Taxing the Good? Distortions, Misallocation, and Productivity in Sub-Saharan Africa

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This paper uses comprehensive and comparable firm-level manufacturing censuses from four Sub-Saharan African (SSA) countries to examine the extent, costs, and nature of within-industry resource misallocation between heterogeneous production units. This paper finds evidence of severe misallocation in which resources are diverted away from high-productivity firms towards low-productivity ones, although the magnitude differs across countries. Estimated aggregate productivity gains from the hypothetical equalization of marginal returns range from 30 percent in Côte d'Ivoire to 160 percent in Kenya. The magnitude of reallocation gains appears considerably lower when performing the same counterfactual exercise based on the World Bank Enterprise Surveys once the value-added shares of industries are adjusted using the census data. This suggests that linking firm-level survey data to aggregate outcomes requires census-type data or sampling methods that take the true structure of production into account.

JEL classification: C83, L11, O11, O47, O55

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1. Introduction

One of the most enduring challenges in the field of economic growth and development is to understand the sources of the large variations in economic well-being across countries. While the literature acknowledges the role of cross-country differences in physical and human capital stocks, the current consensus is that total factor productivity (TFP) constitutes the predominant source of development gaps. This paper explores one of the most promising avenues for explaining TFP gaps – the inefficient allocation of resources across firms – in one of the poorest, yet least explored, regions in the world – Sub-Saharan Africa (SSA). Combining novel census-based firm-level manufacturing databases with a structural theory of misallocation, the paper provides a characterization of the degree and nature of resource misallocation in Côte d'Ivoire, Ethiopia, Ghana, and Kenya, as well as a quantification of the productivity losses associated with these inefficiencies.

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Following the work of [Hsieh and Klenow \(2009\)](#), we measure allocative distortions in the data as deviations from the output-maximizing prescription of equalizing marginal returns across comparable production units. We summarize the information about the degree of misallocation by reporting statistics about the joint distribution of productivity and distortions that we back out from the data. In particular, we report measures of dispersion (interpreted as the deviation from the efficient allocation), and we investigate the correlation between these deviations and idiosyncratic characteristics of the firms, such as physical productivity and age. Then, we quantify the gain in aggregate manufacturing TFP that would result from a reversal of distortions and a reallocation of resources in accordance with the output-maximizing rule.

We find evidence of large misallocation of resources in the four sample countries that we study, with Kenya exhibiting the largest dispersion in idiosyncratic distortions, followed by Ghana, Ethiopia, and Côte d'Ivoire. As points of reference, the degree of misallocation measured by the dispersion in total revenue productivity (TFPR) is larger than in India and China, and in terms of allocative efficiency is similar to that in the most distorted countries in Latin America, such as Venezuela and Colombia.¹ Besides significant dispersion, we find a tight correlation between the distribution of distortions, TFPR, and the distribution of physical productivity across firms, TFPQ. The OLS estimate for the TFPQ elasticity of TFPR ranges from .42 to .53. This statistic is an important determinant of the extent to which the estimated distribution of distortions creates a decline in aggregate productivity in the economy. As shown in [Restuccia and Rogerson \(2008\)](#), when resources are diverted away from high-productivity firms to relatively unproductive ones, distortions carry a larger drag on TFP. Our estimate shows that such perverse misallocation, the one “taxing the good,” is evidenced in the four economies that we study.

Taken together, our findings indicate that the dispersion and productivity-dependence of the distribution of distortions create a substantial decline in manufacturing productivity in the four countries. Had resources been allocated according to the output-maximizing rule, productivity would have been 31 percent higher in Côte d'Ivoire, 67 percent higher in Ethiopia, 76 percent higher in Ghana, and 162 percent higher in Kenya.

Even though the method utilized to measure misallocation is fairly straightforward, it is important to be aware of biases resulting from limitations in the underlying datasets. To emphasize this point, we compare our results based on manufacturing censuses with those obtained from an alternative and readily available source, the World Bank's Enterprise Surveys (ES). We document that the ES overestimates the size of the highest percentiles in the firm size distribution. We then assess how such bias is translated into the resulting misallocation measurements and the counterfactual productivity gains from its reversal. When weighting sectors according to their value-added shares in the Census, we find that the degree and productivity losses implied by misallocation in the ES are significantly smaller. This finding suggests that previous research in Africa that was solely based on survey data ([Kalemli-Ozcan and Sorensen 2012](#)) may have provided inaccurate estimates of the extent of misallocation in the region.

In an attempt to understand the particular source of misallocation, we decompose the overall distortion into its components: one that distorts the establishment's input mix, and another that directly distorts the establishment's size or scale (revenue wedge).² This decomposition is useful to identify the type of policies that are the most distorting.

- 1 The magnitudes of TFPR dispersion in India were established by our own calculations based on the Prowess database. These values, in turn, are very close to those reported by [Hsieh and Klenow \(2009\)](#) from which we take the dispersion in TFPR in China. For Latin America, our reference is [Busso and Madrigal \(2013\)](#).
- 2 To clarify the distinction between factor-intensity distortions and revenue wedges, the former refers to distortions that affect the producer's input mix, while the latter refers to distortions that affect the entire scale of operation of the firm without disrupting the firm's input mix.

We also examine how misallocation relates to the age profile of establishments. We find that the growth of employment over an establishment's life cycle, conditional on survival, is remarkably flat, although the pattern differs across countries.³ This is consistent with the patterns documented in other developing countries such as India and Mexico (Hsieh and Klenow 2014). We also find that the flat pattern of life-cycle growth is mostly accounted for by the life-cycle evolution of physical productivity, with a minor role played by an age-dependent component in the distribution of distortions. This pattern differs somewhat from earlier work that documented that TFPR rises with firm age in developing countries (Hsieh and Klenow 2014).

The remainder of the paper proceeds as follows. Section 2 reviews related literature. Section 3 provides a brief outline of the methodology. Section 4 describes the databases used in the analysis. The main results are presented in section 5. Section 6 compares our results with the survey data. In section 7, we examine how measured misallocation varies across locations and industries. Section 8 assesses the sensitivity of the results, and section 9 concludes.

2. Related Literature

This study is related to recent literature focusing on the importance of firm-level resource misallocation in explaining cross-country productivity differences. Drawing on the seminal work of Restuccia and Rogerson (2008), a growing number of studies have attempted to quantify the extent and costs of resource misallocations generated by idiosyncratic distortions. Hsieh and Klenow (2009) provides the first empirical approach to measure misallocation across firms within four-digit industries in China and India. They find that the misallocation of resources across firms – measured by the dispersion in marginal products of inputs – explains a large part of the difference in aggregate productivity between the United States, China, and India. They find that moving to the U.S. efficiency level would increase manufacturing TFP by 40 percent to 60 percent in India and 30 percent to 50 percent in China. Subsequent research following the methodology of Hsieh and Klenow (2009) confirms the quantitative importance of misallocations for several countries. Examples include Camacho and Conover (2010) for Colombia, Oberfield (2013) for Chile, and Busso and Madrigal (2013) for Latin American countries.

There is a relatively smaller body of work that focuses on Sub-Saharan Africa. Perhaps the most salient contributions in this area are Kalemli-Ozcan and Sorensen (2012) and Aterido, Hallward-Driemeier, and Pagés (2011). The former explores capital misallocation in 10 African countries using the World Bank Enterprise Surveys and studies the extent to which access to finance can explain the dispersion in marginal returns to capital across countries. The latter explores the role of distortions in the business environment in explaining the differential employment growth across firms of different sizes. These studies, however, used sample-based survey data, instead of the manufacturing censuses we use in our paper.

The paper also relates to more recent studies emphasizing the dynamic implications of distortions that affect the firms' life cycle and the distribution of establishment-level productivity (Hsieh and Klenow 2014; Bento and Restuccia 2017; Da-Rocha, Tavares, and Restuccia 2017). In a more recent work, Hsieh and Klenow (2014) focus on differences in the life cycle of firms as an important mechanism by which frictions reduce aggregate productivity by distorting the incentive for firms to grow. They show that firm dynamics differ systematically across countries, with firms in developed countries growing much faster than those in poor countries over their life cycle. They conclude that if U.S. firms exhibited the same dynamics as Indian or Mexican firms, aggregate manufacturing TFP would be roughly 25 percent lower. Bento and Restuccia (2017), building a model that allows for productivity investment (both at the time of entry and along the life cycle), have documented a significant productivity loss in developing countries due to distortions that disproportionately constrain the more productive producers. Adamopoulos et al. (2017)

3 In Côte d'Ivoire, older firms are larger and more productive than their younger counterparts.

find that the selection of workers across sectors can substantially amplify the static misallocation effects of distortionary policies. An important insight from these papers is that the extent to which distortions are correlated with productivity is key to understanding their dynamics implications. Restuccia and Rogerson (2017) provide an excellent summary of this literature.

Since our work focuses on low-income countries in Africa, which are predominantly agricultural, the paper relates to recent literature that has emphasized the importance of misallocation across farms as a potential source of low productivity in African agriculture. For example, Restuccia and Santaaulalia-Llopis (2017), using household-level data for Malawi, document severe resource misallocation in the agricultural sector due to land market restrictions. Chen, Restuccia, and Santaaulia-Llopis (2017) provide evidence of substantial misallocation of resources in Ethiopian agriculture due to imperfect land markets. Chen (2017) also provides cross-country evidence on similar issues. These papers have shown that distortions in farm size may account for a significant fraction of cross-country differences in agricultural productivity.

Because our study emphasizes the importance of representative data, our work is also related to recent papers that utilize representative firm-level data to study the effects of different policy changes. For example, recent works by McCaig and Pavcnik (2014, 2015, 2016) have emphasized the importance of nationally representative data in studying the effects of export opportunities on labor reallocation, workforce transition between formal and informal sectors, and understanding firm dynamics. Vollrath (2014) also highlights the measurement issues arising from the use of unrepresentative data in quantifying labor misallocation across different sectors.

Our paper makes two contributions to the literature. First, it adds to the growing body of work that quantifies the extent of resource misallocation. We expand the literature by exploring a region of the world where the data requirements for the application of the methodology have left the region relatively unexplored. A second contribution of our work stems from the illustration of the importance of adequate coverage of firms in the data, in terms of representativeness of the sectoral coverage of firms in the economy. We show that ES-based distortion measures underestimate the degree of resource misallocation and the productivity gains associated with reallocation once the value-added shares of industries are adjusted using the census weights.

3. Theoretical Framework

To quantify the effect of misallocation on aggregate TFP, we use the accounting framework outlined in Hsieh and Klenow (2009, HK hereafter). This section provides a brief outline of this framework.

We consider an industry s populated by a large number M_s of monopolistically competitive firms. Each sector's output Y_s is obtained by aggregating the output of individual establishments using a CES technology: $Y_s = \left[\sum_{i=1}^{M_s} Y_{si}^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}$, where Y_{si} is a differentiated product by establishment i in sector s , and σ is the elasticity of substitution across producers within industry.

Each establishment produces a differentiated product according to the standard Cobb-Douglas production function: $Y_{si} = A_{si} L_{si}^{1-\alpha_s} K_{si}^{\alpha_s}$, where A_{si} stands for establishment-specific productivity, K_{si} is the establishment's capital stock, L_{si} is labor input, and α_s is the industry-specific capital share.

Each establishment maximizes current profits:

$$\pi_{si} = (1 - \tau_{Y_{si}}) P_{si} Y_{si} - w L_{si} - (1 + \tau_{K_{si}}) R K_{si} \quad (1)$$

where P_{si} is the establishment-specific output price and $P_{si} Y_{si}$ is the value added of firm i , w and R are the common wage rate and the rental cost of capital, respectively. $\tau_{K_{si}}$ denotes the establishment-specific "capital" distortion (which increases the cost of capital *relative* to labor). A large (small) value of $\tau_{K_{si}}$ increases the cost of capital (labor) relative to labor (capital). A wide range of factors could potentially cause such distortion, such as credit market imperfections and labor market regulations that differ across

firms. The “output” distortion is denoted by τ_{Ysi} . Such distortions could arise because of government policies such as tax regulations that favor particular firms or because of corruption. These distortions could also reflect monopoly power or adjustment costs.

The first-order conditions imply that $MRPK_{si} = \frac{R(1+\tau_{Ksi})}{1-\tau_{Ysi}}$ and $MRPL_{si} = \frac{w}{1-\tau_{Ysi}}$. It is straightforward to show that TFPR relate to the wedges:

$$TFPR_{si} = \alpha \frac{(1 + \tau_{Ksi})^{\alpha_s}}{1 - \tau_{Ysi}} \quad (2)$$

In the absence of distortions, $TFPR_{si}$ should be equalized across establishments within in each industry.

Measured TFP at industry level can be calculated as:

$$TFP_s = \left(\sum_{i=1}^{M_s} \left[A_{si} \frac{\overline{TFPR}_s}{TFPR_{si}} \right]^{\sigma-1} \right)^{\frac{1}{\sigma-1}} \quad (3)$$

where $\overline{TFPR}_s$ is a geometric mean of the average marginal revenue product of capital and labor. The industry TFP would be $\bar{A}_s = \left(\sum_{i=1}^{M_s} A_{si}^{\sigma-1} \right)^{\frac{1}{\sigma-1}}$, if marginal products were equalized across establishments within an industry. We measure TFP loss due to misallocation in sector s by comparing actual TFP in 3 to the efficient TFP.

To calculate distortions, we set the elasticity of substitution – σ – to 3, which is a conservative estimate. We set rental price of capital $R = 10$ percent – assuming a real interest rate of 5 percent and a depreciation rate of 5 percent. For the industry-level factor share, α_s , we use the NBER Productivity Database. We assume factor intensities are the same as those of the corresponding U.S. industries, which are assumed to be undistorted.⁴ After obtaining the capital share at the four-digit level, we combine it with our firm-level manufacturing census data.⁵

Once these parameters are fixed, the wedges can be computed as follows:

$$1 + \tau_{ksi} = \frac{\alpha_s}{1 - \alpha_s} \frac{w L_{si}}{R K_{si}} \quad (4)$$

$$\frac{1}{1 - \tau_{ysi}} = \frac{\sigma - 1}{\sigma} \frac{(1 - \alpha_s) P_{si} Y_{si}}{w L_{si}} \quad (5)$$

Equation (4) captures the distortions in input choice relative to the optimal combination of factor inputs. More specifically, it states that a firm faces a high capital distortion (larger τ_k) when the ratio of labor to capital compensation is high compared to the efficient allocation of input. It is worth emphasizing that τ_k measures capital market distortion relative to labor market distortion. Thus, high capital distortion (larger τ_k) should be interpreted as a low labor distortion, and vice versa. Equation (5) states that a firm faces a high “output” distortion (higher τ_y) when the labor compensation of the firm is low compared to what one would expect in a frictionless environment.

4 HK point out that the labor share in the NBER dataset underestimates the labor compensation because it doesn’t include fringe benefits and employer social security contributions. Following Hsieh and Klenow (2009), we inflate the labor cost in the U.S. data by a factor of 3/2. However, our main results that rank the extent of misallocation across countries remain robust to not making this adjustment.

5 Note that industries in Ethiopia, Ghana, and Kenya are classified according to ISIC Rev 3.1, ISIC Rev 3, and ISIC Rev 4, respectively. Industries in Côte d’Ivoire are classified according to NAEMA (equivalent to ISIC Rev 3), whereas the industrial data for the United States are reported based on 1987 SIC and 1997 NAICS classifications. We use appropriate concordance tables to match the datasets. We keep firms that correspond with the U.S. data at four-digit levels.

4. Data

Our analysis exploits firm-level manufacturing census data from four SSA countries: Côte d'Ivoire (2003–2012), Ethiopia (2011), Ghana (2003), and Kenya (2010). The censuses are nationally representative, and both small and large firms in the formal sector are adequately included. Moreover, these countries reasonably represent the diversity of the region in terms of the overall level of development, especially of the manufacturing sector. Ethiopia is the poorest country in the group. In 2015, its income per capita was only 1 percent that of the United States while the corresponding number for Côte d'Ivoire is 2.8, Ghana is 3.3, and Kenya is 2.2. In addition, while Côte d'Ivoire and Kenya have a relatively developed manufacturing sector for the region, manufacturing contributes little to the overall economy in Ethiopia and Ghana.

In what follows, we briefly describe each country's datasets and relegate the details to supplementary online appendix S1. We then present some statistics on the size distribution of firms.

Data Sources

Côte d'Ivoire

For Côte d'Ivoire, we use confidential firm-level census data, the “Registrar of Companies for the Modern Enterprise Sector,” collected by the National Statistics Institute (INS) for the period 2003–2012. The dataset covers all registered firms in the country and contains detailed balance sheet information on firms' revenue, employment, wage bill, book value of fixed assets, intermediate inputs, and other firm characteristics. All registered firms are required to report their financial statements to the INS, the tax administration (DGI), which are reported under the West Africa accounting system standards, *Système Comptable Ouest Africain* (SYSCOA).

Ethiopia

The datasets we use for Ethiopia are the Large and Medium Scale Manufacturing Industries Survey (LMSMI) and the Small Scale Manufacturing Industries Survey (SSMI), both conducted by the Ethiopian Central Statistical Agency (CSA). The LMSMI covers all formal manufacturing firms in the country that use *power-driven* machines in production process and employ *at least 10* persons. The CSA has conducted this census on an annual basis since 1976.⁶ In 2011, the raw dataset contained 1,936 establishments.

The SSMI survey covers establishments that use *power-driven* machinery and engage *fewer than 10 workers*. The CSA conducted five waves of SSMI surveys: 1994–1995, 2001–2002, 2005–2006, 2007–2008, and 2010–2011 – each wave collected on a *sample* basis. The CSA sampling frame consists of all registered establishments employing fewer than 10 workers and using power-driven machines. The SSMI survey was conducted using a stratified sampling procedure to ensure representativeness of all establishments in the country. The CSA also provides a sampling weight for each firm. By merging the two datasets, we obtain complete distribution of establishment sizes for the formal manufacturing sector in the country. After merging, the share of small firms (included in the SSMI survey), in terms of number of establishments, accounts for 96 percent of all manufacturing firms.⁷

Ghana

The data for Ghana are based on the 2003 National Industrial Census (NIC) dataset, conducted by the Ghana Statistical Service (GSS). The census is similar in structure to the Ethiopian data; it covers the universe of establishments employing more than 10 workers and takes a representative sample of firms

6 Note that although the LMSMI targets establishments with more than 10 employees, they remain in the census even if the number of workers decreases.

7 In both LMSMI and SSMI, industries are classified according to the four-digit ISIC Rev 3.1 classification. The manufacture of food products and beverages is the largest subsector, measured by the number of firms.

employing fewer than 10 workers. The census provides detailed information on sales, wage bills, material costs, and book value of fixed assets. The raw data consists of a total of 3,302 manufacturing establishments. Applying the weights constructed by the GSS, sampled establishments represent a population of 22,544 firms in the country.⁸

Firms are categorized in the industry according to the four-digit ISIC Rev 3 classification. There are about 107 subsectors based on the four-digit classification and 23 based on two-digit classification. Manufacture of textiles and wearing apparel is the largest subsector, measured by the number of establishments, accounting for 32.4 percent of the total number of establishments.

Kenya

The Kenyan data come from the 2010 Census of Industrial Production (CIP), conducted by the Kenyan National Bureau of Statistics (KNBS). The dataset provides detailed information needed for our analysis, including total sales, value of production, labor cost, capital, and material and energy costs. The raw data contain information on about 2,089 manufacturing firms. However, a large number of firms report either missing or zero values of capital stock and labor cost, and thus are omitted from our analysis.

Firms are categorized in the industry according to the four-digit ISIC Rev 4 classification. There are about 118 sectors based on the four-digit classification and 31 based on the two-digit classification. Manufacture of food products is the largest sector, measured by the number of firms, accounting for 36.55 percent of the total industry.

The Size Distribution of Firms

Besides affecting the sectoral allocation of production and the aggregate gaps in productivity, frictions that misallocate resources will manifest also in the firm-size distribution. Thus, it is useless to compare the measurement of misallocation that we perform below with some information about the firm-size distribution in our sample countries. Table 1 presents some descriptive statistics. A few features of the table are worth highlighting. The table illustrates that Kenyan firms, on average, are much larger (in

Table 1. Size Distribution of Firms

Size (number of workers)	Côte d'Ivoire Census (2012)	Ethiopia Census (2011)		Ghana Census (2003)		Kenya Census (2010)
	N	N	N (wt)	N	N (wt)	N
<5	469	1,618	17,779	464	13,027	171
5–9	210	1,657	22,813	423	7,044	255
10–19	184	1,540	10,621	1,683	1,706	325
20–49	161	495	810	486	499	410
50–99	81	214	219	110	122	295
>99	123	302	302	138	146	602
Total	1,228	5,826	52,544	3,302	22,544	2,058
Mean	67	30	9	29	8	145
Median	9	8	6	12	4	34
S.D.	390	154	52	118	48	404

Source: Authors' analysis based on firm-level census data from Côte d'Ivoire, Ethiopia, Ghana, and Kenya.

Note: "wt" denotes sample-weighted statistics. For the manufacturing censuses in Ethiopia and Ghana, we use the sampling weights constructed by the respective national statistical offices.

8 The census relies on the business registry, which covers the entire population of firms. The business registry contains a more limited set of variables including information on persons engaged, location, age, and industrial group. For more details about the sampling design and detailed description of the data, see [Kraak, Rankin, and Teal \(2014\)](#).

terms of the number of workers) than firms in the other countries. While the average number of workers is approximately 145 in Kenya and 67 in Côte d’Ivoire, it is only 30 in Ethiopia and 29 in Ghana. The distribution of firm size in all countries is skewed to the left with the median firm in Kenya employing 34 workers while the corresponding figures in Côte d’Ivoire, Ethiopia, and Ghana are only 9, 8, and 12 workers, respectively.

It is important to highlight that re-weighting observations for small firms according to the weights provided by the national statistical offices of Ethiopia and Ghana reduces the average firm size even further, to nine and eight workers respectively.

5. Results and Discussion

Measuring Productivity and Distortions

Figure 1 plots the distribution of $\log(TFPR)$ and $\log(TFPQ)$ demeaned by industry-specific averages. More specifically, it plots $\log(TFPR_{si}/TFPR_s)$ and $\log(TFPQ_{si}/TFPQ_s)$, weighted by the value-added share of industries. The figure shows that the distribution of TFPQ has a thicker left tail and the TFPR distribution has a fat right tail. Table 2 reports various measures of dispersion of TFPQ and TFPR.

Figure 1. Distribution of TFPR and TFPQ

Source: Authors’ analysis based on firm-level census data from Côte d’Ivoire, Ethiopia, Ghana, and Kenya.
Note: Distribution of $\log TFPR$ and $\log TFPQ$ scaled by industry-specific averages. TFPR and TFPQ are calculated for each establishment (i) in industry (s) and then scaled by industry-specific averages before taking their logs, i.e., $\log(TFPR_{si}/TFPR_s)$ and $\log(TFPQ_{si}/TFPQ_s)$.

Table 2. Dispersion of TFPR and TFPQ

	Côte d’Ivoire		Kenya		Ghana		Ethiopia	
	TFPR 2003–12	TFPQ 2003–12	TFPR 2010	TFPQ 2010	TFPR 2003	TFPQ 2003	TFPR 2011	TFPQ 2011
S.D.	0.65	1.24	1.52	2.41	0.95	1.75	0.78	1.30
75–25	0.88	1.74	1.99	3.34	1.43	2.61	1.26	1.94
90–10	1.99	3.25	3.94	5.67	2.89	4.47	2.56	3.67
Cov (TFPQ, TFPR)	0.70		0.85		0.69		0.74	
Reg. Coeff.	0.42		0.52		0.44		0.53	
N	4146	757	757	1151	1151	4012	4012	

Source: Authors’ analysis based on firm-level census data from Côte d’Ivoire, Ethiopia, Ghana, and Kenya.
Note: Dispersion of $\log TFPR$ and $\log TFPQ$ scaled by industry-specific average. TFPR and TFPQ are calculated for each establishment (i) in industry (s) and then scaled by industry-specific averages before taking their logs, i.e., $\log(TFPR_{si}/TFPR_s)$ and $\log(TFPQ_{si}/TFPQ_s)$. Industries are weighted by their value-added shares. The statistics for Côte d’Ivoire are calculated by taking the average for the years 2003–2012. TFPR and TFPQ are revenue and physical productivity, respectively. 75–25 is the ratio of the 75th to 25th percentiles and 90–10 is the ratio of the 90th to the 10th percentiles. Reg. Coeff is the coefficient of a regression of $\log TFPR$ on $\log TFPQ$ scaled by industry-specific average.

There are several points worth noting. First, the findings suggest that there is a substantial dispersion in firm-level productivity in all the sample countries. A comparison of our results with Hsieh and Klenow (2009) reveals that productivity is more dispersed in our sample countries than in the United States, China and India. While all countries exhibit some degree of productivity disparity, the magnitude of this dispersion is particularly striking in Kenya, where many less-productive firms coexist with a few very productive firms. This pattern is consistent across different measures: the standard deviation (S.D.), the ratio of the 75th to the 25th percentile (75–25), and the ratio of the 90th to the 10th percentiles (90–10). To get a sense of the economic magnitude of these numbers, taking the 90th to the 10th spread of TFPQ shows that the productivity gap across establishments is quite high. In Kenya, firms in the 90th percentile of productivity are 290 percent more productive than firms in the 10th percentile, while this gap is 87 percent in Ghana, 39 percent in Ethiopia, and 26 percent in Côte d’Ivoire.

The key question then is why the most productive firms have not expanded their production to replace the less productive ones? A multitude of factors may explain this phenomenon. One way to assess the extent of resource misallocation is to look at the variation in marginal products of inputs across producers. In a frictionless environment, the marginal products of factors should be equalized across firms, and thus the dispersion of marginal products should be zero. Therefore a dispersion in TFPR can be interpreted as indicative of resource misallocation (Hsieh and Klenow 2009). Following Hsieh and Klenow (2009), we estimate the dispersion of TFPR, which is the geometric average of the marginal products of capital and labor. The findings suggest that the TFPR dispersion across firms in our sample countries is much higher than in India, China, and the United States. For example, the ratios of 90th to 10th percentiles of TFPR are 51 in Kenya, 17 in Ghana, 13 in Ethiopia, and 7 in Côte d’Ivoire, which are much larger than the corresponding values in India (5.0), China (4.9) and the United States (3.3). The results offer a *prima facie* evidence that resources are severely misallocated in our sample countries. A plausible explanation for our findings is that policies and institutions in our sample countries may prevent the more productive firms from eliminating the less productive ones.

Calculating Counterfactual Productivity

Next, we use our estimates to perform counterfactual liberalization experiments. Specifically, we assess the potential productivity gains associated with equalizing total factor revenue productivity (TFPR) across the existing set of establishments in each four-digit industry. The results of this liberalization experiment are reported in table 3. The first column of table 3 indicates that the potential TFP gains from better allocation of resources is much higher in the Kenyan manufacturing sector compared to the corresponding values in the other countries. More specifically, fully equalizing total factor revenue productivity (TFPR) across firms in each industry could increase manufacturing productivity by 31.4 percent in Côte d’Ivoire, 66.6 percent in Ethiopia, 75.7 percent in Ghana, and 162.6 percent in Kenya.

A more conservative measure of the gains from reversing the misallocation in Sub-Saharan Africa is to subtract the gains that accrue to the United States from the reversal of its own profile of idiosyncratic

Table 3. Potential TFP Gains from Equalizing TFPR

	TFP Gains (percent)	Relative to U.S. (percent)
Cote d’Ivoire	31.4	–8.3
Ethiopia	66.6	16.4
Ghana	75.7	22.7
Kenya	162.6	83.4

Source: Authors’ calculations based on firm-level census data from Côte d’Ivoire, Ethiopia, Ghana, and Kenya.
Note: The relative TFPR gains are calculated by taking the ratio of TFP_{eff}/TFP to the U.S. ratio in 1997, subtracting 1, and multiplying by 100 to obtain the numbers in the second column. TFPR and TFPQ are revenue and physical productivity, respectively.

distortions. While the underlying assumption when calibrating sectoral factor shares to U.S. levels is that this is an undistorted economy, this is not exactly correct. As shown by [Hsieh and Klenow \(2009\)](#), the United States is also subject to misallocation, albeit of a much weaker degree. Hence, many papers in the literature have adopted the conservative approach of netting the U.S. gains from a given country's TFP improvement.

Expressed in this way, the gains from the hypothetical liberalization are still economically meaningful, but become substantially more modest. For Ethiopia, Ghana, and Kenya, the gains become 16.7, 22.7, and 83.4 percent respectively, while the case of Cote d'Ivoire becomes more puzzling, as we find that this country gains less from an efficient reallocation than the United States does.

Our results open up a fundamental question about the mapping between the degree of dispersion in an economy, as measured by the standard deviation of TFPR, and the magnitude of the gains following a reversal of this dispersion. For the countries that we consider here, TFPR is substantially more dispersed than it was in the United States in 1997, yet the relative gains from liberalization are not proportionally larger. For instance, TFPR dispersion is 0.95 in Ghana, and 0.78 in Ethiopia, more than twice as high as the 0.45 standard deviation reported in [Hsieh and Klenow \(2009\)](#) for the United States. However, the gains are less than twice as high. Côte d'Ivoire is perhaps the best example of the complexity of the elasticity between TFPR dispersion and counterfactual gains. There, the standard deviation of TFPR was equal to 0.65, yet the gains were lower than in the United States, despite the latter exhibiting a lower dispersion of distortions than the former.⁹

As a form of reassurance for our results, we find that this non-monotone elasticity of counterfactual gains to the degree of dispersion in the underlying distortions is a property of many applications of the Hsieh and Klenow methodology in other countries in the world. For instance, the exploration of misallocation in Latin America carried out in [Busso and Madrigal \(2013\)](#) shows the same phenomena. For all of the Latin American countries in their sample, TFPR dispersion is significantly more pronounced relative to the United States, yet the gains before netting the U.S. gains would be on average even lower than what we find in our study for Sub-Saharan Africa.¹⁰

We conclude the section with two comments about the interpretation of our results. First, even though the gains that we find are not negligible, they are still small relative to the development gaps that we are trying to understand. Against this background, it is fair to say that our findings are reasonable lower bounds to the overall costs associated with the misallocation in a nation. We are leaving out many plausible channels that interact with the existence of idiosyncratic distortions in the economy and that would magnify the gain from their reversion. For instance, we are not considering propagation via intersectoral linkages; we are abstracting from misallocation *across* four-digit industries, and we are only accounting for static re-allocative gains, not giving room for any endogenous response of the TFPQ distribution itself to the elimination of distortions. Secondly, our results reveal a gap in our understanding of how the properties of a given distribution of TFPR map into the counterfactual gain in TFP. We can only get this far given the scope of this paper, but leave all these questions as objects of study in future research.

Correlated Distortions

The empirical facts in the previous section establish that the within-industry dispersion of revenue productivity of firms is quite large. As emphasized in [Restuccia and Rogerson \(2008\)](#), distortions would be particularly costly if they are positively correlated with firm's physical productivity. Put differently, distortions would severely reduce aggregate productivity if they penalize more efficient relative to less productive ones.

9 The implied TFP gain comes not only from dispersion in TFPR but also from the correlation between TFPR and physical productivity. However, given strong correlation between TFPR and physical productivity in all our sample countries, this is unlikely to explain the smaller implied gains from removing TFP.

10 See [Busso and Madrigal \(2013\)](#) tables 3 and A1.

Figure 2 nonparametrically plots the $\log(TFPR)$ against $\log(TFPQ)$, both measured relative to the log of industry averages. The figure clearly shows that TFPR is strongly increasing in TFPQ in all four countries, providing some evidence that more productive firms are facing a larger distortions.¹¹ The positive relationship between TFPR and TFPQ is quite consistent with most findings in the literature, especially in developing countries.

Figure 2. Log TFPR vs. Log TFPQ

Source: Authors' analysis based on firm-level census data from Côte d'Ivoire, Ethiopia, Ghana, and Kenya.
Note: TFPR and TFPQ are revenue and physical productivity, respectively. Log TFPR and log TFPQ scaled by industry-specific average. TFPR and TFPQ are calculated for each establishment (*i*) in industry (*s*) and then scaled by industry-specific averages before taking their logs, i.e., $\log(TFPR_{si}/\overline{TFPR}_s)$ and $\log(TFPQ_{si}/\overline{TFPQ}_s)$.

To further highlight the strength of this relationship, we run an OLS regression of a firm's log TFPR on log TFPQ for each sample country. These elasticities turn out to be 0.52 for Kenya, 0.44 for Ghana, 0.53 for Ethiopia, and 0.42 in Côte d'Ivoire. To put these numbers in broader perspective, it is informative to compare and contrast the findings with similar studies for other countries. The elasticity of TFPR with respect to TFPQ in the U.S. manufacturing sector is 0.09 (Hsieh and Klenow 2014). TFPR rises more steeply in our sample countries than in the United States. The fact that these elasticities are significantly larger in our countries suggests that more-productive firms are not able to use resources, and ultimately worsen aggregate productivity (Restuccia and Rogerson 2008). Additionally, the fact that more-productive firms face higher distortions could slow down the growth of firms over their life cycle by discouraging firms from investing in productivity-enhancing technologies (Hsieh and Klenow 2014; Bento and Restuccia 2017). In the next section, we will examine whether these higher elasticities can play a role in affecting life-cycle productivity dynamics of firms in our sample countries.

11 Note that in a frictionless world, establishments with lower TFPR (receiving implicit subsidy) would reduce their production while establishments with a higher TFPR (establishments facing higher implicit tax) would expand, resulting in all establishments to fall along the zero $\log(TFPR/\overline{TFPR})$ line – the undistorted equilibrium line. Along this line establishments differ only on their physical productivity (TFPQ), as in Melitz (2003).

In order to further understand the sources of distortions, it is instructive to decompose the overall distortion into its components: “output” ($\frac{1}{1-\tau_{ysi}}$) and “capital” distortions ($1 + \tau_{ksi}$). Figure 3 plots these distortions versus percentiles of TFPQ. The figures provide a number of interesting insights. To start with, the figure shows that output distortions are monotonically increasing in percentiles of establishment productivity (measured by TFPQ) in all four countries. This suggests that, compared to a frictionless equilibrium, productive establishments face larger output distortions, causing them to produce lower than their optimal output, while the less-productive ones receive an implicit output subsidy and produce beyond their optimal level, resulting in an inefficient allocation of resources and thus lower aggregate TFP. Second, the capital distortion increases in percentile of TFPQ for low-productive firms but flatten out for relatively more-productive firms, albeit with some differences across the sample countries. This suggests that less-productive firms use more capital relative to labor (or less labor relative to capital) than they otherwise would, while more-productive firms tend to use slightly lower capital relative to labor (or higher capital relative to labor). Finally, output frictions appear to explain a large part of the misallocation of resources across firms of different productivity levels in all the four countries.

Figure 3. Distortions vs. Productivity

Source: Authors’ analysis based on firm-level census data from Côte d’Ivoire, Ethiopia, Ghana, and Kenya.
Note: TFPQ is physical productivity of firms. TFPQ is calculated for each establishment (i) in industry (s) and then scaled by industry-specific averages before taking their logs, i.e., $\log(TFPQ_{si}/TFPQ_s)$. Output distortion is measured as: $\log\left(\frac{1}{1-\tau_{ysi}}\right)$ and capital distortion is measured as: $\log(1 + \tau_{ksi})$. Higher value show more distortions.

Productivity and Distortions over the Life Cycle

Our analysis so far has focused on measuring the static effect of resource misallocation, but distortions are also likely to have important dynamic implications through the effect that greater misallocation has on firms’ incentives to invest in technological upgrading. As already mentioned, the fact that more-productive firms are “taxed” more could discourage firms from investing in productivity-enhancing technologies,

and as a result generate slower life-cycle productivity growth, which in turn leads to slower employment growth.

Hsieh and Klenow (2014) document a notable difference in the post-entry dynamics of firm performance between developing and advanced economies. Using comprehensive manufacturing census data, they find that while firms in the United States grow by a factor of 8 by the age of 40, Mexican firms grow by a factor of 2, and such growth is much slower in India. The authors attempt to rationalize the flatter growth of productivity over firms' life cycle in developing countries through an age-dependent component in the distribution of distortions across firms. Indeed, they find that firms get progressively more taxed as they age, and show quantitatively through a model of innovation that this age-dependent component of distortions undermines productivity growth. Furthermore, they show that the dynamic response in the underlying distribution of physical productivity magnifies the losses from misallocation that result from a static analysis.

This section attempts to investigate the evolution of employment, physical productivity, and distortions over the firms' life cycle, as calculated from the distribution of each of these objects in the cross-section of firms across ages. Does such an age-size relationship hold for African countries under consideration? To what extent do distortions explain the age-size and age-productivity patterns in our sample countries?

Before turning to address these questions, it would be informative to understand what the distribution of firms by age looks like in our sample countries. Figure 4 plots the age distribution of firms by country.

Figure 4. Number of Establishments by Birth Cohort

Source: Authors' analysis based on firm-level census data from Côte d'Ivoire, Ethiopia, Ghana, and Kenya.

Note: The X axis shows the age cohort of firms.

The age distribution of firms in Kenya is strikingly different from the other two countries. The figure clearly shows that Kenyan firms are, on average, older than firms in the other sample countries. One potential reason for such difference could be because industrialization in the other countries started after it did in Kenya. Another plausible explanation for this contrast may be due to differences in the macroeconomic environment experienced by firms in these countries. For example, while Ethiopia and Ghana lost a significant level of manufacturing production in the 1980s, Kenya experienced positive manufacturing output growth during the same period (Van Biesebroeck 2005). Thus exit rates following the crisis coupled with the market liberalization could be higher in Ethiopia and Ghana so that fewer firms survive to old age. Another reason could result from the omission of large numbers of young firms operating in the informal sector in Kenya.¹²

To understand whether firms become larger and improve their productivity as they age, fig. 5 presents the average employment and productivity of firms across different age cohorts.¹³ The figure provides preliminary evidence that firms have experienced slow employment and productivity growth over their life cycle, albeit with some differences across countries.

We now turn to an investigation of how important distortions may be in explaining slow employment and productivity dynamics. The figure shows that TFPR steadily increases with establishment age in Ethiopia, suggesting that older firms, on average, face bigger distortions. Older Ethiopian firms are thus smaller than they would be in a frictionless economy. However, the spike in the older age group could simply reflect the outcome of the previous policies that encouraged the establishment of large enterprises. In contrast, TFPR seems to be smaller for older firms in Ghana and Kenya. In Côte d'Ivoire, older firms are larger and more productive than their younger counterparts. There is no apparent relationship between productivity dynamics and TFPR variation. This pattern differs somewhat from earlier work that concluded that TFPR rises with firm age in developing countries (Hsieh and Klenow 2014).¹⁴

Before concluding this section, it is important to highlight some caveats. First, the observed pattern may reflect differences in the time and cohort. As already mentioned, the countries under consideration have instituted major economic reforms over the last three decades. More precisely, beginning in the mid-1980s for Ghana and Kenya, and in 1991 for Ethiopia the various countries moved towards market-oriented reforms. As shown in the figure, for Ethiopia and Ghana the patterns before the reform (younger than 20 years) are somewhat different from the patterns after the reform, but the pattern in Kenya seems to be stable over the life cycle. Second, as emphasized in the literature on firm dynamics, the observed life cycle pattern may reflect firms' selection (Hopenhayn 1992). One way to evaluate whether selection matters is to examine differences across surviving and exiting firms. However, the cross-section structure of our data limits the effort to make this comparison. As highlighted by Hsieh and Klenow (2014), a simple comparison of average employment, productivity and distortion over a group of firms in a cross-section may be a crude measure since it does not account for differences between cohorts at birth and growth of a cohort over its life cycle. It is obviously of interest to reexamine this relationship using longitudinal firm-level data in Africa.

12 As we already noted, we do not consider firms in the informal sector.

13 The average employment, physical, and revenue productivity are relative to weighted averages of the industry in each country. Thus the relationship should be viewed as within-industry patterns.

14 Note that the spike in the older age group could simply reflect the outcome of the previous policies that encouraged the establishment of large enterprises. This observation implies that the size at birth may play an important role in explaining the variation in size across different age profiles. Put differently, the observed size-age relationship may emerge because firms enter at a much bigger size rather than grow as they age.

Figure 5. Employment, Productivity and Distortions over the Life Cycle

Source: Authors' analysis based on firm-level census data from Côte d'Ivoire, Ethiopia, Ghana, and Kenya.
Note: TFPR and TFPQ are revenue and physical productivity, respectively. Average employment, TFPQ and TFPR are relative to the industry specific average.

6. A Comparison with Survey Data

The HK methodology trades off strong assumptions for a clear efficiency benchmark. However, its application is limited by the availability of adequate data sources. In this section we perform the same exercise of measuring and computing the costs of misallocation from an alternative data source, the World Bank's Enterprise Surveys.

First, we diagnose the differences between the two data sources exploring their implications for the firm-size distribution. We show that the ES is not representative of the full spectrum of firms in Ghana, as large firms are over-represented relative to the census. In Kenya, on the other hand, the two distributions match relatively closely.

Then, we investigate the properties of the distribution of TFPQ and TFPR, and compute counterfactual gains in productivity from the ES, in order to highlight differences with the results from the Census. In this case, we find that accounting for the true distribution of industrial value-added share across manufacturing industries is essential for the patterns of misallocation and the aggregate gains in productivity from its reversal.

Because the ES does not aim to ensure representativeness at the four-digit level in these countries, we use industrial weights from the Census. We find that when doing so, the ES depicts a much less distorted economy with significantly lower gains from resource reallocation. We interpret this finding as indicative of the importance of accounting for the real distribution of value-added shares in the economy.

Firm-Size Distribution: Survey vs. Census

The ES is an ongoing project of the World Bank to collect firm-level data from several countries, particularly from low- and middle-income countries.¹⁵ The dataset contains firm-level information including output and input measures in a harmonized fashion for 135 countries for at least one year since 2002.

To ensure proper sample representation, the ES relies on a stratified sampling technique. Three levels of stratification are used: sector of activity, firm size, and geographical location. In each country, regions are selected based on the extent of economic activity. The population of firms are stratified into three size strata: small (5 to 19 employees), medium (20 to 99 employees), and large (more than 99 employees). The degree of industry stratification depends on the size of the economy. In the 2011 survey in Ethiopia, sectors are classified into two strata: manufacturing and service, whereas in Ghana and Kenya the manufacturing is subdivided further into selected two-digit industries according to their contribution to value added, employment, and number of establishments. The various combinations of these strata generate the cells at industry-size-region level.

As a first look at the data, we assess the comparability between the censuses and the ES, based on quantile-quantile (QQ) plots. Figure 6 plots size quantiles in the ES against the quantiles based on manufacturing census data.¹⁶ If the points in the plot lie more or less on the same line, then we expect the ES data to reflect the size distribution in the national censuses. Departures from this relationship indicate that the firm-size distribution in the two datasets are different.¹⁷

A visual comparison of the plots shows that the distributions based on the ES and the census data look different in all the countries except Kenya. The top panel of fig. 6 plots the size quantile in the 2009 ES for Côte d'Ivoire and 2011 ES for Ethiopia with regard to the manufacturing census data in same year. As can be seen from the figure, the distribution in the ES differs considerably from that implied by the manufacturing census. Similarly, the quantile of firm size in ES for the years 2007 and 2013 is plotted

15 The data are freely available from <http://www.enterprisesurveys.org>.

16 Size is defined as a logarithm of employment. To make it comparable with the ES, firms employing fewer than 5 workers are dropped from our census.

17 Note that we choose not to use sampling weights, because they are not appropriate to make this comparison since they are defined at broader strata.

Figure 6. QQ Plot of the Enterprise Censuses vs . Surveys

Source: Authors' analysis based on firm-level census and World Bank's Enterprise Survey data.
Note: The X and Y axes plot the employment quantiles in the Census and ES, respectively.

against the 2003 National Industrial Census of Ghana. A visual comparison shows a clear difference in firm-size distribution between the two sets of data. For the case of Kenya, a comparison of the ES (for the years 2007 and 2013) against the 2010 Census of Business Establishments (CBE) reveals that the size distributions of firms in the two datasets track each other quite closely. This can be explained by the fact that, unlike for the other countries, the CBE is actually being used to create the sampling frame in Kenya.

Even though there is no unique mechanism through which biases in the size distribution could be conveying biases in the distribution of distortions, one would be, in principle, more reassured about Kenya's distribution being close to the Census-based one, assuming the latter is the best representation of the true distribution of firm sizes. We will see below, however, that one also needs to worry about the representativeness of the distribution of sectoral value-added shares.

Extent and Cost of Misallocation: Survey vs. Census

We now turn to evaluating the degree and costs of misallocation as measured from the ES. The goal is to see whether the divergence in the size distribution in the case of Ghana, and its similarity in the case of Kenya, is informative about differences or similarities in the extent of misallocation in these economies when compared to the calculations based on the Census.¹⁸

18 Note that Côte d'Ivoire and Ethiopia are excluded in this exercise due to the large amount of missing capital information in the ES.

There are a number of challenges involved in making the analysis of misallocation in the ES comparable to that in the Census. First, the surveys for the four countries under study are not built to ensure representativeness of a more disaggregated sectoral coverage. As mentioned above, there is stratification across two broad categories, manufacturing and services, in the case of the 2011 Ethiopian survey, while representativeness is captured only at the two-digit level in Ghana and Kenya. Adequate sectoral representativeness is important for our calculation because sufficient aggregate statistics of misallocation and the aggregate counterfactual gains in productivity are all constructed based on four-digit weighted averages. Thus, ensuring that an industry is properly represented in the aggregate is essential for the validity of the results.

To illustrate the importance of the adequate weighting of sectors, we perform two versions of our calculations. In the first one we weight four-digit industries according to the value-added shares implied by the firms sampled in the surveys. In the second one we adopt the value-added shares from the censuses. Under the assumption that Census-based weights are closer to the true ones, the experiments allow us to assess the quantitative significance of the poor sectoral representativeness of the enterprise surveys.

A second challenge that we face, which is related to the same limitations in the construction of the ES that we highlighted above, is that some four-digit industries may not be covered at all. To make the two data sources comparable, we restrict the sample of firms in the censuses to those belonging to industries that are covered both in the censuses and the ES, re-weighting valued-added shares accordingly.

Statistics about the TFPR and TFPQ distributions are reported in [table 4](#). For each country and for each variable, we report statistics of the distributions inferred from the ES that differ in the value-added shares used to weight industries in the aggregation. CW stand for value-added shares imputed from the censuses, while SW are the weights implied by the sample of firms in the ES.

We can see that when aggregating sectors using the census weights, which we view as the most plausible characterization of the true structure of production, all magnitudes of dispersion are reduced relative to the magnitudes that result from the ES’s own weights.

Finally, [table 5](#) reports the counterfactual gains in aggregate manufacturing resulting from reversing distortions in the three types of data that we have been comparing: census, ES with survey weights, and ES with census weights. First, we report the baseline census-based results introduced above (column 1) together with the gains corresponding to the case where we restrict to the subset of industries that overlap with the industries covered in the ES (column 2). The third column reports the TFP gains in the ES when

Table 4. Dispersion of TFPR and TFPQ Based on the Enterprise Surveys

	Kenya				Ghana			
	TFPR		TFPQ		TFPR		TFPQ	
	CW	SW	CW	SW	CW	SW	CW	SW
S.D.	1.30	1.48	2.21	2.72	0.98	1.05	1.28	1.32
75–25	1.34	1.65	3.21	5.20	1.11	1.60	1.97	2.01
90–10	2.86	4.37	5.54	7.29	2.56	2.58	3.43	3.57
Reg. Coeff.	0.46		0.49		0.49		0.49	
N	150	169	150	169	249	258	249	258

Source: Authors’ analysis based on the World Bank Enterprise Survey data.
Note: CW and SW refer to Census-weight and Survey-weight, respectively. Dispersion of log TFPR and log TFPQ scaled by industry-specific average. TFPR and TFPQ are calculated for each establishment (*i*) in industry (*s*) and then scaled by industry-specific averages before taking their logs, i.e., $\log(TFPR_{si}/TFPR_s)$ and $\log(TFPQ_{si}/TFPQ_s)$. Industries are weighted by their value-added shares. TFPR and TFPQ are revenue and physical productivity, respectively. 75–25 is the ratio of the 75th to 25th percentiles and 90–10 is the ratio of the 90th to the 10th percentiles. Reg. Coeff is the coefficient of a regression of log TFPR on log TFPQ scaled by industry-specific average.

Table 5. Potential TFP Gains with Different Industrial Weights

	Census (percent)		Enterprise Surveys (percent)	
	Baseline	Partial	SW	CW
Ghana	75.7	71.1	146.6	54.3
Kenya	162.6	184.2	86.5	51.4

Source: Authors' analysis based on firm-level census data from Kenya and Ghana and World Bank's Enterprise Survey data.

Note: The total factor productivity (TFP) gains are calculated based on different industrial weights. The TFP gains under the column "Partial" are calculated by restricting to the subset of industries that overlap with the enterprise surveys (ES). The last column shows the TFP gains across firms in the ES where industries are aggregated using the census weights. CW and SW refer to Census-weight and Survey-weight, respectively.

industries are aggregated using the ES's own weight (column 3). If, instead, industries in the ES were weighted by their share in the censuses, the TFP gains would be smaller (column 4).

Two observations emerge from the table. First, when aggregating industries in the ES using their value-added shares in the censuses (last column), TFP gains from reallocation would be significantly muted compared to the gains based on the ES's own weights (column 3). The potential TFP gains would decrease from 146.6 percent to 54.3 percent in Ghana and 86.5 percent to 51.4 percent in Kenya. The large drop in the TFP gains in Ghana after re-weighting highlights the potential bias in the sectoral distribution of production in the ES. Second, the ES yields smaller TFP gains than the censuses (column 2 vs column 4): 71.1 percent vs. 54.3 percent for Ghana and 184.2 percent vs. 51.4 percent for Kenya. This suggests that even if industries in ES reflect their true value-added share in the total manufacturing sector, the ES yields a smaller degree of misallocation compared to the census. This could reflect potential differences in the distribution of distortions and/or productivity within each sector.

Why Does the ES Yield Lower Measured Misallocation?

We now turn to investigate why the ES yields different degrees of misallocation from the manufacturing censuses.

One way to explore why measured misallocation becomes smaller in the ES once industries are aggregated using the census weights is by comparing the relative importance of a sector in ES vs. its measured misallocation. [Figure 7](#) plots the relative share of industries in the ES against (a) the dispersion of TFPR in the ES (top panel), and (b) dispersion of TFPR in the ES relative to the censuses (lower panel), with each dot on the graph representing a specific four-digit industry.

These figures clearly highlight the strong positive relationship between the relative importance of sectors and TFPR dispersion, particularly in Ghana. This relationship shows that sectors that are more distorted (with higher TFPR dispersion) appear to be overrepresented in the ES relative to their actual share in the manufacturing sector. This explains why the TFP gains fall significantly in Ghana, from 146 to 54 percent. This finding suggests that accounting for the true industry share is potentially important in order to provide an accurate picture of the extent of economy-wide misallocation and to ensure cross-country comparison.

In the case of Kenya we find that TFP gains fall, but by a smaller amount compared to Ghana (86.5 percent to 51.4 percent). This suggests that adjusting sectoral weights does little to explain why measured misallocation based on the ES is different from the census.

To explore why census and ES yield different findings after adjusting sectoral weights, we compare the measure of misallocation sector by sector. As the lower panel of [fig. 7](#) shows, most industries have smaller TFPR in the ES compared with their dispersion in the census. This result suggests that the survey results can significantly underestimate the extent of misallocation in most sectors.

To further illustrate this, we use an alternative dimension of misallocation – elasticity of distortion to productivity (regression coefficients). We clearly see from [fig. 8](#) that the elasticity of TFPR to TFPQ is

Figure 7. TFPR Dispersion: ES vs. Census

Source: Authors’ analysis based on firm-level census data from national sources and World Bank Enterprise Survey.
Note: Relative VA refers to the logarithm of sector-specific value-added in enterprise surveys (ES) relative to the the censuses, $\log(VA_{intheES}/VA_{intheCensus})$. Relative STD(TFPR) refers to the ratio of sector-specific dispersion in ES relative to the dispersion in the censuses, $(StdofTFPRinES/STDofTFPRinCensus)$.

Figure 8. Regression Coefficient in ES vs. Census

Source: Authors’ analysis based on firm-level census data from national sources and World Bank Enterprise Survey.
Note: ES is Enterprise Surveys. Reg. Coeff is the coefficient of a regression of $\log(TFPR_{si}/TFPR_s)$ on $\log(TFPO_{si}/TFPO_s)$.

smaller in the ES (below the 45 degree line) for most of the industries. This highlights that the ES may underestimate the TFP gain not only because of less dispersed TFPR but also because weaker correlation between TFPR and TFPQ.

To sum up, the analysis highlights that measured misallocation based on survey data may be biased. Two types of biases might play a role. First, if the value-added share of industries at the narrower industry group are constructed incorrectly, we would likely overstate/underestimate measured misallocation as they would reflect both true share and sampling error. In our sample countries, sectors with higher misallocation appear to have been over-represented compared to their shares in the census, and hence the overall misallocation based on the survey weight is overestimated. A second type of error is the biases in the distribution of distortions. We find that most industries have smaller misallocation in the ES compared with their dispersion in the census. This means that the ES may understate the true misallocation in each sector. This highlights the problem that using the survey data to do cross-country comparisons without correcting these biases may be misleading (Inklaar, Lashitew, and Timmer 2017). Thus although the ES represents the best available data for studying misallocation for a broader set of countries, caution must be taken when the results from the ES are compared across countries.

A natural question to ask is whether our findings for Ghana and Kenya can be generalized to other countries. Although our results suggest that measured misallocation based on ES is considerably smaller than manufacturing censuses (once industrial weights are adjusted), drawing a general conclusion is limited by having a sample of only two countries.

7. The Role of Region and Industry Variation

The results presented in the previous section clearly revealed that productive resources are severely misallocated in all our sample countries. A natural follow-up question then arises: what are the underlying causes of these dispersions? Understanding the specific policies and institutions that drive within-industry misallocation is notoriously difficult. In principle, many factors – observable and unobservable – may reasonably contribute to measured misallocation across firms. Putting aside the specific policies, in this section we simply discuss the contribution of region and industry-specific factors to the overall misallocation.¹⁹

First, to assess whether measured misallocation reflects differences across locations, we decompose the overall variance of log TFPR into within-region and between-region components by grouping establishments based on their location.

$$var_s(\omega_{is}) = \underbrace{\frac{1}{M_s} \sum_r^R \sum_i^{N_r} (\omega_{isr} - \bar{\omega}_s)^2}_{\text{Overall Variation}} = \underbrace{\frac{1}{M_s} \sum_r^R N_r var(\omega_{is})_r}_{\text{Within-region}} + \underbrace{\frac{1}{M_s} \sum_r^R N_r (\bar{\omega}_{sr} - \bar{\omega}_s)^2}_{\text{Between-region}} \quad (6)$$

where ω_{istr} is the log of TFPR for establishment i located in region r in the s industry; $\bar{\omega}_s$ is the mean of ω for industry s ; and $\bar{\omega}_{sr}$ is the mean of ω in region r within industry s . The first term on the right-hand side measures the within-region contributions to overall variance. The second term captures the between-region contributions to overall variance.

We find that the between-region component explains a relatively modest share of the overall TFPR variation, accounting for only 3.9 percent in Ethiopia, 5 percent in Côte d'Ivoire, 8.7 percent in Ghana and 11.8 percent in Kenya. These findings suggest that a substantial portion of observed misallocation (within sectors) in our sample countries stems from within-region variation.²⁰

¹⁹ Measured misallocation may differ across industries and regions for a number of reasons.

²⁰ We group firms into two locations: capital city and others. The within-region component remains large when we consider a narrower definition of geographical areas.

As noted above, our work focuses only on misallocation within narrowly defined industries.²¹ Nonetheless, it would be informative to highlight whether cross-industry variation also plays a role. To this end, we run a simple regression of establishment-level log TFPR on sector and regional dummies for each country separately. Table 6 reports the R^2 of the regression of firm-level TFPR on industry dummies (Column 1), regional dummies (Column 2), and industry-region dummies (Column 3). The results suggest that cross-industry differences as opposed to region-specific variations play an important role in explaining the overall TFPR dispersion.²²

Table 6. Industry vs. Region Factors: R^2

	Sector FE	Region FE	Region-Sector FE
Côte d'Ivoire	0.117	0.005	0.141
Ethiopia	0.167	0.008	0.178
Ghana	0.190	0.002	0.239
Kenya	0.237	0.009	0.290

Source: Authors' calculation based on firm-level census data from Côte d'Ivoire, Ethiopia, Ghana, and Kenya.
Note: FE refers to fixed effects.

Table 7. Sensitivity Analysis: Potential Gains from Equalizing TFPR (5)

	Baseline	$\sigma = 5$	Trim 2 percent	$L > 10$	$WL = L$	$\alpha_s = 1/3$	Country α'_s
Côte d'Ivoire	31.4	44.7	25.8	29.4	33.2	21.8	44.9
Ethiopia	66.6	82.0	66.0	60.9	77.97	56.41	101.81
Ghana	75.7	85.1	56.1	66.9	66.88	59.17	93.06
Kenya	162.6	194.6	120.6	141.5	170.55	153.91	440.24

Source: Authors' calculation based on firm-level census data from Côte d'Ivoire, Ethiopia, Ghana and Kenya.
Note: Sigma is the elasticity of substitution across producers within industry, alpha is capital share.

Summing up, although within-industry-region variation explains the largest fraction of the overall misallocation, there is important heterogeneity across industries. Hence, the cross-industry variation in misallocation can be used to assess the importance of various mechanisms that might contribute to re-source misallocation. More work is needed to capture the key differences across industries.

8. Robustness

In this section, we examine the robustness and sensitivity of the counterfactual gains reported in table 3 to alternative assumptions.

Labor Input Variable

To start with, in our baseline analysis, labor input is measured using the wage bill. However, one can also argue that wages reflect rent sharing between the establishment and its workers, resulting in the underestimation of TFPR dispersion across establishments since the most profitable establishments have to pay better wages (Hsieh and Klenow 2009). As a first robustness check, we test our results using the number of people engaged as our measure of labor input instead of the wage bill. The reallocation gains

21 We do not consider the effects of removing distortions across industries, that is, $\overline{TFPR}_s$ are not equalized across sectors s .
22 The difference in measured misallocation across sectors suggests that equalizing $\overline{TFPR}_s$ across sectors may lead to even larger effects on aggregate TFP.

would be modestly larger in Côte d'Ivoire (33.2 percent vs. 31.4 percent), Ethiopia (77.9 percent vs. 66.6 percent), and Kenya (170.6 percent vs. 162.6 percent) but smaller in Ghana (66.9 percent vs. 75.7 percent). This reflects the fact that wage differences can lead to a decrease in TFPR dispersion across establishments in Côte d'Ivoire, Ethiopia, and Kenya, but increases in Ghana. Overall, our results are robust to this change; the potential TFP gains from reallocation continue to be the largest in Kenya.

Industry-Specific Factor Share

In our baseline computation, α_s was set to correspond to the capital share in the United States. One may argue that the characteristics of the U.S industries may be different from those in SSA countries, due to the differences in technology and other factors. As a robustness check, we recalculate the potential TFP gains under two different assumptions of α_s . First, we set $\alpha_s = 1/3$ for all subsectors s . Second, we repeat our computation by setting α_s on the basis of industry-specific capital share in each country instead of capital share in the United States, assuming that the industry is, on average, undistorted in these countries. The result reveals that using country-specific elasticity of capital leads to a much larger potential gains from reallocation in all the four countries. However, it should be noted that country-specific capital shares may reflect a mix of technology and distortions.

Treatment of Outliers

The extent of misallocation is sensitive to the treatment of outliers. To ensure that our results are not affected by outliers, we also estimate the potential aggregate TFP gains by trimming the top and bottom 2 percent tails of TFPR and TFPQ. The potential gains from reallocation decrease from 31.4 percent to 25.8 percent in Côte d'Ivoire, from 75.7 percent to 56.1 percent in Ghana, and from 162.6 percent to 120.6 percent in Kenya but remain unchanged in Ethiopia. The large drop in the TFP gains in Kenya (by about 40 percent) after trimming the 2 percent outliers highlights the fact that large gains can be obtained through reallocation of resources from the least-productive establishments to the most-productive ones. It could also reflect measurement error. While measurement error could be important, the largest potential TFP gains from removing distortion remains for Kenya.²³

Size Threshold

In our benchmark analysis, we include all establishments regardless of their size. Although all the censuses targeted all registered establishments, the proportion of registered establishments may differ across countries. The cross-country comparison would be biased if the proportion of registered firms varied across countries. For example, given the large average firm size in Kenya, one may argue that the Kenyan census may not be comparable to the other censuses in covering the smallest establishments. To examine the extent to which this finding is an artifact of the Kenyadata set, which has sparse coverage of small firms, as a robustness check, we redo the analysis by excluding establishments employing fewer than 10 workers. The result shows that the potential gains from reallocation decrease in all countries (29.4 percent vs. 31.4 percent) in Côte d'Ivoire, (60.9 percent vs. 66.6 percent) in Ethiopia, (66.9 percent vs. 75.7 percent) in Ghana, and (141.5 percent vs. 162.6 percent) in Kenya, implying that part of the gains from reallocation comes from small establishments. However, the qualitative result remains unchanged.²⁴

Overall, the sensitivity analysis clearly shows that the finding that measured misallocation is the highest in Kenya and the lowest in Côte d'Ivoire is robust to alternative assumptions regarding the measures of labor inputs, elasticity of capital, outliers, and alternative size thresholds. However, the figure that emerges

23 In order to ensure that the results for Kenya are not driven by measurement error, we also trimmed up to 5 percent of observations (no reported here). We find that Kenya exhibited the largest TFP gains from removing distortions.

24 We have experimented with several different size thresholds and have found that exclusions of those establishments leave the ranking of countries in terms of misallocation unaffected.

from comparing Ethiopia and Ghana is rather mixed as the relative ranking changes depending on the alternative assumptions.

Alternative Measure of Misallocation

Finally, as an alternative measure of misallocation, we calculate the covariance between firm productivity and size within an industry as in [Bartelsman, Haltiwanger, and Scarpetta \(2013\)](#). The idea of this measure is that firms' productivity and size are positively and strongly correlated in less distorted economies, since optimal allocation requires resources to be allocated based on the productivity level. Thus in a more distorted economy, productive firms have smaller market shares than the optimal.²⁵ We find the cross-sectional covariance between firm size and productivity to be 0.04 for Côte d'Ivoire, -0.04 for Ethiopia, -0.05 for Ghana, and -0.01 for Kenya. As in [Bartelsman, Haltiwanger, and Scarpetta \(2013\)](#), industries in each country are aggregated using the U.S. industry shares. The result shows that the overall covariance is negative for all countries except Côte d'Ivoire, suggesting that more productive firms are typically smaller. Although the HK and Olley-Pakes (OP) results are not directly comparable, both measures point to high degrees of misallocation in our sample countries.²⁶

9. Conclusion

This paper examines the effects of resource misallocation induced by firm-specific distortions on manufacturing productivity using comparable firm-level census data from four Sub-Saharan Africa countries (Côte d'Ivoire, Ethiopia, Ghana, and Kenya).

Our main results are as follows. First, we found strong evidence that resources are severely misallocated in the manufacturing sector in all sample countries. A reversal of such distortions would increase manufacturing TFP by 31.4 percent to 44.7 percent in Côte d'Ivoire, 66.6 percent to 82.0 percent in Ethiopia, 75.7 percent to 85.1 percent in Ghana, and 162.6 percent to 194.6 percent in Kenya. Our results also suggest that distortions are positively correlated with firm-level productivity in all the four countries, providing evidence that more-productive firms ("good") are "taxed" more. Interestingly, the bulk of these misallocations across firms of different productivity levels arise largely due to frictions that directly distort producers' size.

We also show that censuses are the right data source for estimating statistics for overall distortions and TFP gains, given the biases introduced by using sample-based surveys.

Our analysis has abstracted from several factors, which may be worth exploring further. The counterfactual productivity gains can be viewed as reasonable lower bounds since the analysis abstracts from other potential sources of amplification. First, our analysis focus on TFP gain from the reversal of distortion *within* a very tightly defined set of industries within each of these countries, abstracting from between-industry reallocation gains. Thus, reversing the between-industry misallocation may lead to even larger effects on aggregate TFP. Second, our analysis allows *static* productivity gains only. Accommodating the dynamic effect would likely amplify the total TFP gains from removing distortions. Third, reallocation in the manufacturing sector may have economy-wide implications though backward and forward linkages. Thus, productivity gains from the removal of distortions are likely to be higher than otherwise implied by a one-sector model. An interesting area for future research is to assess the extent of misallocation in a multisector framework by accounting all the potential linkages between sectors ([Jones 2011](#)). We also abstract from potential gains from directing resources between formal and informal firms. Since informal

25 [Bartelsman, Haltiwanger, and Scarpetta \(2013\)](#) document that the within-industry covariance between firm size and productivity varies considerably across countries and is systematically related to the level of development across space and time. They found a stronger covariance between firm size and productivity in the United States than in Western European and more pronounced in Eastern European countries.

26 HK and the OP covariance provide a consistent result at the industry level, although the relationship is not linear.

firms are often found to be on average less productive than formal firms, reversing the distortion between formal and informal firms operating in the same sector may yield a larger TFP gains.

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