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

Xavier Cirera† Roberto N. Fattal Jaef ‡ Hibret B. Maemir§

Abstract

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. We find 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 sampling methods that take the true structure of production into account.

Keywords: distortions, misallocation, Enterprise Surveys, Sub-Saharan Africa, total factor productivity.

JEL: C83, L11, O11, O47, 055.

*Any opinions and conclusions expressed herein are solely those of the authors and do not reflect the views of the World Bank. We would like to thank Luis Serven and Nicolas Gonne for valuable comments. We also wish to thank Neil Rankin for generously providing us the Ghanaian Census data.

†The World Bank, Trade and Competitiveness Global Practice, Washington, D.C. E-mail: xcirera@worldbank.org.

‡Corresponding author: The World Bank, Development Research Group, Washington, D.C. E-mail: rfattaljaef@worldbank.org.

§The World Bank, Development Research Group, Washington, D.C. E-mail: hmaemir@worldbank.org.

1 Introduction

One of the most enduring challenges in the field of economic growth and development is to understand the sources of the large variation 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. In this paper, we explore 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 region 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.

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 is among the most distorted countries in Latin America in terms of allocative efficiency, 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

[1] The magnitudes of TFPR dispersion in India are 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 et al. (2013).

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% higher in Côte d'Ivoire, 67% higher in Ethiopia, 76% higher in Ghana, and 162% 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). In particular, the ES overestimates the size of the highest percentiles in the firm size distribution. We then evaluate the implications of this bias for 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. We see this finding as raising a warning to the precipitate application of the methodology. Ensuring adequate size and sectoral representation in the data stands as an important ingredient for the robustness of misallocation measurements.

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 directly distorts the establishment's size or scale (revenue wedge).[2] This decomposition is informative to identify the type of policies that are the most distorting.

We also examine how misallocation relate to the age profile of establishments. We find that the growth of employment over 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

[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.

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

provides an overview of the macroeconomic structure of the countries under study. Section 4 provides a brief outline of the methodology. Section 5 describes the databases used in the analysis. The main results are presented in Section 6. Section 7 compares our results with the survey data. In Section 8, we examine how measured misallocation varies across locations and industries. Section 9 assesses the sensitivity of the results. and Section 10 concludes.

2 Related Literature

This study is related to a recent literature focusing on the importance of firm-level resource misallocation in explaining cross-country productivity difference. 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) provide the first empirical approach to measure misallocation across firms within 4-digit industries in China and India. They find that the misallocation of resources across firms - measured by the dispersion in marginal products of inputs - explain 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% to 60% in India and 30% to 50% in China. Subsequent research following the methodology of Hsieh and Klenow (2009) confirms the quantitative importance of misallocations for several countries. Examples include Gustavo and Cristobal (2012) for Bolivia, Camacho and Conover (2010) for Colombia, Oberfield (2013) for Chile, Busso et al. (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 et al. (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, the manufacturing censuses we use in our paper.

The paper also relates to more recent papers 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 et al., 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% 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) 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 Santaeulalia-Llopis (2017), using household-level data for Malawi, document severe resource misallocation in agricultural sector due to land market restrictions. Chen et al. (2017) provide evidence of substantial misallocation of resources in the Ethiopian agriculture due to the imperfect land markets. Chen (2017) also provides cross-country evidence on similar issue. These papers have shown that distortions in farm size may account for a significant fraction of cross-country differences in agricultural productivity. .

Because our work 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), McCaig and Pavcnik (2015) and McCaig and Pavcnik (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 body of work replicating the theory of misallocation and the strategy to measure it from the data developed by Hsieh and Klenow (2009). We expand the literature in exploring a region of the world where the data requirements for the application of the methodology have left it 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, because it is not representative at the sector level, ES-based distortion measures underestimate the degree of resource misallocation and the productivity gains associated with reallocation.

3 Background

We motivate our study reviewing features of the structure of production and the magnitude of the development gaps that characterize the sample countries. Then, in order to get a sense of the quality of the business climate in which firms operate in these economies, we provide a brief account of reforms and salient packages of government interventions that were implemented over the course of the years.

3.1 Macroeconomic Performance

As a background for our analysis, we first compare the countries along different measures of aggregate economic indicators. The left panel of Figure 1 summarizes the performance of the sample countries by showing the evolution of real per capital GDP relative to that of the United States from 1980 to 2015. Ethiopia is the poorest country in the group. In 2015, its income per capita is only 1 percent that of the United States. The corresponding number for Côte d'Ivoire is 2.8, Ghana is 3.3 and 2.2 for Kenya.

Although these countries are all developing, there are clearly some differences in terms of their economic structure and performance. Looking at the share of sectors to GDP (right panel of Figure 1), while manufacturing is a more important sector of activity in Côte d'Ivoire and Kenya with a share in GDP of more than 10 percent, it accounts a small share of GDP in Ethiopia and Ghana. Ethiopia's manufacturing sector contributes relatively little (about 4.1 percent) to the overall economy, which is far below the SSA average. The figure for Ghana is slightly higher (about 5.1 percent), but still roughly half of Kenya's and Côte d'Ivoire's.

The challenge that emerges from the figure is clear. SSA needs to find ways to catch up to the technological frontier if its going to have any hope of igniting a period of sustained growth. It also needs to undergo a structural transformation in the sectoral allocation of production, raising the participation of the manufacturing sector away from agriculture. Our paper will provide a sense of how much of the convergence towards the frontier can be achieved by reallocating resources efficiently in the manufacturing sector.

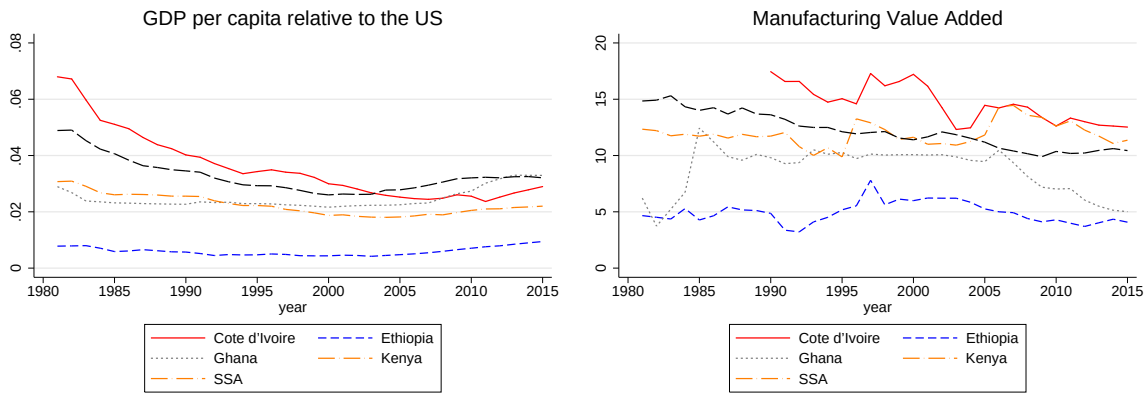


Figure 1: GDP per capita and Manufacturing Value Added (percentage of GDP)

One concern that may arise from looking at the left panel of the figure is that our analysis is focusing on a sector that contributes little to the total value added, specially in Ethiopia and Ghana. In principle, no matter how large the productivity gains we find associated with a potential reversal of misallocation distortions, these are going to be down-weighed by the small share of manufacturing in value added. Even though this is a fair concern, there are at least two reasons why understanding barriers to productivity growth in manufacturing is essential for the development prospects of the region. Firstly, the aggregate implications of manufacturing activity go beyond its contribution to valued added because of linkages in the input-output network with other sectors. Jones (2011) finds evidence of large input-output multipliers resulting from an increase in a given sector's aggregate productivity through linkages in production. Even though market frictions presumably reduce the degree of interconnectedness in SSA, there is still a multiplier effect at stake. Secondly, increasing productivity in manufacturing, by raising income levels, can help accelerate the typical process of structural transformation accompanying development in which resources are shifted away from agriculture. Quantifying the effects of manufacturing productivity gains are objects of future research.

3.2 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 shape of the firm size distribution. Thus, it is informative to confront the measurement of misallocation that we perform below with some information about the shape of the firm size distribution in the countries that we cover in this study.

Table 1 presents some descriptive statistics. The table illustrates that, Kenyan firms, on average, are much larger (in terms of the number of workers) than firms in the other countries. While the average

number of workers is approximately 145 in Keny 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.

Table 1: Size Distribution of Firms

	Côte d'Ivoire	**Ethiopia**		**Ghana**		**Kenya**
	Census (2012)	Census (2011)		Census (2003)		Census (2010)
Size	**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

Note: 'wt' denotes for the wighted statistics. For the manufacturing censuses in Ethiopia and Ghana, we use the sampling weights constructed by the respective national statistical offices.

Notice, too, that re-weighting observations for small firms according to the weights provided by the national statistical offices of Ethiopia and Ghana reduce the average firm size even further, to 9 and 8 workers respectively. The bottom line is that misallocation frictions in these economies have a strong depressing effect over average firm size.

3.3 Policy and Institutions

In this sub-section we present the institutional and macroeconomic environment within which firms operate since the 1960s.

The 1950s and 1960s marked era of Import Substitution Industrialization (ISI) for Ethiopia, Ghana and Kenya. In Ethiopia, a deliberate move to stimulate industrial growth began in the mid-1950s under the imperial regime, with a focus on import-substituting light industries (Gebreeyesus, 2013). Ghana's first industrial reform since independence – the ISI strategy of 1960-1983 – was centered on the development of large-scale, capital-intensive state-owned manufacturing industries. The strategy was marked by massive government intervention in the allocation of substantial resources (Ackah et al., 2014). Similarly, Kenya pursued an ISI strategy following independence in 1963, with a large amount of its manufacturing investment went into heavily protected import-substituting industries, such as textiles, food processing, and metal industries (Chege et al., 2014). Unlike the three other countries,

Côte d'Ivoire pursued agricultural export oriented growth strategy, creating a liberal policy environment that was relatively conducive to domestic and foreign private investment during the first two decades after independence. During this period, the Ivorian economy overall was growing at an average rate of 7 percent per year, well above the SSA average. Over the same period manufacturing value added by more than 9 percent.

Since early 1980s all the sample countries have implemented Structural Adjustment Programs (SAP) under the support of the World Bank and IMF. Côte d'Ivoire launched structural adjustment policy in early 1980s in response to external and internal macroeconomic imbalances, which was mainly triggered by a sharp decline in the prices of key commodities such as cocoa, and coffee (World Bank, 2015). This resulted in massive government fiscal deficit that forced the government to adopt an austerity program in 1982 (Harrison, 1994). Côte d'Ivoire instituted a series of trade, fiscal, and monetary reforms. The trade reforms constituted several components that aimed to increase competition in the economy. Ghana instituted a number of policy reforms since the mid-1980s under the Economic Recovery Program (ERP) (1984-2000) - the second of its three major industrialization reforms. The ERP introduced a reform in the industrial policy of Ghana from the traditional ISI to an outward-oriented private sector-led industrial strategy. Some of the policy reforms include: privatization of the SOEs, removal of price and distribution controls, and liberalization of the financial sector and interest rates (Sandefur, 2010). The government has made progress in reforming the regulatory framework and liberalizing the financial sector in which the government enhanced competition in commercial banking through a program of divestiture of state-owned commercial banks. The liberalization has entailed the removal of controls on interest rates and the sectoral composition of bank lending, and the introduction of market based instruments of monetary control (Brownbridge and Gockel, 1996). During the 1980s and in the early 1990s, the Kenyan government also introduced a series of reforms to support export, following growing concerns about the distortionary effects of the ISI.

Ethiopia launched the market-oriented reforms much later than the rest of the group in 1991, the major ones being the privatization of SOEs, easing of market entry for privately-owned financial institutions, limiting the role of the state in economic activities and promotion of greater private capital participation, among others (Gebreeyesus, 2013). Despite the instituting reforms, the Ethiopian financial market still seems to be lagging behind those of the other two. For instance, while capital market regulations were liberalized, there is still substantial domination of the state-owned banks.

Ethiopia, Ghana, and Kenya launched full-fledged industrial policies at nearly the same time (a bit later for Kenya): Ghana's private sector-led accelerated industrial development strategy in 2001, Ethiopia's Industrial Policy Strategy (IDS) in 2002/2003, and Kenya's National Industrial Policy (NIP)

in 2007. The industrial policy of Ghana emphasized value-added processing of the country's natural resource endowments through the private sector-led accelerated industrial development strategy (Ackah et al., 2014). Under this broad industrial development strategy, Ghana formulated series of sector-specific strategies. The priority sectors include: the textile industry, food processing sector, chemical industry, and other ago-processing industries.

The Ethiopian government also formulated a series of sector-specific strategies with some sectors receiving preferential treatment from the government, under the ambitious Growth and Transformation Plan (GTP) 2010/11 - 2014/15. The priority sectors include textile and garment; meat, leather and leather products; and other ago-processing and labor-intensive industries. The number of priority sectors, however, has been updated sequentially. For example, metal and engineering, chemicals and pharmaceuticals were sequentially added to the list (Gebreeyesus, 2013). These sectors receive substantial support from the government including economic incentives, capacity building and cluster development. For example, investors in the priority sectors can access credit from the Development Bank of Ethiopia (DBE) at preferential lending rates. In addition, firms in favored sectors can receive much more generous tax treatment with five-year tax holiday on profits. Furthermore, imports of all investment capital goods and raw materials necessary for the production goods are fully exempted from import tariff, and investors in selected sectors can easily access land. To fill the perceived gaps not served by the private sector, the government has also recently increased its direct investment in several economic activities e.g. textile, garment, rubber tree production, coal phosphate fertilizer, cement factory, ceramics, pulp and paper (Gebreeyesus, 2013). Critics argue, however, that the practice of selective interventions that favor some activities and firms over others may distort the allocation of resources. For example, Altenburg (2010) highlights that "resource allocation for industrial policy is not fully transparent, e.g. it is not clear when firms are eligible to get preferential treatment in term of access to licenses, land, credit and foreign exchange, on what condition ailing firms will be bailed out, and whether these conditions vary between state-owned enterprises, firms affiliated with the ruling political parties, and independent private firms."

4 Theoretical Framework

To quantify the effect of misallocation on aggregate TFP, we use accounting framework outlined in Hsieh and Klenow (2009, HK hereafter). This section provides 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 establishment's capital stock, L_{si} is labor input, and α_s is industry-specific capital share.

Each establishment maximizes current profits:

$$\pi_{si} = (1-\tau_{Ysi})P_{si}Y_{si} - wL_{si} - (1+\tau_{Ksi})RK_{si} \tag{1}$$

where P_{si} is establishment-specific output price and $P_{si}Y_{si}$ is value added of firm i, w and R are the common wage rate and the rental cost of capital, respectively. τ_{Ksi} denotes establishment-specific "capital" distortion (which increases the cost of capital *relative* to labor). A large (small) value of τ_{Ksi} increases the cost of capital (labor) relative to labor(capital). A wide range of factors could potentially cause such distortion, e.g. credit market imperfection and labor market regulations that differ across firms. "output" distortion is denoted by τ_{Ysi}. Such distortions could arise because of government policies such as tax regulation that favor particular firms or corruption. These distortions could also reflect monopoly power or adjustment costs.

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

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

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:

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

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 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 $R = 10\%$ - assuming a real interest rate of 5% and depreciation

rate of 5%. For the industry-level factor share, α_s, we use NBER Productivity Database. We assume factor intensities are the same as those of the corresponding U.S. industries, which is assumed to be undistorted.[4] After obtaining the capital share at 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:

$$1 + \tau_{ksi} = \frac{\alpha_s}{1 - \alpha_s} \frac{wL_{si}}{RK_{si}} \tag{4}$$

$$\frac{1}{1 - \tau_{ysi}} = \frac{\sigma - 1}{\sigma} \frac{(1 - \alpha_s) P_{si} Y_{si}}{wL_{si}} \tag{5}$$

Eq. (4) captures the distortions in input choice relative to the optimal combination of factor input. 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 distortions, and vice versa. Eq. (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.

5 Data Description

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.

In what follows, we describe each country's datasets, we relegate the details to the Appendix.

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

[4] HK point out that the labor share in this dataset underestimates the labor compensation because it doesn't include fringe benefits and employer social security contribution. Following Hsieh and Klenow (2009), we inflate the labor cost by a factor of 3/2.

[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 US is 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 US data at four-digit levels.

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, Systeme Comptable Ouest Africain (SYSCOA).

Ethiopia The datasets we use for Ethiopia are the Large and Medium Scale Manufacturing Industries Survey (LMSMI) and 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 conducted this census on annual basis since 1976.[6] In 2011, the raw dataset contains 1,936 establishments.

The SSMI survey covers establishments which use *power-driven* machinery and engage *less than ten 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 less than 10 workers and using power driven machines. The SSMI survey was conducted using stratified sampling procedure to ensure representativeness of all establishments in the country. The CSA also provide a sampling weight for each firm. By merging the two dataset, we obtain complete distribution of establishments 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 % 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 with the Ethiopian data; it covers the universe of establishments employing more than 10 workers and takes a representative sample of firms employing less 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 sub-sectors based on four-digit and 23 based on two-digit classification. Manufactures

[6] Note that although the LSMI targets establishments with more than 10 employees, they remain in the census even if the number of workers decrease.

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

[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 Krakah et al. (2014).

of textiles and wearing apparel is the largest sub-sector, 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 data set provides detailed information needed for our analysis, including total sales, value of production, labor cost, capital, 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 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 four-digit and 31 based on two-digit classification. Manufactures of food products is the largest sector, measured by the number of firms, accounting for 36.55 percent of the total industry.

6 Results and Discussion

6.1 Measuring Productivity and Distortions

Figure 2 plots the distribution of $\log(TFPR)$ and $\log(TFPQ)$ demeaned by industry-specific averages. More specifically, it plots $\log(TFPR_{si}/\overline{TFPR}_s)$ and $\log(TFPQ_{si}/\overline{TFPQ}_s)$, 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.

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 US, 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 establishment 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 is then why have not the most productive firms expand their production to replace the less productive ones? A multitude of factors may have explained 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 friction-less environment, the marginal products of factors should be equalized across firms and this the dispersion of marginal products should be zero. Thus a dispersion in TFPR can be interpreted as an indicative of resource misallocation (Hsieh and Klenow, 2009). Following Hsieh and Klenow (2009), we estimate the dispersion of TFPR, which is 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 US. 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 U.S. (3.3). The results offers 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.

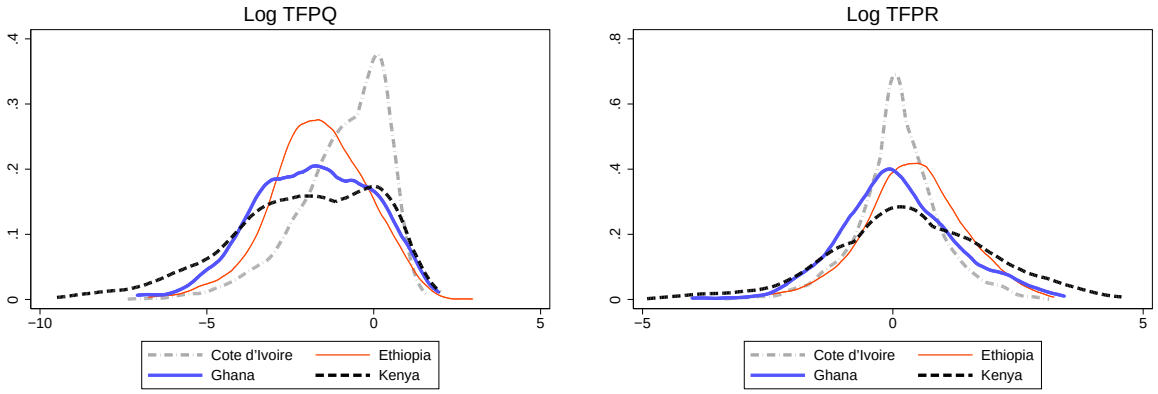


Figure 2: Distribution of TFPR and TFPQ

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	

Note: Log(TFPR) and Log(TFPQ) are demeaned by industry-specific average. 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.

6.2 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 4-digit industry. The results of this liberalization experiment is 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 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, 75.5 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 that gains that accrue to the United States from the reversal of its own profile of idiosyncratic distortions. While the underlying assumption when calibrating sectoral factor shares to US levels is that this is an undistorted economy, this is not exactly correct. As shown by Hsieh and Klenow (2009), the U.S. 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% respectively, while the case of Cote d' Ivoire becomes more puzzling, as we find this country to gain less from an efficient reallocation than the U.S. does.

Our results open up a fundamental question about the mapping between the degree of dispersion in 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 is in the U.S. 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 US. However, the gains are less than twice as high. Cote 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 U.S., despite the latter exhibiting a lower dispersion of distortions than the former.

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 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 et al. (2013) shows the same phenomena. For all of the Latin American countries in their sample, TFPR dispersion is significantly more pronounced relative to the US , yet the gains before netting the US gains would be on average even lower than what we find in our study for Sub-Saharan Africa [9].

Table 3: Potential TFP Gains from Equalizing TFPR

	TFP Gains	Relative to US
Cote d'Ivoire	31.4	-8.3
Ethiopia	66.6	16.4
Ghana	75.7	22.7
Kenya	162.6	83.4

Note: The relative TFPR gains is calculated by taking the ratio of TFP_{eff}/TFP to the U.S. ratio in 1997.

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 inter-sectoral linkages, we are abstracting from misallocation *across* 4-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

[9] see Busso et al. (2013) tables 3 and A1

objects of study in future research.

6.3 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.

Figure 3 non-parametrically 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.[10] The positive relationship between TFPR and TFPQ is quite consistent with most findings in the literature, especially in developing countries.

[10] Note that in a friction-less 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).

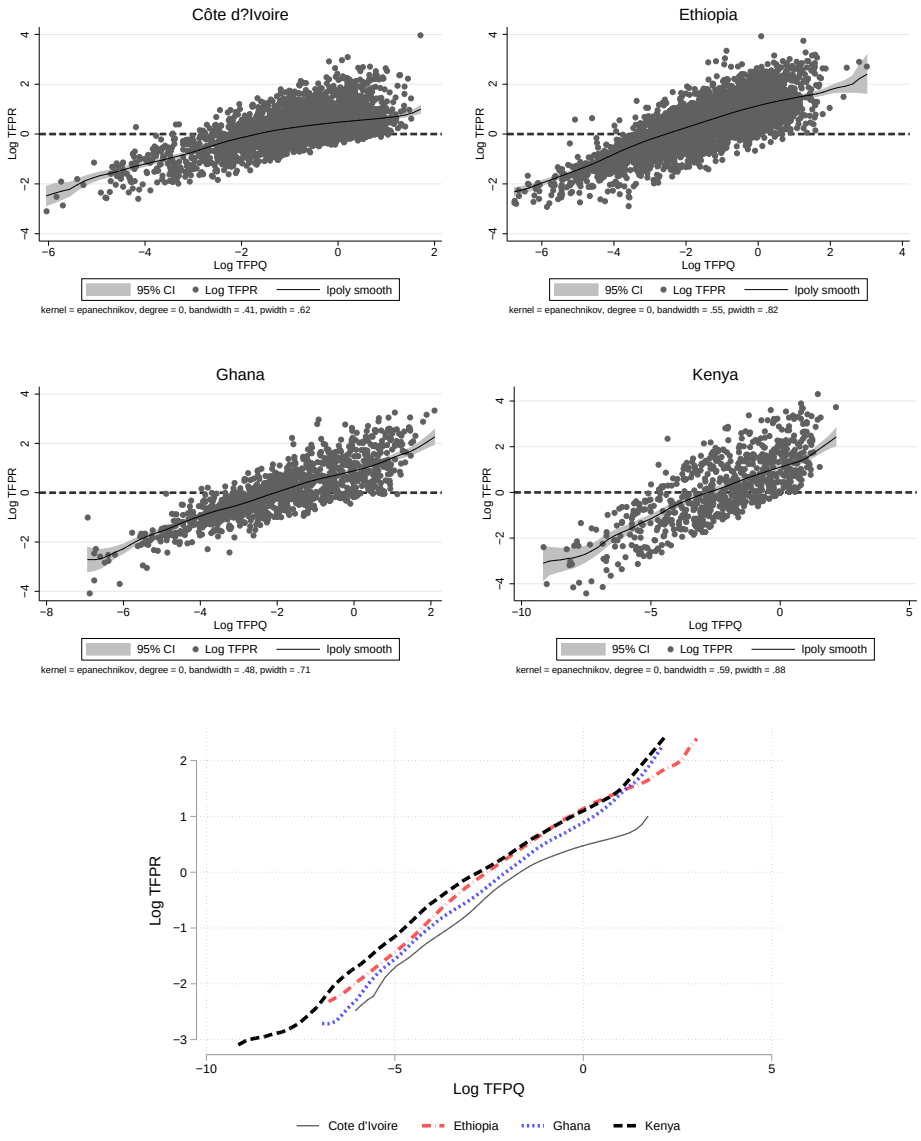


Figure 3: Log TFPR vs Log TFPQ

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 US manufacturing sector is 0.09 (Hsieh and Klenow, 2014). TFPR rises more steeply in our sample countries than in the US. The fact that these elasticities are significantly larger in our countries suggest 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 slowdown the growth of firms over their life cycle by discourage firms from investing in productivity enhancing technologies (Hsieh and Klenow, 2014; Bento and Restuccia, 2017). In the next section, we will examine whether this higher elasticities can play role in affecting life cycle productivity dynamics of firms in our sample countries.

In order to further understand the sources of distortions, it is instructive to decompose the overall distortion into its components: 'output' $\left(\frac{1}{1-\tau_{ysi}}\right)$ and 'capital' distortions $(1+\tau_{ksi})$. Figure 4 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 friction-less 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 to 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 productivity firms, albeit 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.

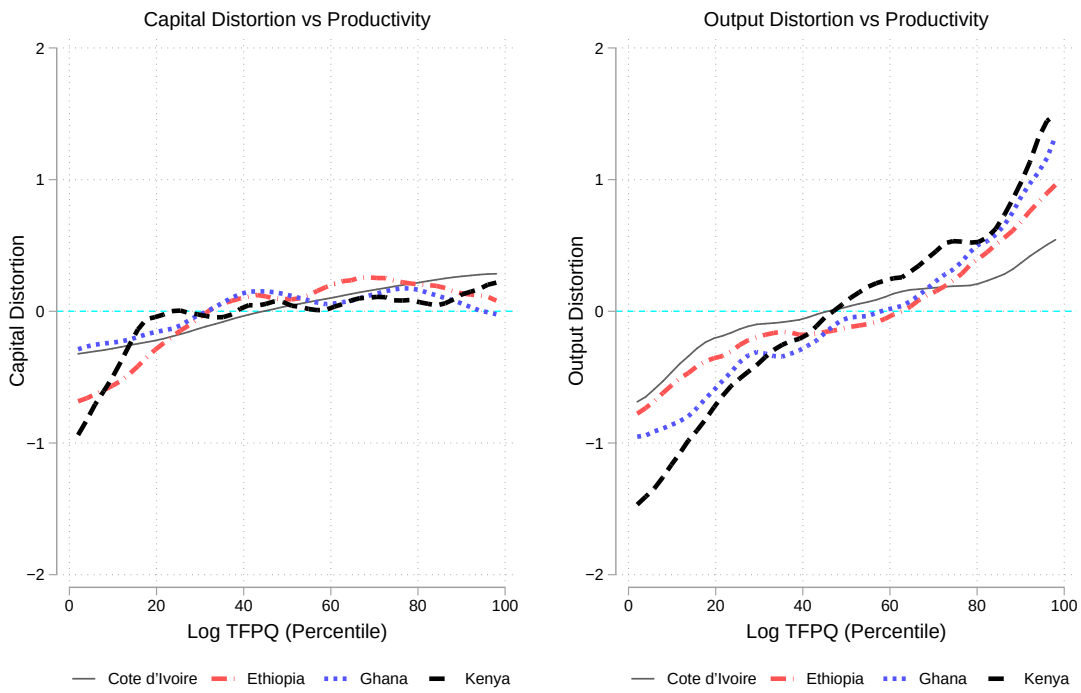


Figure 4: Distortions vs. Productivity

6.4 Productivity and Distortions Over the Life Cycle

Our analysis so far has focused on measuring the static effect of resource misallocation, but distortions are likely to also 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 a comprehensive manufacturing census data, they find that while firms in the US grow by a factor of eight by the age of forty, Mexican firms grow by a factor of two 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 magnify 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 age-size relationship hold for African countries under consideration? To what extent distortions explain the age-size and age-productivity pattern in our sample countries?

Before turning to address these questions, it would be informative to understand how the distribution of firms by age look like in our sample countries. Figure 5 plots the age distribution of firms by country. 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 Kenya. Another plausible explanation for this contrast may be due to differences in 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 because of the omission of large number of young firms operating in the informal sector in Kenya.[11]

[11] As we already noted, we do not consider firms in the informal sector.

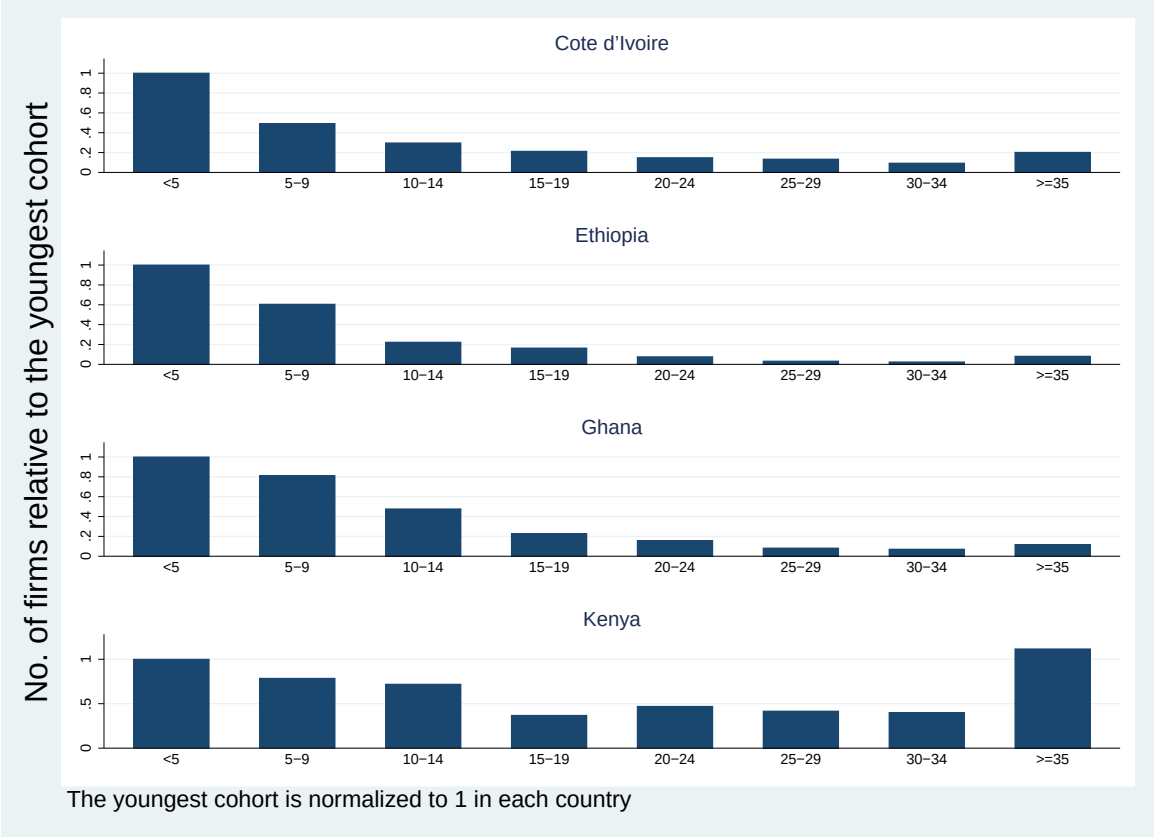
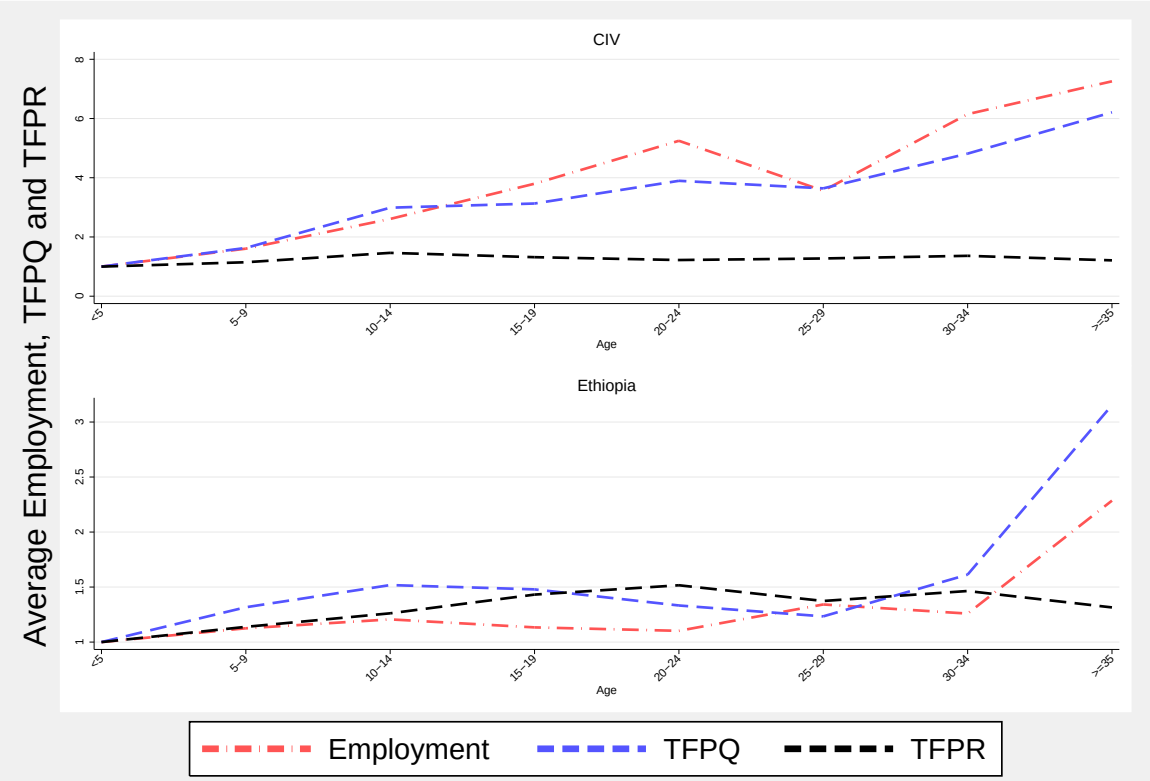


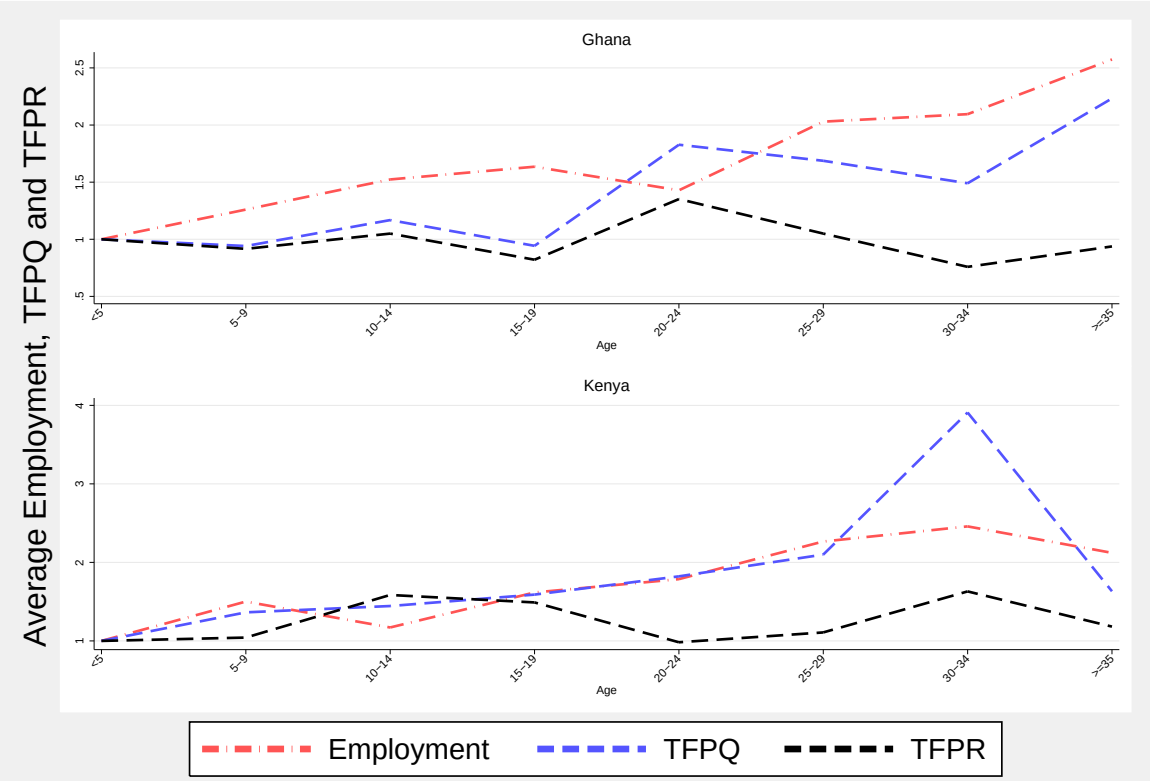
Figure 5: Number of Establishments by Birth Cohort

To understand whether firms become larger and improve their productivity as they age, Figure 6 presents the average employment and productivity of firms across different age cohorts.[12] The figure provides preliminary evidence that firms have experienced slow employment and productivity growth over their life cycle, albeit some differences across countries.

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



The youngest cohort is normalized to 1 in each country.



The youngest cohort is normalized to 1 in each country.

Figure 6: Employment, Productivity and Distortions over the Life Cycle.

We now turn to an investigation of how important distortions may be in explaining slow employment and productivity dynamics. The figures 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 friction-less economy. 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).[13]

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 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 was the era of moving towards market-oriented reforms. As shown in the figure, for Ethiopia and Ghana, the pattern before the reform (younger than 20 years) are somewhat different from the patterns after but the pattern in Kenya seems to be stable over the life cycle. Second, as emphasized in the literature on firm dynamics, the observed the 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 group of firms in a cross-section is may be crude measure since it does not account for differences between cohorts at birth with growth of a cohort over its life cycle. It is obviously of interest to reexamine this relationship using longitudinal firm-level data in Africa.

7 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

[13] 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 profile. Put differently, the observed size-age relationship may emerge because firms enter at much bigger size rather than grow as they age.

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 4-digit level in these countries, we use industrial weights from the Census. We find that when doing so, the ES depict 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.

7.1 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.[14] 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 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. 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 2-digit industries according to their contribution to value added, employment and number of establishments. The various combinations of these strata generate the cells at industrysizeregion 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 7 plots size quantiles in the ES against the quantiles based on manufacturing census data. [15] If the points in the plot more or less lie on the same line, then we expect the ES data to reflect the size distribution in the national censuses. Departures from this relationship

[14] The data are freely available from http://www.enterprisesurveys.org.

[15] 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

indicate that the firm size distribution in the two dataset are different.[16]

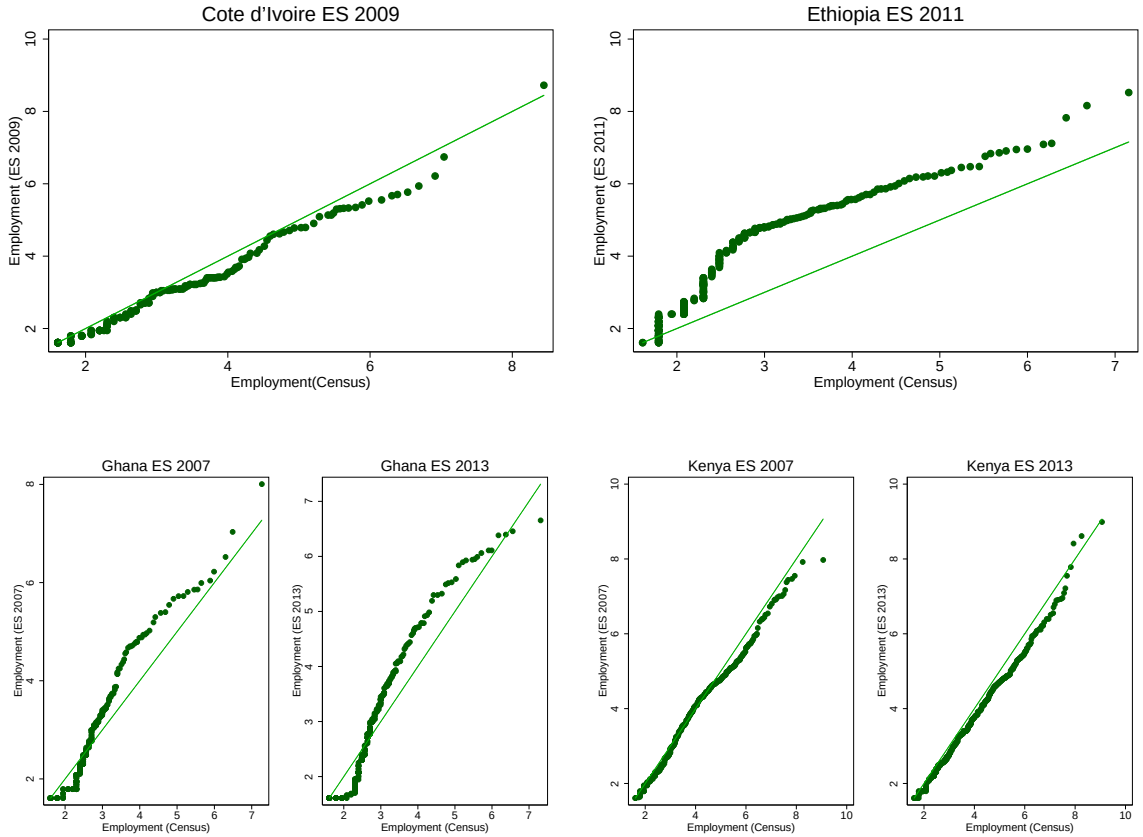


Figure 7: QQ plot of the enterprise censuses vs surveys

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 figure 7 plots size quantile in the 2009 ES for Côte d'Ivoire and 2011 ES for Ethiopia vis-a-vis 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 year 2007 and 2013 is plotted against the 2003 National Industrial Census of Ghana. A visual comparison shows a clear difference in firm size distribution between the two 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 distribution of firms in the two data sets 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

[16] Note that we choose not to use sampling weights as they are not appropriate to make this comparison since they are defined at broader strata.

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.

7.2 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, are informative about differences or similarities in the extent of misallocation in these economies when compared to the calculations based on the Census.[17]

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 build to ensure representativeness of in terms 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 aggregate sufficient statistics of misallocation and the aggregate counterfactual gains in productivity are all constructed based on 4-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 4-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 4-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.

[17] Note that Côte d'Ivoire and Ethiopia are excluded in this exercise due to the large number of missing capital information in the ES.

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			
N	150	169	150	169	249	258	249	258

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.

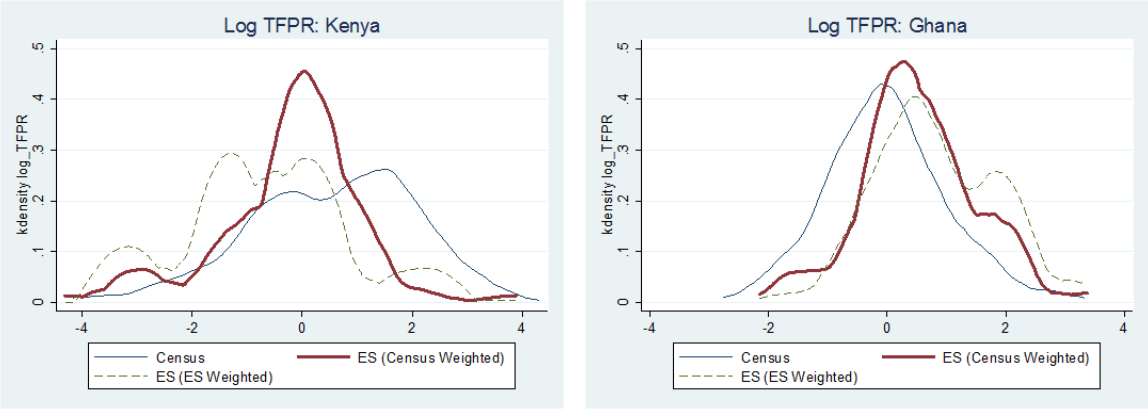


Figure 8: Distribution of TFPR: Census, ES with Census weights, and ES with survey Weights

We can see that when aggregating sectors using the census weights, which we view as the most plausible characterization of true structure of production, all magnitudes of dispersion are reduced relative to the magnitudes that result from the ESs own weights. A visual representation of the same conclusion can be observed in figure 8, which illustrates the distributions of TFPR from the ES with census weights, the ES with survey weights, and the Census.

Table 5: Potential TFP Gains with Different Industrial Weights

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

Note: The 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 ES. The last column shows the TFP gains across firms in the ES where industries are aggregated using the census 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 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 would be significantly muted compared to the gains based on the ESs own weights (column 3). The potential TFP gains would decrease from 146.6% to 54.3% in Ghana and 86.5% to 51.4% 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 a smaller TFP gains than the censuses (column 2 vs column 4): 71.1% vs 54.3% for Ghana and 184.2% vs 51.4% for Kenya. This suggests that even if industries in ES reflect their true value-added share in the total manufacturing, the ES yields smaller degree of misallocation compared to the census. This could reflect potential differences in the distribution of distortions and/or productivity within each sector.

7.3 Why does the ES Yield Lower Measured Misallocation?

We now turn to investigate why the ES yields different degree of misallocation than 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 10 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 explain why the TFP gains significantly fall 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 ensure cross-country comparison.

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

To explore the 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 Figure 10 shows, most industries have smaller TFPR in the ES compared with their dispersion in the census. This result suggest that the survey results can significantly underestimate the extent of misallocation in most sectors.

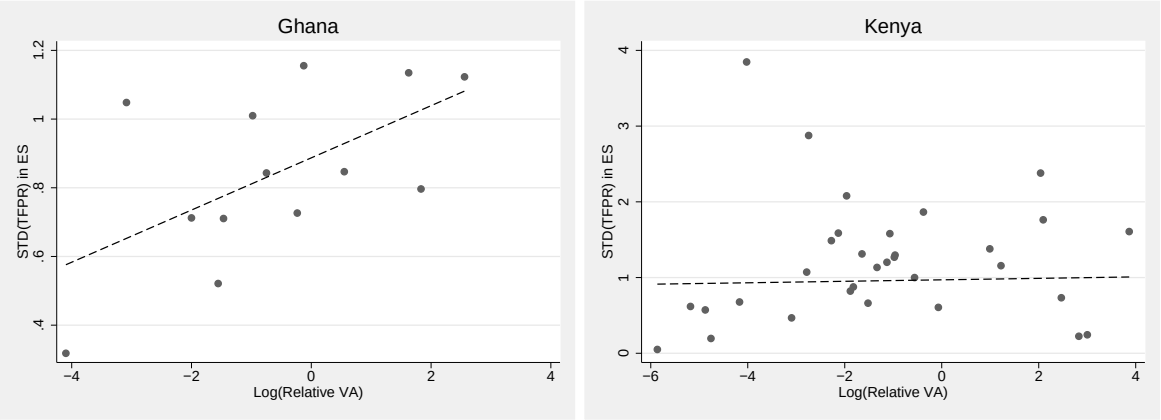


Figure 9: ES vs Manufacturing Censuses

Note: Relative VA refers to the logarithm of sector-specific value-added in ES relative to the the manufacturing censuses.

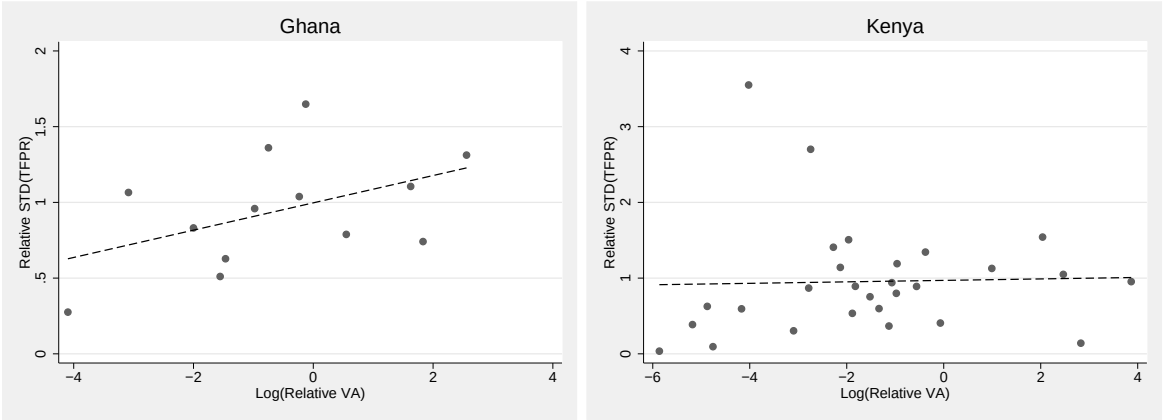


Figure 10: TFPR Dispersion: ES vs Census

Note: Relative VA refers to the logarithm of sector-specific value-added in ES relative to the the censuses, $log(VAintheES/VAintheCensus)$. Relative STD(TFPR) refers to the ratio of sector-specific dispersion in ES relative to the dispersion in the censuses, $STDofTFPRinES/STDofTFPRinCensus$)

To further illustrate this, we use an alternative dimension of misallocation - elasticity of distortion to productivity (regression coefficients). We clearly see from the figure 11 that the elasticity of TFPR to TFPQ is 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 weaker correlation between TFPR and TFPQ.

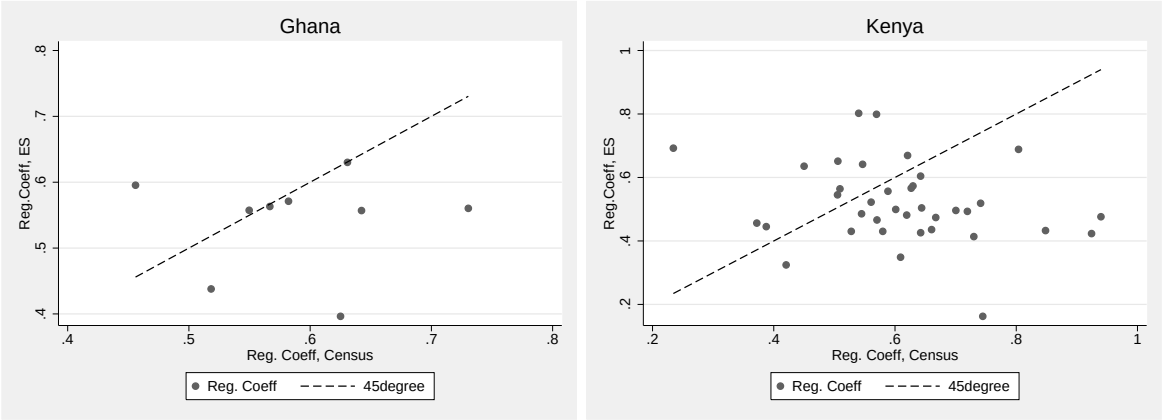


Figure 11: Regression Coefficient in ES vs Census

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 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 might understate the true misallocation in each sector, and hence manufacturing productivity. This highlights that using the survey data to do cross-country comparison without correcting these biases may be misleading (Inklaar et al., 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 the Ghana and Kenya generalize 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.

8 The role of Region and Industry Heterogeneity

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 is then: what are the underlying causes of these dispersion? 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.[18]

8.1 Cross-Region Variations

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

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

where ω_{istr} is the log of TFPR for establishment i located in region r in the s industry; $\overline{\omega_s}$ is the

[18] Measured misallocation may differ across industries and regions for a number of reasons.

mean of ω for industry s; and $\overline{\omega_{sr}}$ is the mean of ω in region r within industry s. The first term the right-hand side measures the within-region contributions to overall variance. The second terms captures the between-region contributions to overall variance.

Figure 12 presents the results of the decomposition. we find that the between-region component explains a relatively modest share of the variance in TFPR, accounting only 5% to 11% of overall dispersion. These findings suggest that a substantial portion of observed misallocation (within sectors) in our sample countries stems from within-region variation.[19]

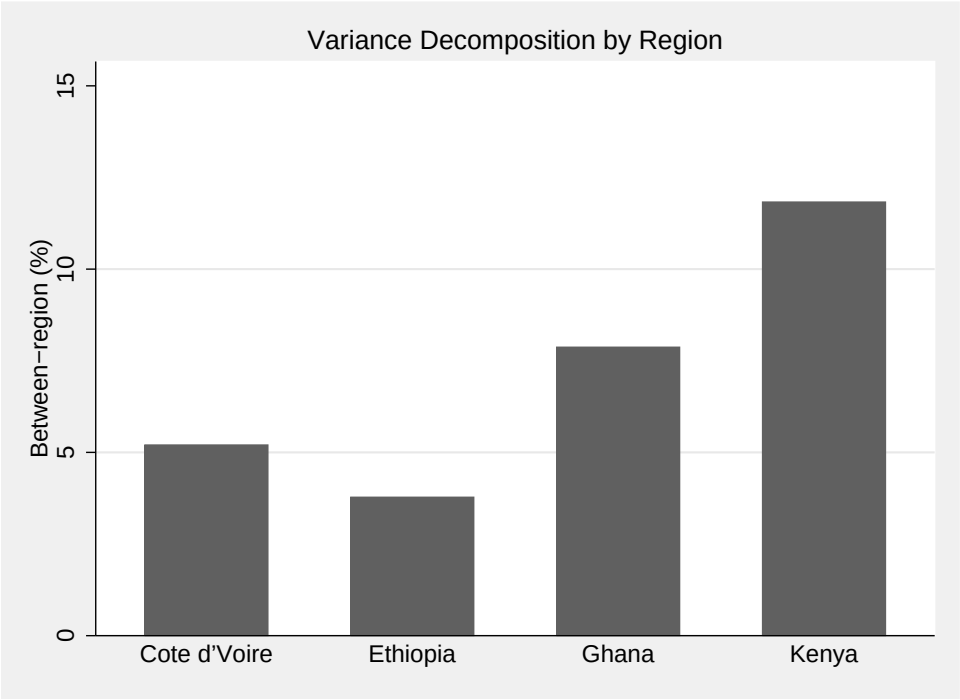


Figure 12: Decomposition of Overall TFPR by Region

8.2 Industry Heterogeneity

As noted above, our work focuses only on misallocation within narrowly defined industries.[20] Nonetheless, it would be informative to highlight whether 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 R2 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 plays an important role

[19] We group firms into two location: capital city and others. The within-region component remains large when we consider a narrower definitions of geographical areas.

[20] We do not consider the effects removing distortions across industries, that is, $\overline{TFPR}_s$ are not equalized across sectors s.

in explaining the overall TFPR dispersion.[21]

Table 6: Industry vs Region Factors: R2

	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

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 resource misallocation. More work is needed to capture the key differences across industries.

9 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 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 wage bill. The reallocation gains would be modestly larger in Côte d'Ivoire (33.2 vs 31.4), Ethiopia (77.9 vs. 66.6) and Kenya (170.6 vs. 162.6) but smaller in Ghana (66.9 vs. 75.7). This reflects 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 U.S. One may argue that the characteristics of the U.S industries can be different from those in SSA countries, due to the differences in technology and other factors. As a robustness check, we

[21] The difference in measured misallocation across sectors suggests that equalizing $\overline{TFPR}_s$ across sectors may lead to even larger effect on aggregate TFP.

recalculate the potential TFP gains under two different assumptions of α_s. First, we set $\alpha_s = 1/3$ for all sub-sectors 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 US, 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.

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 % tails of TFPR and TFPQ. The potential gains from reallocation decrease from 31.4% to 25.8% in Côte d'Ivoire, 75.7% to 56.1% in Ghana and from 162.6 % to 120.6 % in Kenya but remains unchanged in Ethiopia. The large drop in the TFP gains in Kenya (by about 40%) after trimming the 2% outliers highlights that large gains can be obtained through reallocation resources from the least productive establishments to the most productive ones.

Size threshold In our benchmark analysis, we include all establishments regardless of their size. Although the all 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 the other censuses in covering the smallest establishments. To examine the extent to which this finding is an artifact of the Kenyan data set that has sparse coverage of small firms, as a robustness check, we redo the analysis by excluding establishments employing less than 10 workers. The result shows that the potential gains from reallocation decreases in all countries (29.4% vs. 31.4%) in Côte d'Ivoire, (60.9% vs. 66.6%) in Ethiopia, (66.9% vs. 75.7%) in Ghana and (141.5% vs. 162.6%) in Kenya, implying that part of the gains from reallocation comes from small establishments. However, the qualitative result remains unchanged.[22]

Table 7: Sensitivity Analysis: Potential Gains from Equalizing TFPR

	Baseline	σ=5	Trim 2%	L > 10	WL=L	$\alpha_s = 1/3$	Country $\alpha_s' s$
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

Overall, the sensitivity analysis clearly shows that the finding that measured misallocation is the

[22] 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.

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 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 et al. (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.[23] We find the cross-sectional covariance between firm size and productivity to be 0.04 Côte d'Ivoire, -0.04 for Ethiopia, -0.05 for Ghana, and -0.01 for Kenya. As in Bartelsman et al. (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 OP results are not directly comparable, both measures point to high degree of misallocation in our sample countries.[24]

10 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% to 44.7% in Côte d'Ivoire, 66.6% – 82.0% in Ethiopia, 75.7% – 85.1% in Ghana, and 162.6% – 194.6% 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.

Our analysis has abstracted from several factors which may be worth exploring further. First,

[23] Bartelsman et al. (2013) document that the within-industry covariance between firm size and productivity vary considerably across countries and it is systematically related to the level of development across space and time. They found a stronger covariance between firm size and productivity in the U.S than in Western European and more pronounced in Eastern European countries.

[24] HK and the OP covaraince provide a consistent result at industry level, although the relationship is not linear.

our analysis covers firms in the manufacturing sector, ignoring non-manufacturing sectors. Distortions affecting firms only in the manufacturing sector may have potential economy-wide implications though backward and forward linkages (Jones, 2011). An interesting area for future research is to assess the extent of misallocation in a multi-sector framework by accounting all the potential linkages between sectors. Second, our analysis present an interesting cross-sectional relationship between misallocation and manufacturing productivity. In future work, it will be important to explore the link between misallocation and firm dynamics using panel data in Africa.

References

Ackah, C., Adjasi, C., and Turkson, F. (2014). Scoping study on the evolution of industry in ghana. Technical report, WIDER Working Paper.

Adamopoulos, T., Brandt, L., Leight, J., and Restuccia, D. (2017). Misallocation, selection and productivity: A quantitative analysis with panel data from china. Technical report, National Bureau of Economic Research.

Altenburg, T. (2010). Industrial policy in ethiopia.

Aterido, R., Hallward-Driemeier, M., and Pagés, C. (2011). Big constraints to small firms growth? business environment and employment growth across firms. *Economic Development and Cultural Change*, 59(3):609–647.

Bartelsman, E., Haltiwanger, J., and Scarpetta, S. (2013). Cross-country differences in productivity: The role of allocation and selection. *American Economic Review*, 103(1):305–34.

Bento, P. and Restuccia, D. (2017). Misallocation, establishment size, and productivity. *American Economic Journal: Macroeconomics*, 9(3):267–303.

Brownbridge, M. and Gockel, A. F. (1996). *The impact of financial sector policies on banking in Ghana*. Institute of Development Studies.

Busso, M., Madrigal, L., et al. (2013). Productivity and resource misallocation in latin america. *The BE Journal of Macroeconomics*, 13(1):903–932.

Camacho, A. and Conover, E. (2010). Misallocation and productivity in colombias manufacturing industries.

Chege, J., Ngui, D., and Kimuyu, P. (2014). Scoping paper on kenyan manufacturing. Technical report, WIDER Working Paper.

Chen, C. (2017). Untitled land, occupational choice, and agricultural productivity. *American Economic Journal: Macroeconomics*, 9(4):91–121.

Chen, C., Restuccia, D., and Santaeullia-Llopis, R. (2017). The effects of land markets on resource allocation and agricultural productivity. Working Paper 24034, National Bureau of Economic Research.

Da-Rocha, J.-M., Tavares, M. M., and Restuccia, D. (2017). Policy distortions and aggregate productivity with endogenous establishment-level productivity. Technical report, National Bureau of Economic Research.

Gebreeyesus, M. (2013). Industrial policy and development in ethiopia: Evolution and present experimentation. Technical report, WIDER Working Paper.

Gustavo, M. C. and Cristobal, B. J. (2012). Misallocation and manufacturing tfp in bolivia during the market liberalization period. *The B.E. Journal of Macroeconomics*, 12(1):1–45.

Harrison, A. E. (1994). Productivity, imperfect competition and trade reform: Theory and evidence. *Journal of international Economics*, 36(1-2):53–73.

Hopenhayn, H. A. (1992). Entry, exit, and firm dynamics in long run equilibrium. *Econometrica*, pages 1127–1150.

Hsieh, C.-T. and Klenow, P. J. (2009). Misallocation and manufacturing tfp in china and india. *The Quarterly Journal of Economics*, 124(4):1403–1448.

Hsieh, C.-T. and Klenow, P. J. (2014). The life cycle of plants in india and mexico. *The Quarterly Journal of Economics*, 129:1035–1084.

Inklaar, R., Lashitew, A. A., and Timmer, M. P. (2017). The role of resource misallocation in cross-country differences in manufacturing productivity. *Macroeconomic Dynamics*, 21(3):733–756.

Jones, C. I. (2011). Misallocation, economic growth, and input-output economics. NBER Working Papers 16742, National Bureau of Economic Research, Inc.

Kalemli-Ozcan, S. and Sorensen, B. E. (2012). Misallocation, property rights, and access to finance: Evidence from within and across africa. Working Paper 18030, National Bureau of Economic Research.

Krakah, T., Rankin, N., and Teal, F. (2014). Report on the 1987 and 2003 industrial censuses in ghana.

La Porta, R. and Shleifer, A. (2008). The unofficial economy and economic development. *Brookings Papers on Economic Activity*, 2008(2):275–363.

McCaig, B. and Pavcnik, N. (2014). Export markets and labor allocation in a low-income country. Technical report, National Bureau of Economic Research.

McCaig, B. and Pavcnik, N. (2015). Informal employment in a growing and globalizing low-income country. *The American Economic Review*, 105(5):545–550.

McCaig, B. and Pavcnik, N. (2016). Out with the old and unproductive, in with the new and similarly unproductive: Microenterprise dynamics in a growing low–income economy.

Melitz, M. J. (2003). The impact of trade on intra-industry reallocations and aggregate industry productivity. *Econometrica*, 71(6):1695–1725.

Oberfield, E. (2013). Productivity and misallocation during a crisis: Evidence from the chilean crisis of 1982. *Review of Economic Dynamics*, 16(1):100–119.

Restuccia, D. and Rogerson, R. (2008). Policy distortions and aggregate productivity with heterogeneous establishments. *Review of Economic Dynamics*, 11(4):707–720.

Restuccia, D. and Rogerson, R. (2017). The Causes and Costs of Misallocation. *Journal of Economic Perspectives*, 31(3):151–174.

Restuccia, D. and Santaeulalia-Llopis, R. (2017). Land misallocation and productivity. Technical report, National Bureau of Economic Research.

Sandefur, J. (2010). On the evolution of the firm size distribution in an african economy.

Van Biesebroeck, J. (2005). Firm size matters: Growth and productivity growth in african manufacturing. *Economic Development and Cultural Change*, 53(3):545–583.

Vollrath, D. (2014). The efficiency of human capital allocations in developing countries. *Journal of Development Economics*, 108:106–118.

White, T. K., Reiter, J. P., and Petrin, A. (2016). Imputation in us manufacturing data and its implications for productivity dispersion. Technical report, National Bureau of Economic Research.

World Bank (2015). *Côte d'Ivoire: From Crisis to Sustained Growth Priorities for Ending Poverty and Boosting Shared Prosperity.* The World Bank.

APPENDIX

A Data Appendix

Cross-country comparisons of measured misallocation requires having comprehensive and comparable firm-level data sets. A considerable effort has been made to clean and harmonize the data sets to ensure cross-country comparisons. This appendix describes in more detail about the data sets and highlights important caveats.

A.1 Data Cleaning

Measured misallocation is sensitive to how the data is cleaned. The data for all countries have cleaned in a similar fashion. We clean the data sets in the following steps.

Internal Quality Checks As with most firm-level dataset, our data contain observations that have misreported values. Accordingly, we clean the data for these basic reporting mistakes. More specifically, we drop establishments if capital, payments to labor, or value added, are either non-positive or missing.

Second, we check the internal consistency of the data by comparing the sum of variables belonging to some aggregate to their respective aggregate. For example, the total sales reported by a particular establishment must equal to the sum of the components.

Treatment of outliers As discussed in the main text, the extent of measured misallocation is sensitive to how the tails are handled. We followed a common methodology to deal with the outliers: trimming the top and bottom 1 % tails of TFPR and TFPQ.

Harmonizing variables The analysis also requires harmonizing the key definitions and concepts across countries. The firm-level data of the four countries underlying our analysis cover registered establishments in the manufacturing sector and include the key variables needed for the analysis output, employment, materials, and capital inputs. In each census, labor is defined as the total number of persons engaged - paid and unpaid workers (with no correction for hours worked.).[25] The definition of labor cost includes wages and salaries of workers as well as other benefits. The capital input is defined as a book value of fixed assets. Value added is defined as the difference between the value of production minus cost of raw materials and energy and purchase of services.

Industry classification Special efforts have been made to organize the data along a common industry classification (ISIC Rev.3). In Ethiopia and Ghana firms are categorized in the industry according

[25] Note that unpaid workers account for a large portion of manufacturing employment in SSA in general and in our sample countries in particular.

to the four-digit ISIC Rev 3 classification. In Kenya, industries are defined at four-digit ISIC Rev 4 classification. Industries were converted to ISIC 3 using the United Nations Statistical Division (UNSD) industry concordance table. Since there is no one-to-one mapping between industries in the official correspondence table, we assign industries manually by reading the industry descriptions when the mapping is one-to-many.

The industry classification for Côte d'Ivoire is based on the Harmonized Nomenclature of Activities for Afristat member states (NAEMA), which came into force in Afristat's member states in January 2001. NAEMA follows ISIC by following 17 sections (one-digit level), 60 divisions (two-digit level), and 149 groups (three-digit level). Compared to the ISIC, NAEMA has a broader classes in the primary sector and a smaller classes for manufacturing activities given that the Afristat member countries are characterized by a significant share of the primary sector and little industrial activities. Since NAEMA-ISIC conversion is a many-to-many mapping, we derive our own concordance by reading the industry descriptions.

A.2 Caveats

Despite our efforts to harmonize the data and high quality of the census data we use, there are some important caveats that should be considered when interpreting our results.

Unregistered firms

One important caveat is that our data cover only registered (formal) firms, and exclude unregistered (informal) firms, which make up a large portion of employment and businesses in low-income countries. Since informal firms are often found to be substantially less productive than their formal sector counterparts (La Porta and Shleifer, 2008), we are missing a potentially important source of misallocation.[26]

The size of the informal sector may vary across our sample countries due to many reasons such as costs of entry, quality of institutions - corruption, rule of law, and regulatory burden - etc. This may affect the cross-country comparison of size of distribution of firms in the formal sector. Presumably, the effects of the omission of unregistered firms are more serious in Kenya as the Kenyan firms are on average, larger and older than those in the other sample countries. Figure A1 compares the size distribution of firms using the 2016 Micro, Small and Medium Establishment (MSME) Survey, which is a nationally representative sample of registered and unregistered businesses identified and interviewed from the households in Kenya. The figure shows that unregistered firms are smaller than registered

[26] A recent paper by McCaig and Pavcnik (2014) document that export opportunities led to an increase in aggregate productivity in Vietnam through the reallocation of labor from household business to employers in the formal enterprise sectors.

ones. Omitting the unregistered firms may bias the implied TFP gain downward. However, without production data on unregistered firms it is not possible to be conclusive. While this is an important limitation of our paper and most work is needed to fully include informal firms in the misallocation exercise, our work is a significant advance in relation to other studies that use sample-based surveys.

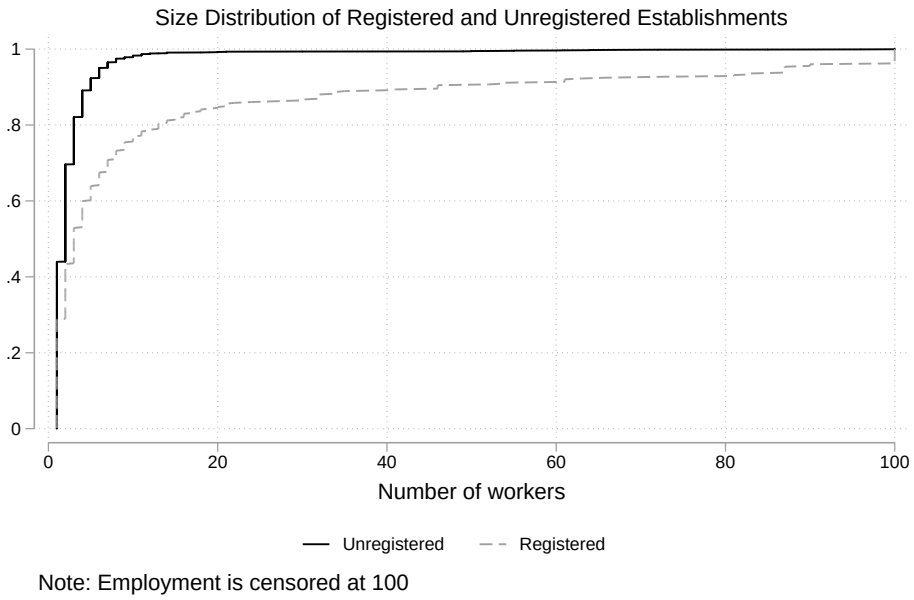


Figure A1: Size Distribution of Registered vs Unregistered Establishments in Kenya

In addition, although the coverage of all registered establishments irrespective of size was the objective of all the census data in all countries, the data also suffer from non-response problem. For example, although the Kenyan Census targeted all registered establishments irrespective of their size, the response rate was 82 per cent in terms of establishments and 95% in terms of gross output.

Sample Selection

Another issue with the data is the presence of large number of non-positive and missing data. In the analysis, firms are dropped if capital, payments to labor, or value added, are either non-positive or missing, leading to a significant reduction of the sample size. This is particularly sizable in the Kenyan census with about 42 percent of firms reporting either non-zero or missing capital stock. This could potentially generate a selection bias if establishments with missing capital information are systematically different from those with complete data.

To assess whether sample selection due to missing data affects our results, we performed two consistency checks. A first way of trying to gauge the importance of this concern, is to look at whether

and how of missing capital information is correlated to particular establishment characteristics, such as firm size (measured by value added) and age. To this end, we estimate a linear probability model where the dependent variable is an indicator for establishment with missing capital information. Results reported in Table A1 suggest that the missing capital information is not significantly correlated with establishment size and age. This suggests that ignoring missing capital information may not severely affect our results.

Another way to gauge whether the missing capital information is driving our results is to compare labor productivity dispersion instead of TFPR, which allows us to increase increases the number of observations significantly. We find that misallocation - measured by dispersion in revenue labor productivity - is still the highest in Kenya. The standard deviation of revenue labor productivity are 1.66 in Kenya, 1.58 in Ghana, 1.23 in Ethiopia, and 1.13 in Côte d'Ivoire. Although the LPR and TFPR results are not directly comparable, the result suggests that our results are not likely to be driven by selection due missing capital information.

Table A1: Probability of missing capital

	(1) Missing K	(2) Missing K
Size (Value Added)	-0.009	
	(0.009)	
lnAge		0.017
		(0.025)
R^2	0.002	0.002

A common practice in the literature to correct the biases cause by missing data is imputation. While imputation can partly address the missing data problem, it does so at the expense of introducing new errors. As described in (White et al., 2016), data imputation might understate measured misallocation. We eschew this approach in light of these concerns.

While these caveats should be borne in mind when interpreting our results, we believe that the findings nonetheless provide important new evidence on the extent of misallocation in the region.

Table A2: Data Sources.

Country	**Provider**	**Size Threshold**	**# Observations**
Côte d'Ivoire	National Statistics Institute (INS): Registrar of Companies for the modern enterprise sectors.	*Census* of all registered firms.	Raw data: 6,746

Continued on next page

Table A2 – continued from previous page

Country	Provider and Survey Type	Size Cutoff	Observations/Year
Ethiopia	Central Statistical Agency (CSA): Large and Medium Scale Manufacturing and Electricity Industries Survey	*Census* of firms employing more than 10 workers.	Raw data: 1,936
	Central Statistical Agency (CSA): Small-Scale Manufacturing Industries Survey	Survey of firms employing less than 10 workers and use power-driven machinery.	Raw data: 3,882
Ghana	Ghanaian Statistical Service (GSS). National Industrial Census	Census of more than 10 workers and representative sample of establishments engaging less than 10 workers. Raw data: 3,302	
Kenya	Kenya National Bureau of Statistics (KNBS)- Census of Industrial Sector.	Census of all formal firms.	Raw data: 2,089