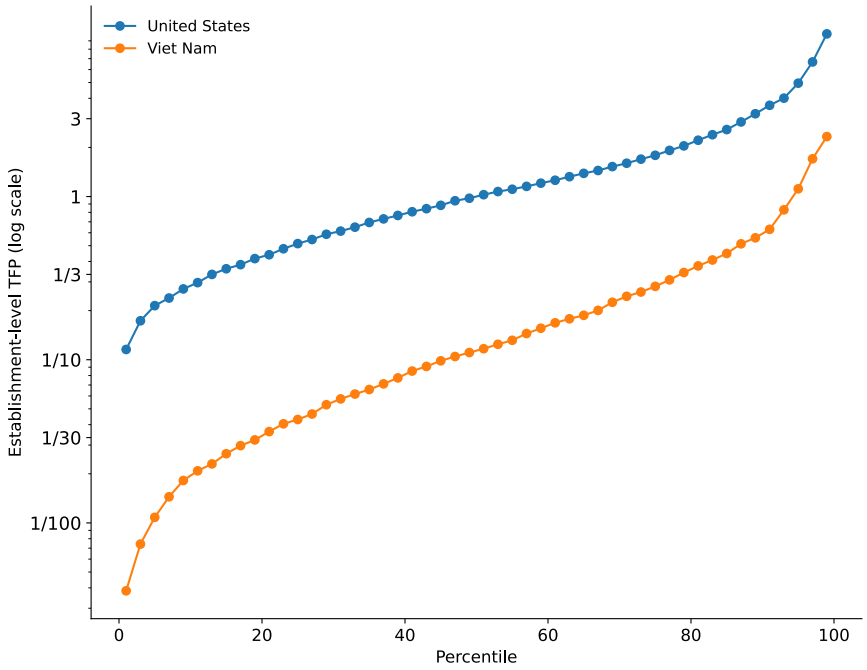
(c) Manufacturing

(d) Services

Notes: Average employment size of establishments in manufacturing and services from WBES data and census data from Bento and Restuccia (2017) for Manufacturing and Bento and Restuccia (2021) for Services. Aggregate labor productivity and GDP per capita in logs from the Penn World Table (Feenstra et al., 2015).

Figure 4 highlights important differences between the countries. First, the United States (USA), a high-income country, has less dispersed productivity than Vietnam (VNM). This implies that the productivity gap between the more productive firms and the less productive ones is larger in VNM than USA. Second, the productivity distribution in Vietnam appears to "fan out" from the top end of the distribution. The most productive firms in USA and VNM have relatively similar productivity while the productivity gap at the bottom percentile of the distribution is much larger. For instance, around 60 percent of firms in Vietnam have

Figure 4: Percentile Distribution of Establishment-Level Productivity, Some Countries



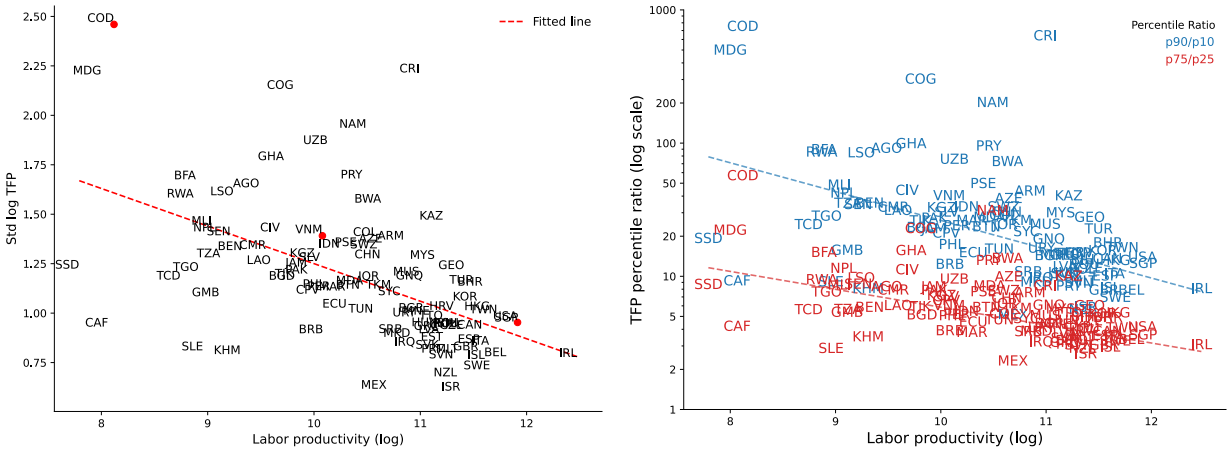
Notes: The figure reports values for 50 percentile points of the firm-level TFP distribution, from percentile one (p1) to percentile 99 (p99).

lower TFP than the percentile one firm in the USA, whereas around 20 percent of firms in the USA have higher TFP than the percentile 99 firm in Vietnam. I now assess whether these patterns hold systematically across countries and using the residualized values.

Dispersion in firm-level TFP across countries. I use the cross-country data to draw broader conclusions on productivity observations. In the comparisons that follow, I use the residualized establishment-level TFP discussed earlier. In this regard, I am comparing the distribution of relative firm productivity excluding the level, unlike Figure 4. This is to potentially reduce the influence of year differences and the sectoral composition of the economy in the characterization of firm productivity.

Figure 5 reports the standard deviation of firm-level productivity in countries against development, measured by aggregate labor productivity (real GDP per worker) from the Penn World Table (Feenstra et al., 2015). Data are the residualized measures of firm-level productivity. Productivity tends to be more dispersed in lower income countries. The pattern

Figure 5: Cross-Country Productivity Dispersion



(a) Standard deviation (b) Inter-quartile, decile ranges

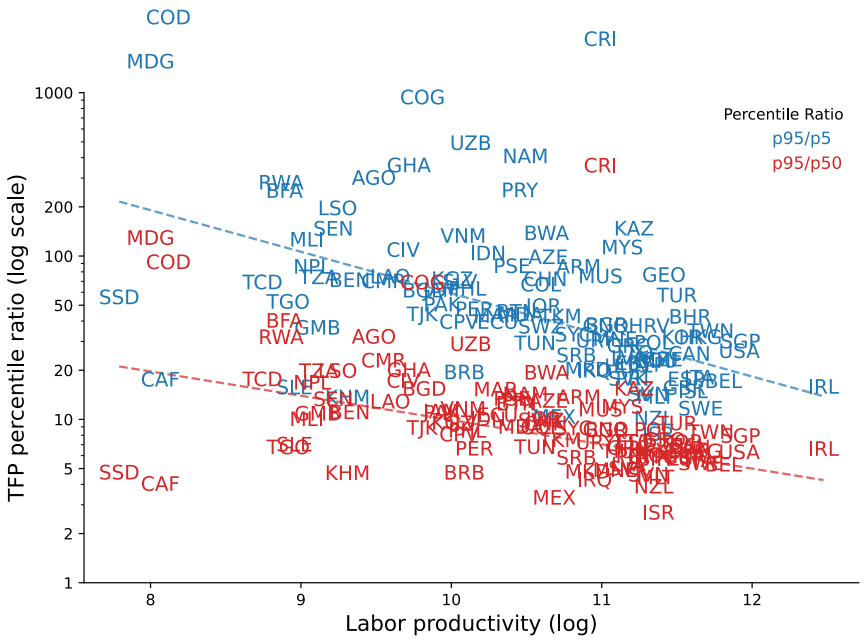
Notes: Productivity dispersion is measured by the standard deviation of log TFP across firms in each country. Each observation is the estimated value for the indicated country. Aggregate labor productivity in logs for the year 2023 from the Penn World Table v11.0 (Feenstra et al., 2015).

is robust to other measures of dispersion, such as the inter-quartile or inter-decile range, that place less weight on outliers. Focusing on the inter-decile range in panel (b), whereas the productivity gap between the 90 and 10 percentile firms is 12-fold in USA, the productivity gap is 35-fold in VNM. This finding of larger productivity gaps in less developed countries is consistent with Ayerst et al. (2024) who document this fact using Orbis data for a smaller set of countries.

Fanning out of productivity distribution. Figure 6 reports the comparison of firms at different percentiles of the productivity distribution to provide information on the overall shape of the distribution across countries, and whether, in general, the productivity distribution fans out or shifts down in countries at lower levels of output per worker.

We compare firms at the top of the distribution (p99) to firms at different points of the distribution (p50 and p5) in all countries. Figure 6 confirms the pattern emphasized earlier for Vietnam compared to the United States that the productivity distribution tends to narrow in more developed countries. This is stronger in the bottom of the distribution than in the top of the distribution.

Figure 6: Comparison of Productivity Distribution

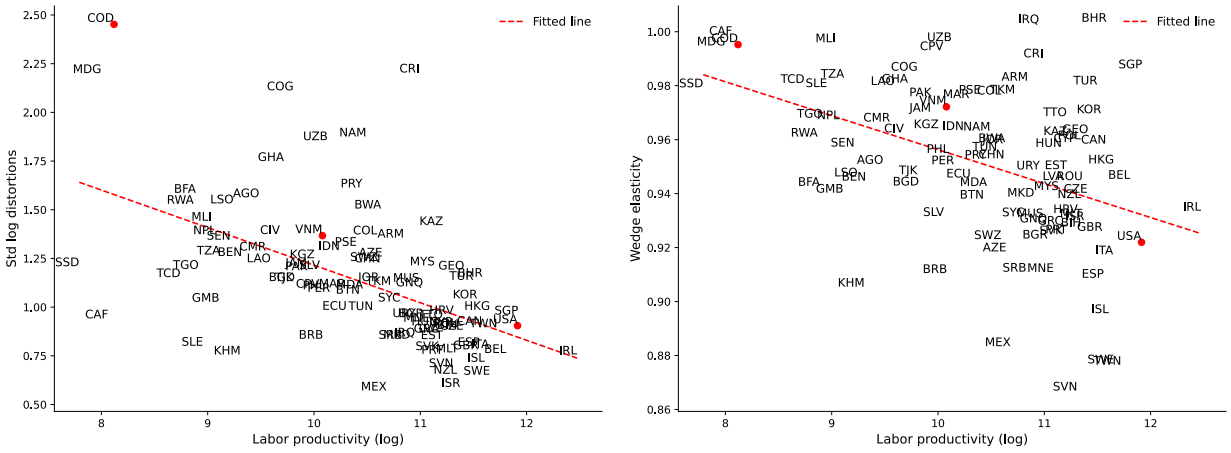


Notes: Each observation is the value for the indicated country. The dashed lines are the best fit. The TFP ratio in the y-axis is in log scale. Aggregate labor productivity for the year 2023 from the Penn World Table v11.0 (Feenstra et al., 2015).

Properties of firm-level distortions. I now characterize measured distortions in WBES data. I examine how the wedge distribution varies across countries at different levels of development. As in Ayerst et al. (2024) and a large literature in misallocation, I focus on two commonly reported moments: the standard deviation of log wedges and the elasticity of firm wedges with respect to firm productivity. Recall that that an economy without distortions is one where there is no dispersion in wedges across producers, and an economy without systematic distortions is one where the elasticity of distortions (the elasticity of wedge with respect to productivity across firms) is low. There are many reasons why the dispersion in wedges and the elasticity of distortions may not reflect actual policy distortions including mismeasurement, selection of operating firms, and technology choices. See Ayerst et al. (2024) for a detailed discussion of these biases in measures of distortions.

Figure 7 reports two measures of distortions for all the countries in the data: the standard deviation of log wedge across firms in panel (a) and the elasticity of distortions in panel

Figure 7: Cross-Country Measures of Distortions



(a) Dispersion of distortions

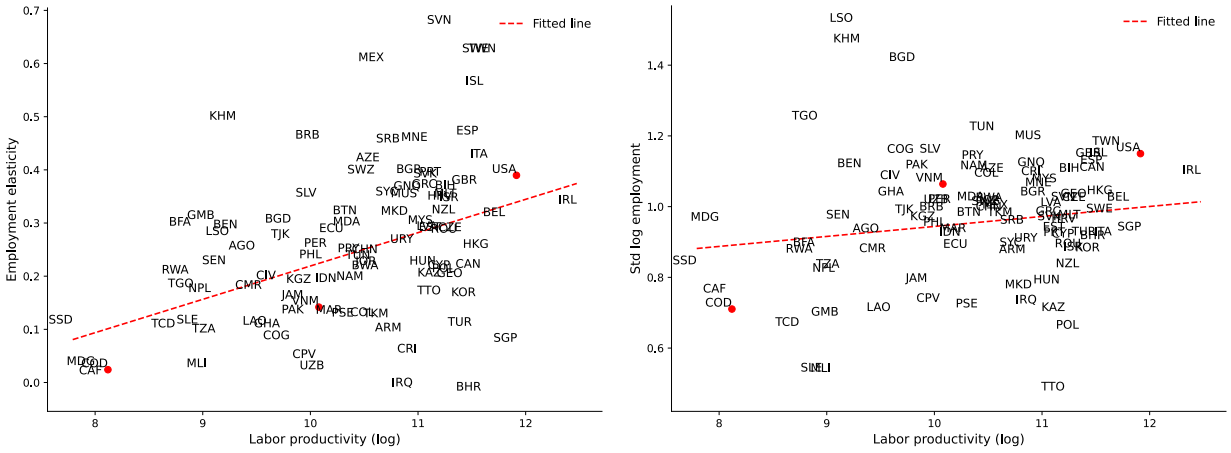
(b) Elasticity of distortions

Notes: Dispersion in distortions is measured by the standard deviation of log wedge across firms in each country. Each observation is the estimated value for the indicated country. Elasticity of distortions measured by the slope coefficient of a regression between log wedge and log TFP in each country. Aggregate labor productivity in logs for the year 2023 from the Penn World Table v11.0 (Feenstra et al., 2015).

(b), the elasticity of firm wedge with respect to firm productivity. Consistent with previous findings for some countries in the literature, Figure 7(a) shows that lower income countries tend to have more dispersed wedges, whereas Figure 7(b) show that wedges are more highly correlated in developing countries.

Recall that distortions are inferred from the relationship between employment and productivity and hence reflect deviations of marginal products of labor across firms. Figure 8(a) reports more directly the relationship between firm-level employment and firm productivity in the cross-country data. Developing countries have a much lower elasticity of firm employment to firm productivity, much like the stylized misallocation case discussed earlier. Figure 8(b) reports the dispersion in employment across countries, showing that the employment gap across firms is slightly smaller in developing countries than in advanced countries. Since systematic distortions mean that employment is moved from more productive to less productive firms, on this factor alone we would expect that the employment distribution is more compressed in developing countries. But between the random component of distortions which may be larger in developing countries and the fact that productivity is more dispersed

Figure 8: Cross-Country Elasticity of Employment and Employment Dispersion



(a) Elasticity of employment

(b) Dispersion in employment

Notes: Elasticity of employment measured by the slope coefficient of a regression between log employment and log TFP in each country. Employment dispersion measured by the standard deviation of log employment across firms in each country. Aggregate labor productivity in logs for the year 2023 from the Penn World Table v11.0 (Feenstra et al., 2015).

in developing countries, factors that counteract the compression of employment across firms in developing countries.

3.3 Assessing the Cost of Misallocation

The aggregate productivity cost of misallocation generally depends on the joint distribution of establishment-level productivity and distortions, but a simple summary statistic relates to the aggregate productivity loss relative to the first-best allocation. In this regard, I compute allocative efficiency measured as the ratio of aggregate actual output relative to aggregate efficient output. Since, aggregate inputs are constant in these static allocations (actual and efficient), the loss in output relative to efficient is a measure of the aggregate productivity loss. Aggregate actual output can be readily computed from the data, with just the caveat that the measure of actual output uses the residualized TFP calculated earlier and hence controls for sector, time, and country specific factors. The efficient allocation can also be readily computed from the equilibrium allocations derived in equation (5) assuming no distortions and solving for the wage rate that clears the labor market. Alternatively, it is instructive

to directly solve the efficient allocations from a planners' problem that maximizes aggregate output given the fixed set of establishments and aggregate inputs. The planner's problem can be written as:

$$\max_{\{h_i^e \geq 0\}} Y^e = \sum_{i=1}^{M} z_i h_i^e, \qquad \text{subject to} \quad \sum_{i=1}^{M} h_i^e = H.$$

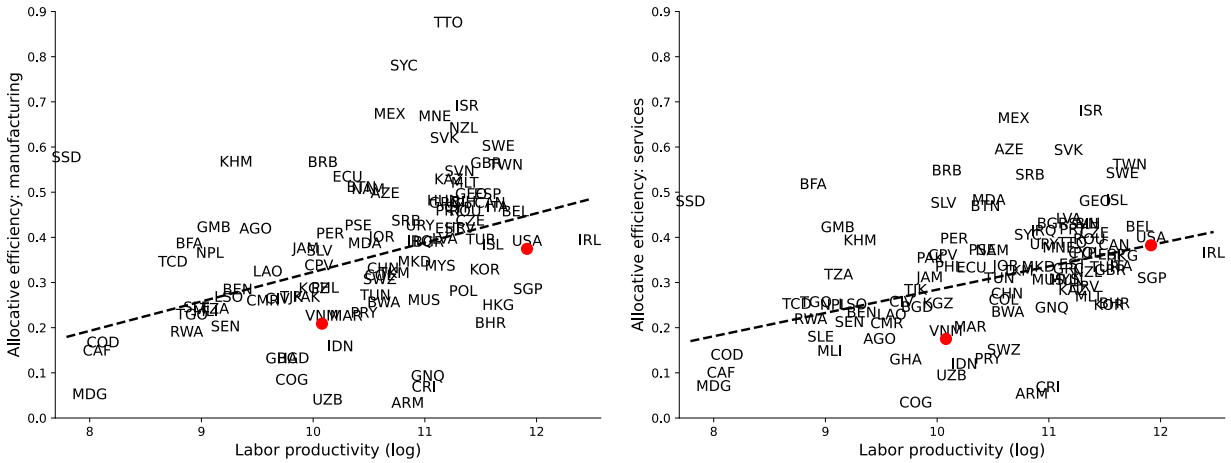
The first order condition from this problem equates the marginal product of labor at an arbitrary firm i to the shadow cost of labor, which is given by the lagrange multiplier of the resource constraint. Hence, as alluded earlier since the shadow cost of labor is the same for all firms, the planner maximizes aggregate output by equating the marginal product of labor across all firms in the economy. Then substituting this equation into the resource constraint determines the value of the lagrange multiplier that satisfies the resource constraint, and back into the first order condition implies the following efficient allocation across establishments:

$$h_i^e = \frac{z_i^{1/(1-\gamma)}}{\sum_{i=1}^{M} z_i^{1/(1-\gamma)}} H.$$

The efficient allocation coincides with the competitive equilibrium allocation when there are no distortions or distortions are constant across producers, and involves operating more productive establishments at a larger scale (more employment) to the point where the marginal product of labor is equalized across all establishments. Note that because of decreasing returns to scale at the establishment level, the allocation of employment is highly non-linear across establishments with different productivity, with an elasticity of employment with respect to productivity equal to $1/(1-\gamma)$. Given the value of $\gamma = 0.8$, this elasticity is equal to 5. This implies that an establishment with a one percent higher productivity than another efficiently operates with a 5 percent greater employment.

For each country and separately for each sector (manufacturing and services), I compute allocative efficiency (AE) and report the findings in Figure 9. Two observations stand out. First, allocative efficiency is much lower in developing countries, a result that is consistent

Figure 9: Allocative Efficiency across Countries within Manufacturing and Services



(a) Manufacturing (b) Services

Notes: Allocative efficiency is the ratio of aggregate actual relative to efficient output which reflects aggregate productivity differences since aggregate factors are the same in actual and efficient calculations. Aggregate labor productivity in logs for the year 2023 from the Penn World Table v11.0 (Feenstra et al., 2015).

with many studies of misallocation focusing on small subsets of countries. Second, generally, allocative efficiency is somewhat smaller in the services sector than in the manufacturing sector. While this result is to be expected given that the services sector involves non-tradable and heavily regulated activities, only a few studies report misallocation for manufacturing and services consistent with this fact (Dias et al., 2020).

Focusing on the United States and Vietnam where allocative efficiency is 0.42 and 0.20 in the manufacturing sector. The value of allocative efficiency in the United States is somewhat lower than the one reported in Hsieh and Klenow (2009) (around 0.70), whereas the value for Vietnam is consistent with that reported in Ayerst et al. (2024) for Vietnam using Orbis data and Nguyen (2024) using even more comprehensive data from all registered firms in the Vietnam Annual Enterprise Survey. On possible explanation for the differences is of course the restricted sample of establishments in WBES data, an issue that I return to in the next section. Also, allocative efficiency is a measure of the cost of misallocation that is susceptible to potential mismeasurement (Ayerst et al., 2024) and it is quite possible that given the cross-section nature of WBES data and the small sample sizes, measurement error may be

more prevalent in these data that can differ across countries.

4 Analysis of Restricted Sample and Indicators

A simple parametric form of firm productivity and distortions is able to fit the data in each country quite well. I exploit this property and use this parametric version of the data to make inferences about key statistics for the entire population of establishments in each country relative to the restricted sample of firms with five or more employees in WBES data. This allows me to provide some guidance regarding the sample restriction in WBES data as to the direction of bias and how it differs across countries for key moments relevant for studying misallocation. I also discuss some indicators of the economic environment in WBES that differ across firms to assess their consistency with the broad pattern of distortions documented earlier.

4.1 Restricted Sample

To assess the quantitative relevance of the restricted sample (firms with five or more employees) in WBES data for measures of productivity dispersion and misallocation, I proceed in four steps. First, I approximate establishment-level productivity and distortions by parameterizing each distribution following Restuccia (2019) and Ayerst et al. (2024). I show that the parameterization and estimates provide a good fit of the TFP, distortions, and allocative efficiency data. Second, using the parametric form of TFP and distortions, I consistently calibrate to the selected sample in the data, in particular, I match moments of the TFP distribution and distortions based on the same selection criteria as in the data, that is from the simulated population sample I focus on firms with five or more employees to construct empirical moments. Third, I compare the estimated population parameters and selected moments across countries to illustrate the bias introduced by the restricted sample.

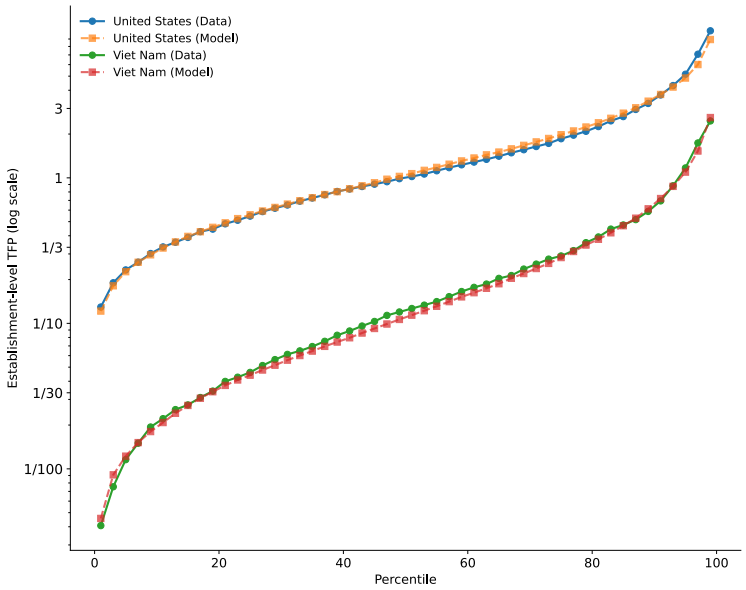
I now provide the details of each step. I approximate firm-level productivity by a log

normal distribution with mean zero and standard deviation denoted σ_z. I then approximate firm-level wedge allowing for a systematic component of distortions and a random component as follows:

$$\log(\text{wedge}) = -\log(1-\tau_i) = \rho \log(z) + \epsilon,$$

where ϵ is normal distributed with mean zero and standard deviation σ_ϵ. This implies that the firm-level data on productivity and distortions are approximated by just three parameters: σ_z, ρ, and σ_ϵ.

Figure 10: Comparison of Productivity Distribution



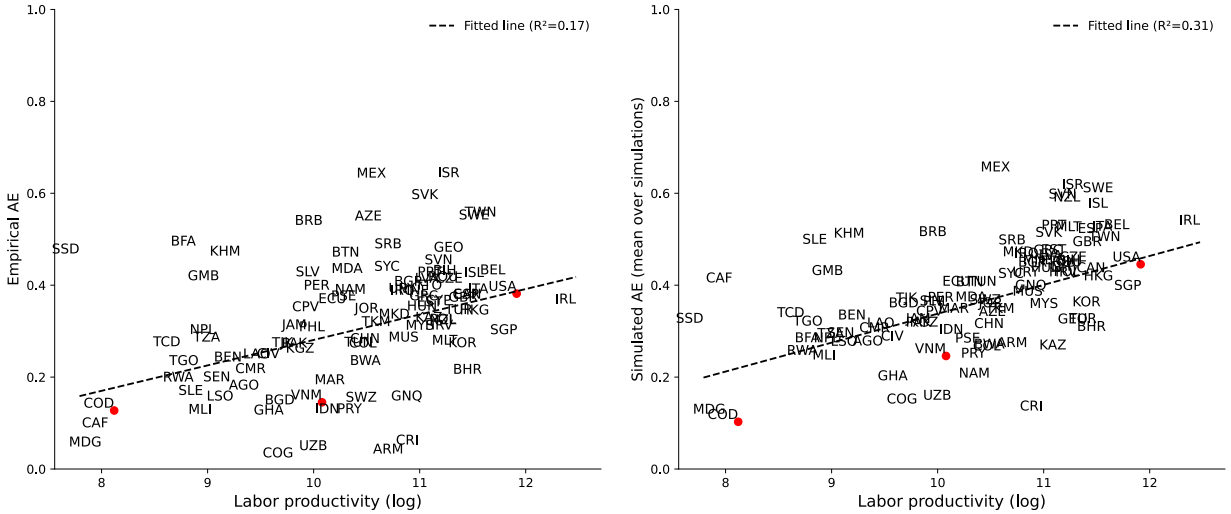
Notes: Values for 50 percentile points of the firm-level TFP distribution, from percentile one (p1) to percentile 99 (p99) in Vietnam and the United States for both the data and the model (simulations). Means of the distributions are normalized to the data in each country.

I estimate these parameters for each country and show that they fit the granular data well. For instance, Figure 10 compares the percentile distribution of firm TFP in Vietnam and the United States in the data and in the simulated data. Even though dispersion differences in firm TFP is governed by one parameter under the log normal assumption, the simulated firms fit the firm-level data quite well.

Similarly, Figure 11 documents the comparison of allocative efficiency between the data (panel a) and the simulations (panel b). While there is somewhat less dispersion in allocative

efficiency across countries in the simulated data, the patterns are well approximated by the simulated data, especially considering that the granular data on productivity and distortions are summarized with three parameters under strict distributional assumptions.

Figure 11: Allocative Efficiency across Countries, Empirical versus Simulated

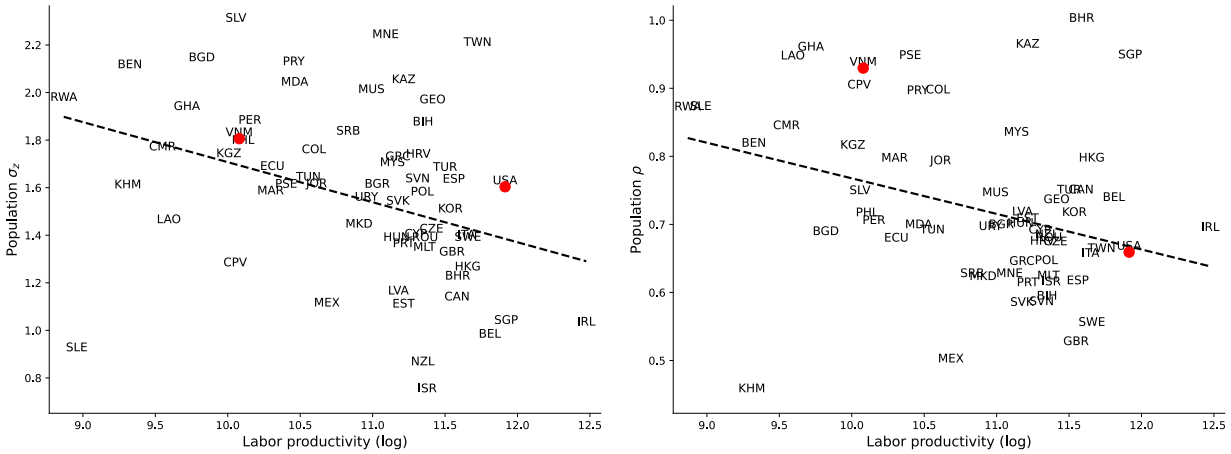


(a) Empirical (b) Simulated

Notes: Allocative efficiency is the ratio of aggregate actual relative to efficient output which reflects aggregate productivity differences since aggregate factors are the same in actual and efficient calculations. Aggregate labor productivity in logs for the year 2023 from the Penn World Table v11.0 (Feenstra et al., 2015).

The estimated parameters in the previous step correspond to firms in the restricted WBES sample, that is firms with five or more employees. I then use the parametric forms to simulate economies based on population parameters, and then constructing moments restricted to firms with five or more workers, as in the data. This allows for a comparison of moments between the hypothetical population of firms without the size restriction and the restricted data. I simulate a large number of firms (100,000) in each country to reproduce the moments on productivity and distortions observed in the data and report the average of 10 simulations for each country. In particular, in each simulation I target three moments: (1) the standard deviation of log TFP, (2) the elasticity of wedge with respect to productivity, and (3) the standard deviation of log wedge. I then report how the estimated parameter values and allocative efficiency vary between the restricted sample and the hypothetical population.

Figure 12: Population Estimates with Simulated Data



(a) Std log TFP

(b) Elasticity of distortions

(c) Random distortions

(d) Allocative efficiency

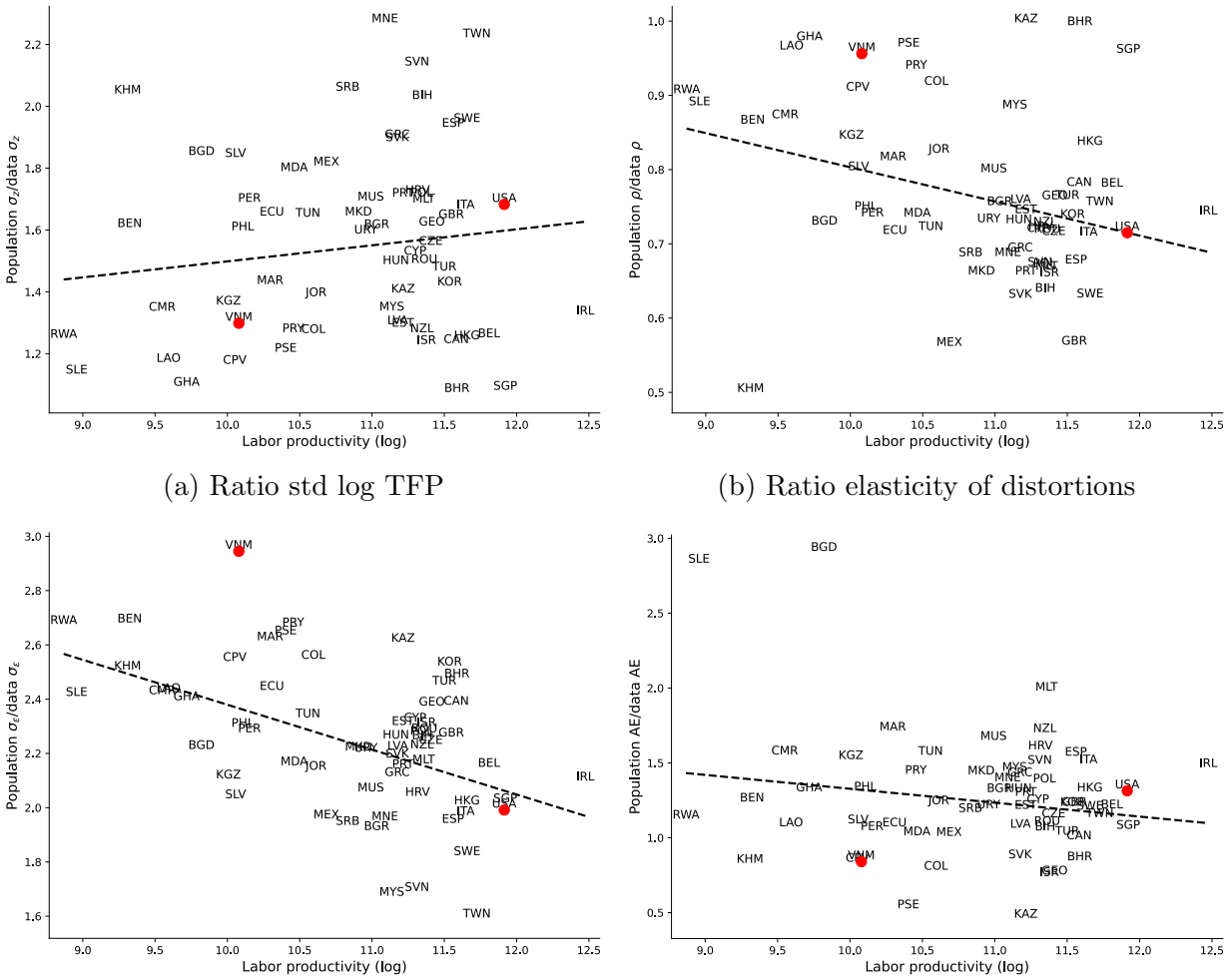
Notes: Population parameters are the estimates for the entire population of firms that fit moments for the restricted sample of firms with five or more workers. Allocative efficiency refers to the entire population of firms implied by the population parameter estimates. Aggregate labor productivity in logs for the year 2023 from the Penn World Table v11.0 (Feenstra et al., 2015).

Figure 12 reports the population parameter estimates (σ_z, ρ, σ_ϵ) and allocative efficiency. The main takeaway is that the estimates of population parameters and resulting allocative efficiency follow similar patterns across countries than that found for the empirical estimates from the restricted sample of firms in WBES. This result is reassuring in that it implies that the WBES data provides an accurate characterization of productivity and distortions across countries despite the sample restriction.

Figure 13 reports the ratio of parameter estimates and allocative efficiency between the population and data (the restricted sample of firms with five or more workers) against aggregate labor productivity across countries to identify systematic bias with the restricted sample. Regarding dispersion in firm-level TFP in panel (a), there is more dispersion in the population of firms than in the restricted sample (about 40 percent higher dispersion measured by the standard deviation of log TFP), but the bias does not show a strong relationship with aggregate labor productivity. While we expect that the size restriction in WBES would affect more firms in developing countries, distortions in these countries impart a disconnect between productivity and size and, hence, the size restriction is not as strong on the productivity dimension.

Regarding distortions in panels (b) and (c), the bias is that distortions in the population are more severe in developing economies relative to developed countries than what the restricted sample indicates. In particular, while estimates of ρ between the population and empirical are about the same for developing economies, the population ρ is much lower than what the empirical sample of firms indicates in advanced economies. Allocative efficiency in panel (d) is higher in the population of firms than in the restricted sample with little systematic variation across aggregate labor productivity, although for the specific cases of Vietnam and the United States, the difference in allocative efficiency between these countries is larger in the population of firms than in the WBES data.

Figure 13: Population Estimates Relative to WBES Data



(a) Ratio std log TFP

(b) Ratio elasticity of distortions

(c) Ratio random distortions

(d) Ratio allocative efficiency

Notes: Population estimates for each parameter and allocative efficiency relative to estimates from WBES data. Aggregate labor productivity in logs for the year 2023 from the Penn World Table v11.0 (Feenstra et al., 2015).

4.2 Economic Environment Indicators

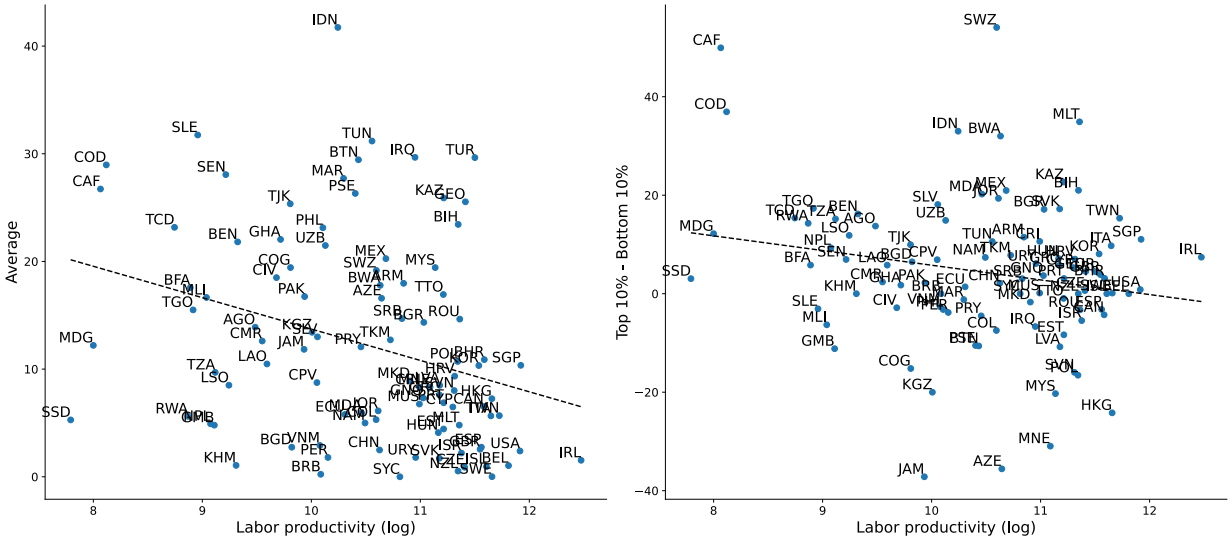
A key empirical observation of firms in developing countries is that their employment is much less systematically related to their productivity compared to the relationship observed in developed countries. This implies that distortions (implicit or explicit) faced by firms in developing countries are more highly correlated with the productivity of the firm. That is, more productive firms in developing countries face greater distortions than the less productive counterparts, compared to the gradient prevalent in developed countries.

I now exploit a unique feature of WBES data, the opinion-based questions on the economic environment faced by the firm, to assess which indicators of the economic environment, such as issues of regulation, credit, human capital, corruption, among many others, are consistent with the correlated property of distortions in developing countries. In particular, I compare the cross-country patterns of specific economic-environment indicators across the productivity distribution of establishments. This allows an identification of specific aspects of the economic environment faced by firms that have the potential to be the most damaging in terms of aggregate productivity, and hence provide specific direction for public policy actions.

I emphasize though that the purpose in this section is not to be comprehensive in the evaluation of indicators since the WBES dataset comprises a large number of indicators, instead I focus on documenting the empirical properties of a few indicators that are suspected to be most damaging for productivity in developing countries, leaving a more comprehensive analysis of indicators for future work.

I document a sample of economic-environment indicators that relate to regulation, corruption, finance, and infrastructure. Figure 14 documents cross-country observations on firms reporting that their prices are regulated. The average percentage of firms is reported in panel (a) and as expected declines with aggregate labor productivity across countries, the percentage of firms reporting their prices to be regulated is less than 5% in advanced economies, whereas it represents more than 30% of firms in developing countries. Panel (b) documents

Figure 14: Regulation–Firms Reporting their Prices are Regulated

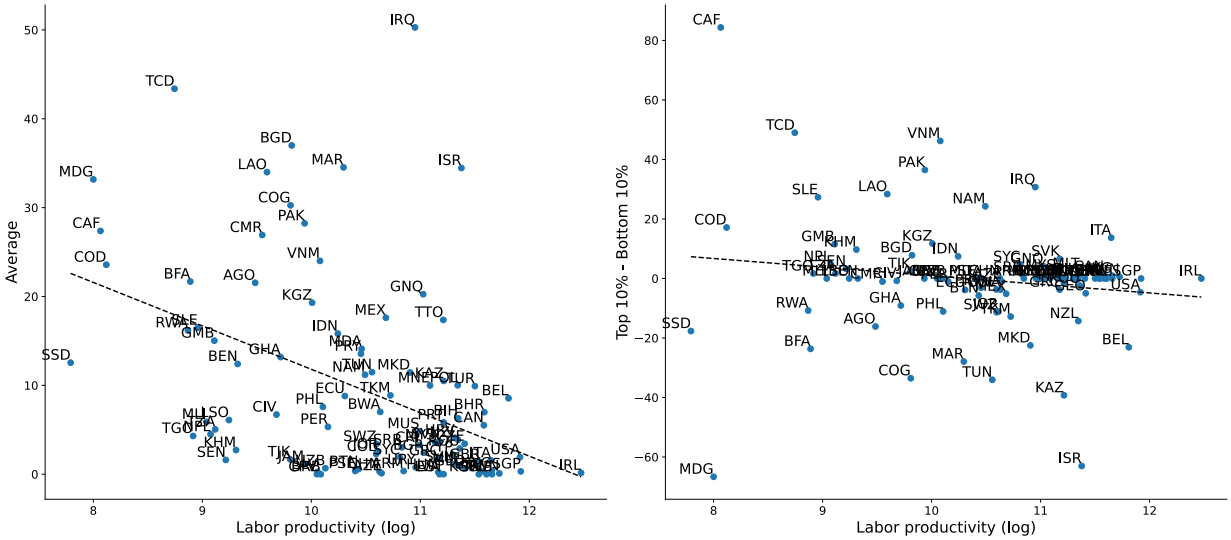


Notes: Average in panel (a) refers to the average percentage of firms reporting their prices are regulated in each country, whereas Top 10%− Bottom 10% in panel (b) refers to the difference in the indicator between the 10% most productive and least productive firms. Aggregate labor productivity in logs for 2023 from the Penn World Table v11.0 (Feenstra et al., 2015).

the proportion of firms with regulated prices but as the difference between the top 10% most productive firms and the bottom 10% least productive firms in each country. Price regulation would act as a correlated idiosyncratic distortion if it affects relatively more the more productive firms in developing countries. This is indeed what is observed on price regulation in panel (b), in advanced economies the low incidence of price regulation is roughly shared among high and low productivity firms, whereas in developing countries the more productive firms face price regulation more intensively than the less productive firms by 10 percentage points.

Figure 15 reports similar moments for an indicator of corruption in the country. In particular, it reports the Graft Index which is defined as the proportion of instances in which firms were expected or requested to pay a gift or informal payment out of the total solicitations for public services, licenses, or permits. In panel (a), the average Graft Index is higher for developing economies, more than 30%, whereas it is nearly zero for advanced economies. Panel (b) shows that indeed the more productive firms in developing are affected more by

Figure 15: Corruption–Graft Index



Notes: The Graft Index is defined as the proportion of instances in which firms were expected or requested to pay a gift or informal payment out of the total solicitations for public services, licenses, or permits. Average in panel (a) refers to the average Graft Index in percent in each country, whereas Top 10%− Bottom 10% in panel (b) refers to the difference in the indicator between the 10% most productive and the 10% least productive firms. Aggregate labor productivity in logs for 2023 from the Penn World Table v11.0 (Feenstra et al., 2015).

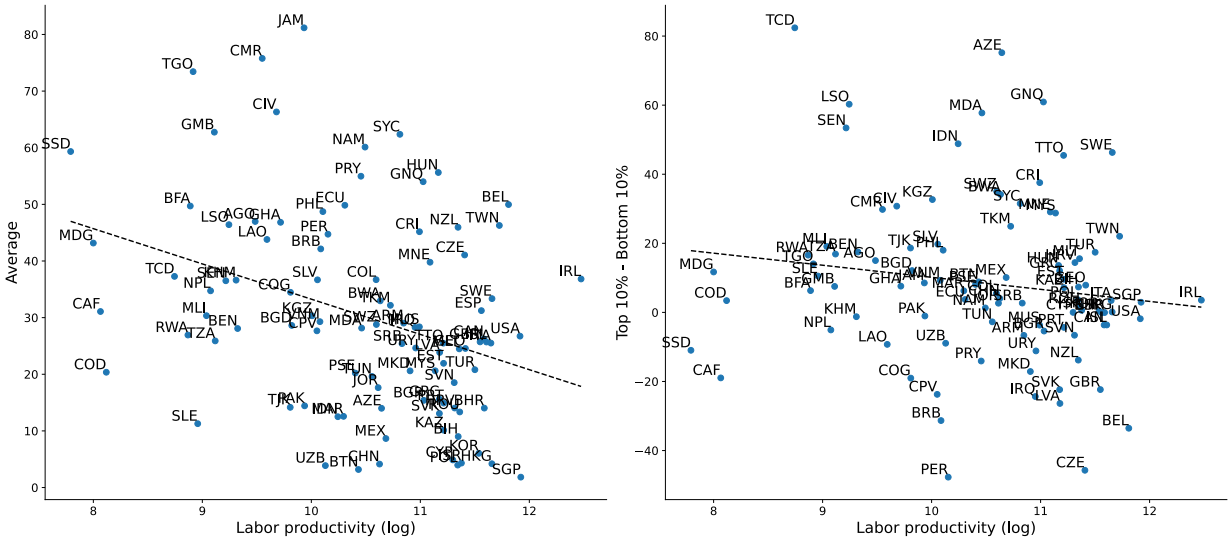
corruption.

Figure 16 documents an indicator of infrastructure issues, the firms that experience internet disruptions. In average, internet disruptions are twice as prevalent in developing countries than in advanced economies (panel a), whereas panel (b) shows that internet disruptions affect productive firms more in developing economies.

Figure 17 documents an indicator of labor regulations, the percentage of social security and employment-based taxes in annual costs of labor, the average in panel (a). As expected, formal employment taxes are somewhat larger in advanced economies. Yet, panel (b) shows that it is the more productive firms in developing countries that pay these taxes to a greater extent.

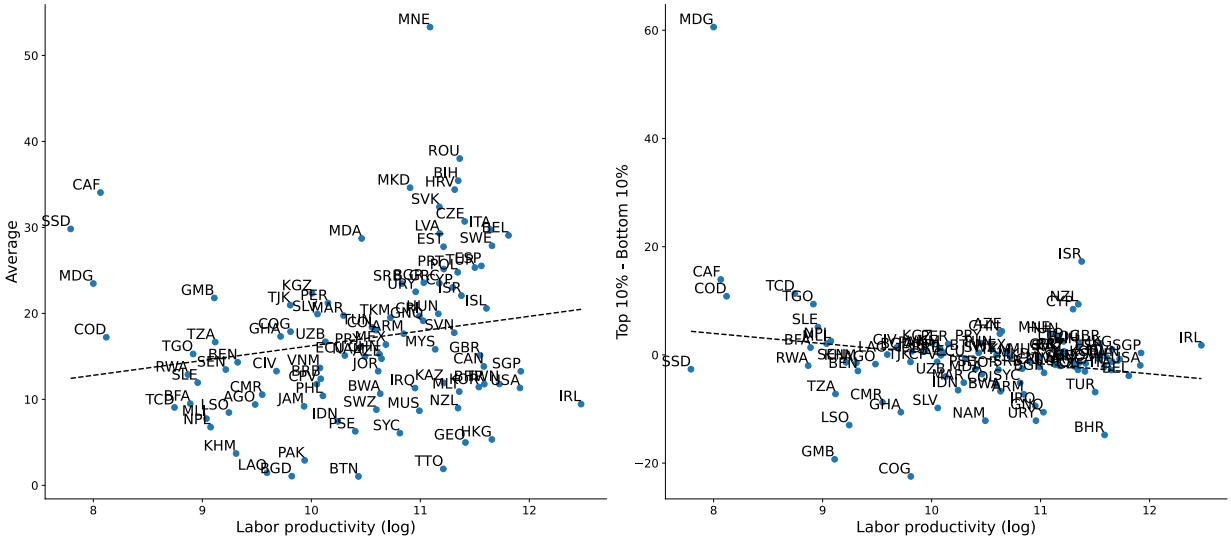
Figures 18 and 19 document indicators related to financial frictions on firms which do not fit the empirical patterns of distortions despite their average being strongly related to aggregate labor productivity across countries. Figure 18 documents the percentage of firms

Figure 16: Infrastructure–Firms Experiencing Internet Disruptions



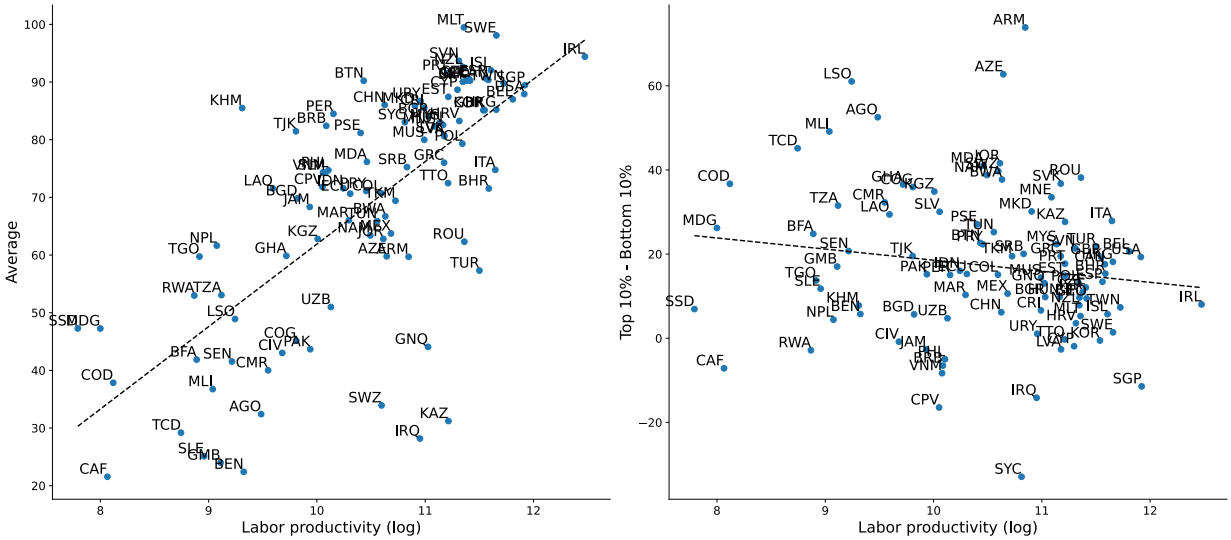
Notes: Average in panel (a) refers to the average percentage of firms experiencing internet disruptions in each country, whereas Top 10%− Bottom 10% in panel (b) refers to the difference in the indicator between the 10% most productive and the 10% least productive firms. Aggregate labor productivity in logs for 2023 from the Penn World Table v11.0 (Feenstra et al., 2015).

Figure 17: Labor Regulation–Share of Labor Taxes of Annual Cost of Labor



Notes: Average in panel (a) refers to the average percentage of social security and employment-based taxes in annual cost of labor in each country, whereas Top 10%− Bottom 10% in panel (b) refers to the difference in the indicator between the 10% most productive and the 10% least productive firms. Aggregate labor productivity in logs for 2023 from the Penn World Table v11.0 (Feenstra et al., 2015).

Figure 18: Finance–Firms that are Credit Unconstrained

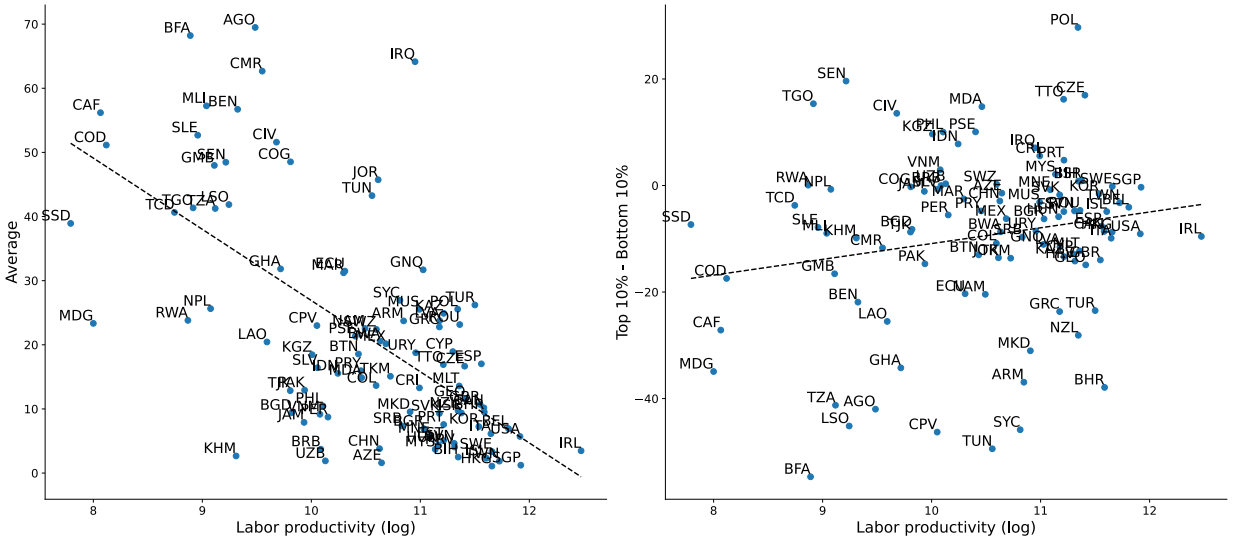


Notes: Average in panel (a) refers to the average percentage of firms reporting that are credit unconstrained in each country, whereas Top 10%− Bottom 10% in panel (b) refers to the difference in the indicator between the 10% most productive and the 10% least productive firms. Aggregate labor productivity in logs for 2023 from the Penn World Table v11.0 (Feenstra et al., 2015).

reporting they are credit unconstrained. In panel (a) this average rises strongly with aggregate labor productivity across countries, around 20-30% of firms are credit unconstrained in developing countries and more than 90% of firms are unconstrained in developed countries. Despite this strong incidence of financial frictions on firms across countries, the evidence in panel (b) is that credit constraints on this indicator are not necessarily more severe for the more productive firms in developing countries. Note that while the cross-country pattern from this indicator is not consistent with the empirical evidence of distortions emphasized earlier, for some countries (the lower left-hand quadrant in panel b) the pattern is consistent in that the top productive firms are relatively more constrained than low productivity firms. This suggests that some indicators may be more relevant in some countries than others and that would require a more country-specific analysis.

Figure 19 documents the percentage of firms identifying access to finance as a major or very severe constraint. Again, panel (a) shows that on average more firms in developing countries report access to finance as an important constraint to their operation, whereas in

Figure 19: Finance–Firms Identifying Access to Finance as Major or Very Severe Constraint



Notes: Average in panel (a) refers to the average percentage of firms identifying access to finance as a major or very severe constraint in each country, whereas Top 10%− Bottom 10% in panel (b) refers to the difference in the indicator between the 10% most productive and the 10% least productive firms. Aggregate labor productivity in logs for 2023 from the Penn World Table v11.0 (Feenstra et al., 2015).

panel (b) it is not necessarily the more productive firms in developing economies that report being more constrained on this indicator.

5 Conclusions

I examined the empirical properties of firm-level productivity and distortions across countries using the newly released World Bank Enterprise Surveys (WBES). Using a standard framework of production heterogeneity, I showed that the gap in productivity and distortions between high and low productivity firms is larger in developing countries, generating large aggregate productivity losses from misallocation.

A key empirical property of distortions in developing countries is that they systematically weaken the relationship between firm size and firm productivity. I exploited a unique feature of the WBES data to document which specific aspects of the economic environment faced by firms, such as financial constraints, regulation, corruption, and weak infrastructure, are consistent with the empirical pattern of distortions across countries. Many indicators of

the economic environment feature an average that reflects worse for developing countries but that are not consistent with the basic property of distortions that create misallocation across countries, an issue that requires further study. In working with the specific indicators, I also learned that most of them do not illuminate the fundamental aspect of the economic environment that may drive differential outcomes, instead are simply the reflection of the economic environment in place, suggesting the possibility of fine tuning indicator questions for future surveys.

I also did not examine the relevance of indicators by sector, for instance it is possible that finance is a more relevant aspect for manufacturing firms where scale tends to be larger. I focused on the relevance of indicators in the cross-country variation, but to the extent that certain features of the environment may be more relevant in some countries than others, an exploration of indicators for individual countries in specific contexts may be useful. The analysis in this paper is suggestive of the importance of indicators, future work should address the quantitative significance of the specific aspects of the economic environment singled out by firms. For example, Ranasinghe and Restuccia (2018) emphasize the role of crime and access to finance as substantial obstacles to business operation in some developing countries using an earlier version of the WBES data. All these are important areas for future research where the WBES data would be an essential tool.

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