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Taxing the Good?

Distortions, Misallocation, and Productivity in Sub-Saharan Africa

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Abstract

This paper uses comprehensive and comparable firm-level manufacturing census data from four Sub-Saharan African countries to examine the extent, costs, and nature of within-industry resource misallocation across heterogeneous firms. The paper finds evidence of severe misallocation in which resources are diverted away from high-productivity firms toward low-productivity ones in all four countries, although the magnitude differs across countries. The paper shows that a hypothetical reallocation of resources that equalizes marginal returns across firms would increase manufacturing productivity by 31.4 percent in Côte d'Ivoire and as much as 162.7 percent in Kenya. The paper emphasizes the importance of the quality of the underlying data, by comparing the results against those from the World Bank Enterprise Surveys. The comparison finds that the survey-based results underestimate the extent of misallocation vis-a-vis the census. Finally, the paper finds that the size of existing distortions is correlated with various measures of business environment, such as lack of access to finance, corruption, and regulations.

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

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1 Introduction

One of the most enduring challenges in the field of economic growth and development is to understand the sources of the large variation in economic well-being across countries. The current consensus in the literature is that even though cross-country differences in physical and human capital stocks are important factors explaining development gaps, aggregate productivity remains the predominant source. In this paper, we provide a systematic study of one of the most promising avenues for accounting for total factor productivity (TFP) gaps, those stemming from an inefficient allocation of resources across firms in one of the poorest yet least explored regions in the world: Sub-Saharan Africa (SSA). Combining novel census-based firm-level manufacturing databases with a structural theory of misallocation, the paper provides a characterization of the degree and nature of resource misallocation as well as a quantification of the productivity losses associated with these inefficiencies in Côte d'Ivoire, Ethiopia, Ghana, and Kenya.

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 in the deviation from the efficient allocation and investigate the correlation between these deviations with idiosyncratic characteristics of the firms, such us their physical productivity and their age. We then undertake a counterfactual exercise to quantify the aggregate manufacturing TFP gains that would result from a reversal of these distortions and a reallocation of resources in accordance with the output maximizing rule.

We find evidence of large within-industry misallocation of resources in the four countries that we study, with Kenya exhibiting the largest idiosyncratic distortions, followed by Ghana, Ethiopia, and Côte d'Ivoire. As points of reference, the degree of misallocation measured by the dispersion in revenue total factor productivity (TFPR) is on average larger than in India and China, and is similar to those of the worst performing countries in Latin America in terms of allocative efficiency, such as the República Bolivariana de Venezuela and Colombia.[1] Besides significant dispersion, we find a tight correlation between the distribution of distortions, TFPR, and the distribution of physical productivities across firms, TFPQ. Controlling for other firm characteristics, we estimate a regression coefficient for the relationship between the logarithm of TFPR and the logarithm of TFPQ to be between 0.42 and 0.53. This statistic is an important determinant of the extent to which the estimated distribution of distortions creates a decline in aggregate productivity in the economy. As shown in Restuccia and Rogerson (2008), when resources are diverted away from high productivity firms to relatively unproductive ones, distortions carry a larger drag on TFP. Our estimate shows that such perverse misallocation, the one "taxing the good", is evident in the four economies that we study.

Taken together, these findings imply that, the distortion 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

[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).

higher by at least 31 % in Côte d'Ivoire, 67% in Ethiopia, 76% in Ghana, and 162% in Kenya.

Even though the method utilized to measure misallocation is fairly straightforward to apply, we highlight the biases that can be incurred in the interpretation of the results from limitations in the underlying datasets. To emphasize this point, we compare our results, obtained from Census-based datasets, with those obtained from an alternative and readily available source, the World Bank's Enterprise Surveys (ES). We start assessing the accuracy of the ES in terms of capturing the features of the size distribution of firms relative to the Censuses. We show that except in Kenya, where the sample in the ES is taken straight from the Census, the size distribution in Côte d'Ivoire's, Ghana's and Ethiopia's ES diverges from their census-based counterparts. In particular, the pattern is that the ES overestimates the size of the highest percentiles in the firm size distribution. We then evaluate the implication of this bias for the resulting measures of misallocation and the counterfactual gains in productivity from its reversal. When weighting sectors according to sectoral value added shares in the Census, we find that the degree of 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 the results.

As a first step in an attempt to connect the observed misallocation to concrete policies and distortions, we explore two additional dimensions of the distribution of distortions: its decomposition into capital/labor ratio wedges and revenue wedges, and its evolution over the firm's life cycle.[2] The first dimension is informative to identify whether it is the policies affecting the functioning of financial and labor markets that are a more binding constraint for the economy, or if it is the case that policies affecting capital and labor equally, such as monopoly power and other product market frictions, are more prevalent. We find that output distortions are more strongly correlated with firms' physical productivities than capital-labor ratio distortions and, thus, are relatively more important in accounting for that total gains from efficient reallocation. In terms of the firms' life-cycle pattern of growth and the role distortions play in shaping it, we find the growth of employment over time, conditional on survival, is remarkably flat. This is consistent with evidence documented by Hsieh and Klenow (2014) for India and Mexico. 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.

We conclude the paper with an econometric exercise aimed at further tightening the connection between observed misallocation and actual policies and distortions that increase the cost of doing business. Appealing to quantitative measures of the quality of the business environment captured in the World Bank's Enterprise Surveys, such as accessibility to credit or fees and payments to government officials; and exploiting sub-national variation of these costs, we find suggestive evidence that some of these business environment indicators have a significant correlation with the observed distortions that we find in the data. Nonetheless, the lack of variation in the data at the level of the firm as well as many potential confounding factors in the identification raise a word of caution in interpreting the size and direction of our results. Our view, which is shared by similar attempts at connecting distortions to

[2]To clarify the distinction between capital/labor and revenue wedges, the former refers to distortions that interfere with the optimal capital to labor ratio in the firm, while the latter refers to distortions that affect the entire scale of operation of the firm without disrupting the ratio of capital to labor.

policies in the literature, is that although we do not have sufficient variation in the data to accurately identify causality, the significant correlation that exists suggests that costs of doing business are likely to play an important role in explaining misallocation in these countries.

2 Related Literature

This study is related to a recent literature focusing on the importance of within-industry resource misallocation in explaining cross-country productivity difference. At the macro level, the relative importance of technology in explaining productivity difference has been a subject of much research. A key assumption in much of this literature is that firms face a common technology in their production, assuming away firm-level productivity differences. The assumption of identical firms is not a plausible reflection of economic reality, as empirical evidence has shown that firms differ substantially in their productivity even within a narrowly defined industrial group and such productivity differences are found to be more pronounced in developing countries than in advanced economies.

Motivated by these empirical facts, recent research has started to link heterogeneity in firm performance within sectors to cross-country productivity gap at the macro level. Restuccia and Rogerson (2008) provide the first framework to examine the aggregate productivity effects of resource misallocation in a standard neoclassical growth model with heterogeneous firms in the spirit of Melitz (2003). More specifically, they consider distortions that generate a wedge in the prices faced by *individual firms* but leave the aggregate relative prices and aggregate capital accumulation unchanged. Restuccia and Rogerson (2008) termed these policies as *idiosyncratic distortions* to stress that frictions are firm-specific. They emphasize that the productivity losses due to misalloction would be even more sizable if the distortions are positively correlated with the level of productivity of firms. This is what Restuccia and Rogerson (2008) referred to as *"correlated idiosyncratic distortions"*.

Drawing on the seminal work of Restuccia and Rogerson (2008), a growing number of studies have quantified the extent and costs of within-industry resource misallocations generated by idiosyncratic distortions using various approaches. Hsieh and Klenow (2009) provide the first empirical approach to measure misallocation across firms within 4-digit industry groups in China and India. The underlying assumption behind this approach is that if input and output markets are functioning well, the marginal revenue products of inputs should be equal across firms. Thus the difference in marginal value of inputs across firms indicates the presence of distortions that prevent the efficient allocation of resources in an industry, resulting in aggregate productivity losses. 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, and Kalemli-Ozcan and Sorensen (2012) for African countries.

Bartelsman et al. (2013) propose an alternative methodology by looking at the covariance between within-industry firm-level productivity and firm-size. This approach relies on the assumption 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. They document that the within-industry covariance between firm size and productivity varies considerably across countries and

it is systematically related to the level of development across space and time. More precisely, they found a stronger covariance between firm size and productivity in the United States than in Western European and more pronouncedly in Eastern European countries.

While the preceding papers have all focused on measuring the extent and cost of misallocation without knowing a particular policy/institution that may have caused such frictions, a number of recent papers have explicitly studied the consequences of specific policies or institutions. The theoretical contributions include: size-dependent policies (Guner et al., 2008; García-Santana and Pijoan-Mas, 2014), credit-market imperfections (Midrigan and Xu, 2014), trade-related distortions (Melitz, 2003), capital-adjustment costs (Asker et al., 2014) and imperfect-information (David et al., 2014). Restuccia and Rogerson (2013) provide a good summary of this literature.

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. Hsieh and Klenow (2014) for instance, estimate that if U.S. firms exhibited the same dynamics as Indian or Mexican firms, aggregate manufacturing TFP would be roughly 25% lower.

There is a relatively smaller body of work that focuses on exploring misallocation and distortions in the business environment for firms in 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.

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. We remove this limitation assembling comprehensive and comparable data on manufacturing form in four countries. 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 the misrepresentation of sectors in the ES leads to lower degrees of measured misallocation and subdued gains from reallocation than what you would otherwise estimate from the census data.

3 Background

We motivate our study reviewing features of the structure of production and the magnitude of the development gaps that characterize the economies of Côte d'Ivoire, Ethiopia, Ghana, and Kenya. 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 Cote 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 percentage in Ghana is about 5.1 percent, but still roughly half of Kenya's and Côte d'Ivoire's.

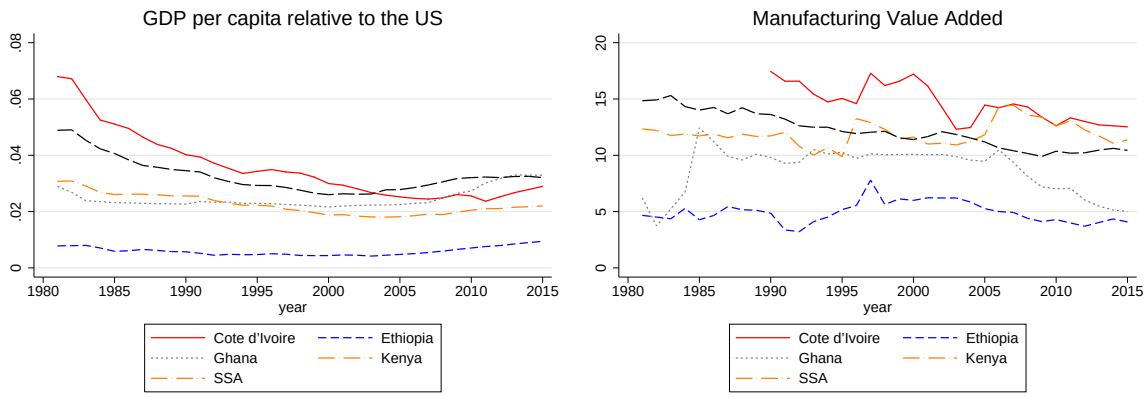


Figure 1: GDP per capita and Manufacturing Value Added (percentage of GDP)

One concern that may arise from looking at the right 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 should be a subject 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 Kenya and 67 in Côte d'Ivoire, it is only 30 in Ethiopia and 29 in Ghana. The distribution of firm size in all countries is skewed to the left with the median firm in Kenya employing 34 workers while the corresponding figures in Côte d'Ivoire, Ethiopia and Ghana are only 9, 8 and 12 workers, respectively. Figure 2 clearly shows that the size distribution of firms in Kenya looks different from the distribution in the other countries.[3]

Table 1: Size Distribution of Firms

	Cote 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. Each census covers all formal manufacturing firms in the respective countries.

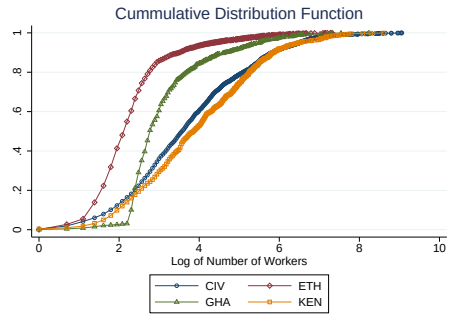


Figure 2: Commutative Density Function (Log Number of Workers)

Notice, too, that re-weighting observations for small firms according to the weights provided by the

[3]Since there is no alternative data source, we are not able to verify if this is an the quality of Kenyan data. Nevertheless, the size distribution of firms in Kenya looks similar to Uruguay and the República Bolivariana de Venezuela (Busso et al., 2013).

national statistical offices of Ethiopia and Ghana reduces the average firm size even further, to 9 and 8 workers respectively.

3.3 Policy and Institutions

In this sub-section we present the institutional and macroeconomic environment within which firms operate in the four countries 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). Ethiopia has also experienced a socialist military regime (1974 to 1991), in which the manufacturing sector was largely dominated by state-owned enterprises (SOEs) with SOEs accounting for 95 percent of the value added and 93 percent of the employment of the manufacturing sector in the country (Gebreeyesus, 2013). 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 grew 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 terms 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 the accounting framework outlined in Hsieh and Klenow (2009, HK hereafter). This section provides a brief outline of this framework.

A final output Y is produced in each country using a Cobb-Douglas production technology:

$$Y = \prod_{s=1}^{S} Y_s^{\theta_s} \text{ with } \sum_{s=1}^{S} \theta_s = 1 \tag{1}$$

where θ_s is the value added share of sector s, and S is the number of sectors in each country.

Each sector's output Y_s is obtained by aggregating the output of individual establishments using a CES technology:

$$Y_s = \left[\sum_{i=1}^{M_s} Y_{si}^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \tag{2}$$

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:

$$Y_{si} = A_{si} L_{si}^{1-\alpha_s} K_{si}^{\alpha_s} \tag{3}$$

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:

$$\pi_{si} = (1 - \tau_{Ysi}) P_{si} Y_{si} - w L_{si} - (1 + \tau_{Ksi}) R K_{si} \tag{4}$$

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 $MRPL_{si} = \frac{w}{1-\tau_{Y_{si}}}$. From the first-order conditions, the optimal capital-labor ratio is given by:

$$\frac{K_{si}}{L_{si}} = \frac{\alpha_s}{1-\alpha_s} \frac{w}{R} \frac{1}{1+\tau_{K_{si}}} \tag{5}$$

Building on the work of Foster et al. (2008), Hsieh and Klenow (2009) distinguish between two productivity measures: one expressed in physical units (TFPQ) and the other in monetary values (TFPR)

$$TFPQ_{si} = A_{si} = \frac{Y_{si}}{L_{si}^{1-\alpha_s} K_{si}^{\alpha_s}} \tag{6}$$

$$TFPR_{si} = P_{si} A_{si} = \frac{P_{si} Y_{si}}{L_{si}^{1-\alpha_s} K_{si}^{\alpha_s}} \tag{7}$$

Their analysis shows how measures of TFPR relate to the wedges. More specifically, HK show that

$$TFPR_{si} = \frac{\sigma}{\sigma - 1}\left(\frac{R}{\alpha_s}\right)^{\alpha_s}\left(\frac{w}{1-\alpha_s}\right)^{1-\alpha_s}\frac{(1+\tau_{Ksi})^{\alpha_s}}{1-\tau_{Ysi}} \tag{8}$$

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

The actual TFP at industry level can be calculated as

$$TFP_s = \left(\sum_{i=1}^{M_s}\left[A_{si}\frac{\overline{TFPR_s}}{TFPR_{si}}\right]^{\sigma-1}\right)^{\frac{1}{\sigma-1}} \tag{9}$$

where $\overline{TFPR}_s$ is a geometric mean of the average marginal revenue product of capital and labor:

$$\overline{TFPR}_s = \frac{\sigma}{\sigma-1}\left[\frac{R}{\alpha_s\sum_{i=1}^{M_s}\left(\frac{1-\tau_{Ysi}}{1+\tau_{Ksi}}\right)\left(\frac{P_{si}Y_{si}}{P_sY_s}\right)}\right]^{\alpha_s}\left[\frac{w}{1-\alpha_s\sum_{i=1}^{M_s}(1-\tau_{Ysi})\left(\frac{P_{si}Y_{si}}{P_sY_s}\right)}\right]^{1-\alpha_s}$$

When $A_{si}(=TFPQ_{si})$ and $TFPR_{si}$ are jointly lognormally distributed, HK show that

$$\log TFP_s = \frac{1}{\sigma-1}\left[\log M_s + \log E(A_{si}^{\sigma-1})\right] - \frac{\sigma}{2}var(\log TFPR_{si}) \tag{10}$$

To empirically implement the HK framework, we require information for several parameters. The primary parameter we need to fix is the elasticity of substitution – σ. There is little agreement in the literature on the plausible magnitude of this parameter. We follow Hsieh and Klenow (2009) and set a conservative estimate $\sigma = 3$.[4]. Again, following Hsieh and Klenow (2009), we set $R = 10\%$ assuming a real interest rate of 5% and depreciation rate of 5 %. There is some evidence that the cost of capital is high in Africa. But the different values of R only affect the average capital distortion but not the differences between firms in a given industry. Thus, it doesn't affect our calculation of gains from reallocation. 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.[5] After obtaining the capital share at four-digit level, we combine it with our firm-level datasets.[6]

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

$$1 + \tau_{ksi} = \frac{\alpha_s}{1-\alpha_s}\frac{wL_{si}}{RK_{si}} \tag{11}$$

$$\frac{1}{1-\tau_{ysi}} = \frac{\sigma-1}{\sigma}\frac{(1-\alpha_s)P_{si}Y_{si}}{wL_{si}} \tag{12}$$

[4]Note that this parameter doesn't affect the basic measure of dispersion but only alters their effect on aggregate productivity

[5]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.

[6]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.

Eq. (11) 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. (12) 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.

The establishment-level productivity can be inferred as:

$$A_{si} = \frac{Y_{si}}{(wL)_{si}^{1-\alpha_s} K_{si}^{\alpha_s}} = \kappa \frac{(P_{si} Y_{si})^{\frac{\sigma}{\sigma-1}}}{(wL)_{si}^{1-\alpha_s} K_{si}^{\alpha_s}}$$

where $\kappa = (P_s Y_s)^{-\frac{1}{\sigma-1}} / P_s$, which is normalized to 1, as in HK.

It is worth emphasizing that the HK framework allows to obtain physical output Y using the CES demand relationship.

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. HK show that the ratio of the actual TFP in 9 to the efficient level of TFP[7]:

$$\frac{Y}{Y_{\text{eff}}} = \prod_{s=1}^{S} \left[\sum_{i=1}^{M_s} \left[\frac{A_{si}}{\bar{A}_s} \frac{\overline{TFPR_s}}{TFPR_{si}} \right]^{\sigma-1} \right]^{\frac{\theta_s}{\sigma-1}} \tag{13}$$

Eq. 13 shows how within industry misallocation of resources leads to a lower measured TFP.

5 Data Description

Our analysis exploits census data for manufacturing firms in each of the four SSA countries we study: Côte d'Ivoire (2003-2012), Ethiopia (2011), Ghana (2003), and Kenya (2010). These countries provide comprehensive and comparable census data. The censuses are nationally representative and both small and large firms in the formal sector are adequately included in all countries. In all four countries, the data are restricted to manufacturing sector (ISIC Rev 3 15-37).

In what follows, we describe each country's datasets.

Côte d'Ivoire The data source for Côte d'Ivoire is balance sheets and income statements associated with tax reporting. The data is available for all registered firms in the country and contains detailed balance sheet information on firms' revenue, employment, cost of labor, book value of fixed assets, intermediate inputs and other firm characteristics. All registered firms are required to report their financial statements to the National Statistics Institute (INS), the tax administration (DGI), the court of justice, and the Central Bank (BCEAO), which are reported under the West Africa accounting system standards, Systeme Comptable Ouest Africain (SYSCOA). INS processed the data after firms hand in hard copies of their forms between March and June following the closing of the fiscal year in December. The Côte d'Ivoire data cover 2003 to 2012.

[7] Following Hsieh and Klenow (2009), we use an establishment's total wage bill (including benefits) instead of employment in order to account for differences in the quality of labor across establishments.

Ethiopia The datasets we use for Ethiopia are the *census* of 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 ten* persons. The CSA conducted this census on annual basis since 1976.[8] 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 datasets, 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.[9]

Ghana The data for Ghana are based on the 2003 National Industrial Census (NIC) dataset, conducted by the Ghana Statistical Service (GSS). Three industrial censuses have been conducted: 1962, 1987 and 2003. The study is based on the 2003 census data , which includes establishments employing less than 10 workers. The census is similar in sampling design 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 was undertaken in two phases. In the first phase, the registry covers all establishment (25,865) and includes information on persons engaged, location, age and industrial group. However, it contains no balance sheet information. In the second phase, the survey covers *all* establishments with at-least 10 workers and a 5 % sample of manufacturing establishments engaging less than 10 workers. Data on production, sales, wages and salaries, material costs, fixed assets are reported for these firms. The raw data consist 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.[10]

Kenya The Kenyan data come from the 2010 Census of Industrial Production (CIP), conducted by the Kenyan National Bureau of Statistics (KNBS). The dataset provides detailed information needed for our analysis, including total sales, value of production, labor cost, capital, 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 labor cost and capital stock, and thus were omitted from our analysis.

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

[9] 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.

[10] For more details about the sampling design and detailed description of the data, see Krakah et al. (2014).

Definition of variables Variables are defined as follows. In each census, labor is defined as the total number of paid and unpaid workers plus proprietors.[11] The capital input is defined as a book value of fixed assets. The definition of labor cost includes wages and salaries of workers as well as other benefits. Value added is defined as the difference between the value of production minus cost of raw materials and energy and purchase of services. See Table A1 for the definition of each variable and parameter.

Data cleaning These data have been extensively cleaned to remove inconsistencies and ensure cross-country comparisons.

6 Main Results

6.1 Measuring Productivity and Distortions

Figure 3 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 the most productive firms have not expanded their production to replace the less productive ones. A multitude of factors may have explained this phenomenon in our sample countries. One way to assess the extent of resource misallocation is to look at the variation in marginal products of inputs across producers. In a frictionless environment, the marginal products of factors should be equalized across firms and 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,

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

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.

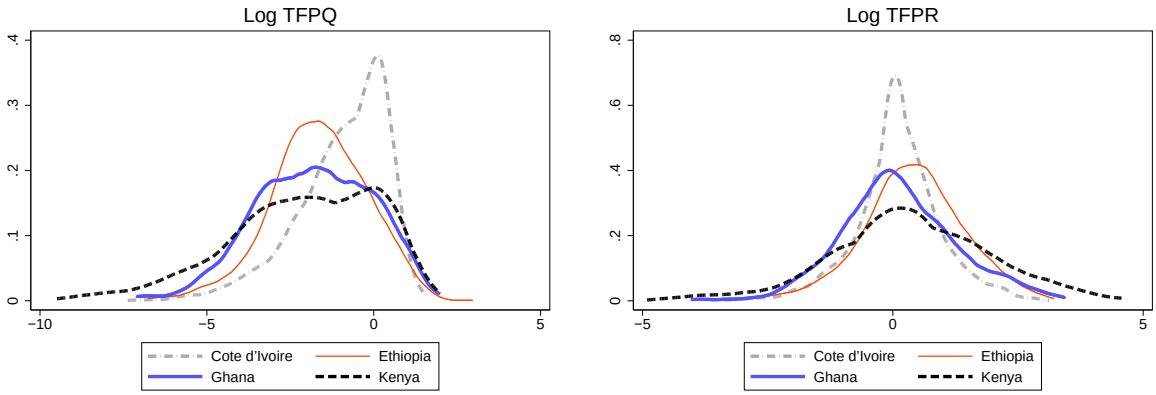


Figure 3: Distribution of TFPR and TFPQ

Table 2: Dispersion of TFPR and TFPQ

	Côte d'Ivoire		Kenya		Ghana		Ethiopia		India		China	
	TFPR	TFPQ	TFPR	TFPQ	TFPR	TFPQ	TFPR	TFPQ	TFPR	TFPQ	TFPR	TFPQ
	2003-12	2003-12	2010	2010	2003	2003	2011	2011	1994	1994	2005	2005
S.D	0.65	1.24	1.52	2.41	0.95	1.75	0.78	1.30	0.67	1.23	0.63	0.95
75–25	0.88	1.74	1.99	3.34	1.43	2.61	1.26	1.94	0.81	1.60	0.82	1.28
90–10	1.99	3.25	3.94	5.67	2.89	4.47	2.56	3.67	1.60	3.11	1.59	2.44
Cov (TFPQ,TFPR)	0.70		0.85		0.69		0.74					
Reg.Coeff	0.42		0.52		0.44		0.53					
N	4146	4146	757	757	1151	1151	4012	4012	41,006	41,006	211,304	211,304

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. The statistics for India and China are taken from Hsieh and Klenow (2009). We compute these statistics for India using the Prowess database and obtain similar values as in Hsieh and Klenow (2009).

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 firms in each 4-digit industry. The results of this liberalization experiment are reported in Table 3. The first column of Table 3 indicates that the potential TFP gains from better allocation of resources are much higher in Kenyan manufacturing sector compared to the corresponding values in Ethiopia, Ghana, and Côte d'Ivoire. More specifically, fully equalizing total factor revenue productivity (TFPR) across firms in each industry, could increase total 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.[12]

[12]Note that the gains from reallocation increase with σ. As Hsieh and Klenow (2009) point out, when σ is larger, the TFPR gaps are closed more slowly in response to a reallocation of resources from low to high TFPR establishments, leading to a higher gains from reallocation.

Table 3: Potential TFP Gains from Equalizing TFPR

	Total Gains
Cote d'Ivoire	31.4
Ethiopia	66.6
Ghana	75.7
Kenya	162.6

These estimates can be viewed as a reasonable lower bounds since the counterfactual analysis abstracts from other potential sources of amplification. First, our analysis focuses on TFP gain from the reversal of distortion *within* four-digit manufacturing industries, abstracting from between-industry reallocation gains.[13] Thus, reversing the between-industry misallocation – equalizing $\overline{TFPR}_s$ across industries within the manufacturing sector– may lead to even larger effect on aggregate TFP. Second, our analysis allows *static* productivity gains only. Accommodating the dynamic effect would likely amplify the total TFP gains from removing distortions. Third, reallocation in the manufacturing sector may have economy-wide implications through backward and forward linkages. The improvement in productivity in the manufacturing sector could lead to a process of structural change in our sample countries. Thus, productivity gains from the removal of distortions are likely to be higher than otherwise implied by a one-sector model. Finally, it is also worth emphasizing that we abstract from potential gains from directing resources between formal and informal firms. Since informal firms are often found to be on average less productive than formal firms, reversing the distortion between formal and informal firms operating in the same sector may yield a larger TFP gains.

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 4 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.[14] The positive relationship between TFPR and TFPQ is quite consistent with most findings in the literature, especially in developing countries.

[13] Note that $\overline{TFPR}_s$ are not equalized across sectors s.

[14] Note that in a frictionless world, firms with lower TFPR (establishment 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).

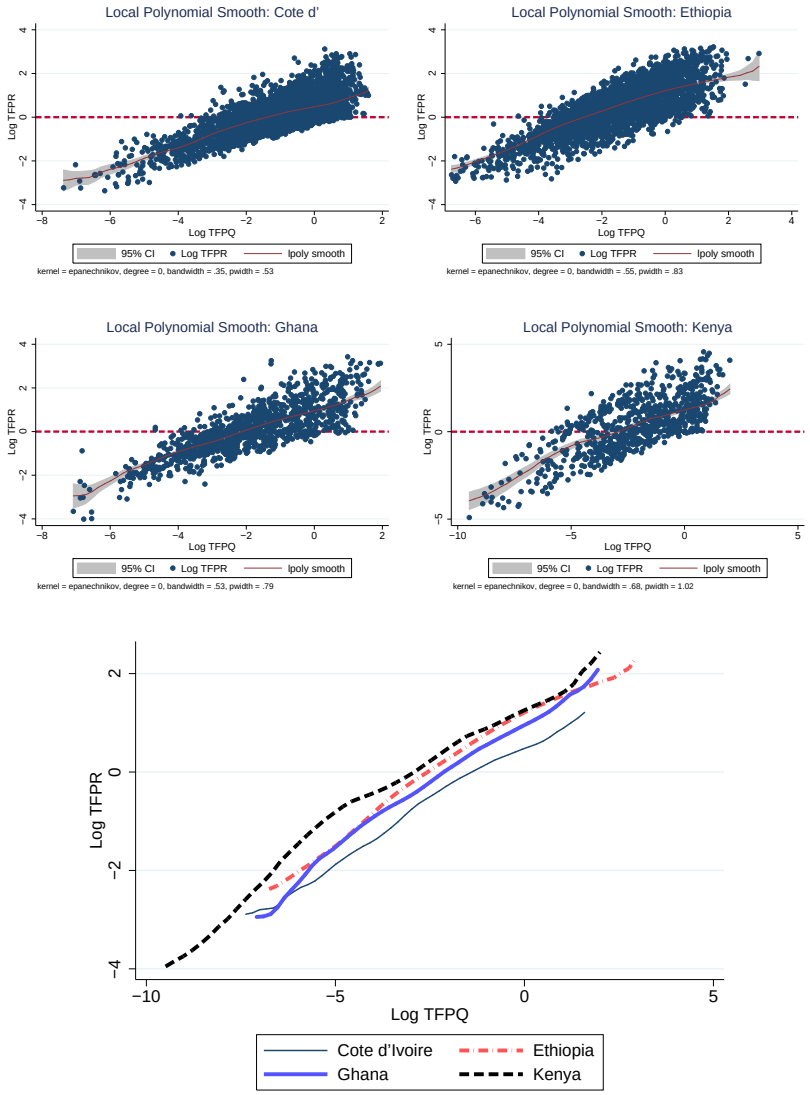


Figure 4: Log TFPR vs Log TFPQ

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. These elasticities again reveal that more productive firms are "taxed" at a higher rate in our sample countries than in the US. The fact that these elasticities are significantly larger in our countries suggests that more productive firms are not able to use resources, and ultimately worsen aggregate productivity (Restuccia and Rogerson, 2008). Additionally, the fact that more productive firms face higher distortions could slow down the growth of firms over their life cycle by discouraging firms from investing in productivity enhancing technologies (Hsieh and Klenow, 2014). In the next section, we will examine whether these higher elasticities can

play a role in affecting the 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 5 plots these distortions versus percentiles of TFPQ, using local polynomial regression. The figures provides a number of interesting insights. To start with, the figure shows that output distortions are monotonically increasing in percentiles of establishment productivity (measured by TFPQ) in all four countries. This suggests that, compared to a frictionless equilibrium, productive establishments face larger output distortions, causing them to produce lower than their optimal output, while the less productive ones receive an implicit output subsidy and produce beyond their optimal level, resulting in an inefficient allocation of resources and thus lower TFP. Second, the capital distortion increases in percentile of TFPQ for low productive firms but flattens out for relatively more productivity firms, albeit some differences across the four 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 four countries. Put differently, the positive relationship between productivity and overall distortions seems to be mainly driven by frictions in the product market. Thus removing output distortion could potentially lead to a higher manufacturing TFP. In other words, the loss in productivity due to misallocation arising from distortion in the input markets is likely to be modest.

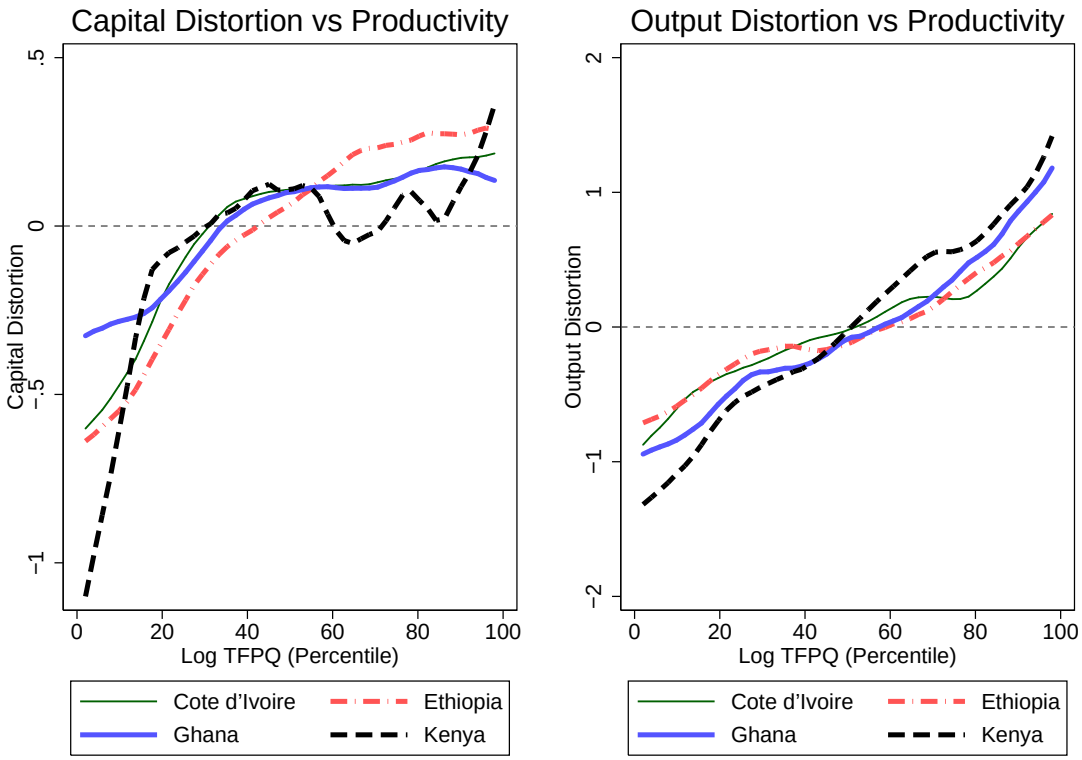


Figure 5: Distortions vs. Productivity

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 comprehensive manufacturing census data, they find that while firms in the US grow by a factor of eight by the age of 40, 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 magnifies the losses from misallocation that result from a static analysis.

This section attempts to investigate the evolution of employment, physical productivity, and distortions over the firms' life-cycle, as inputed from the distribution of each of these objects in the cross-section of firms across ages. Does such age-size relationship hold for the African countries under consideration? To what extent do 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 looks in our sample countries. Figure 6 plots the age distribution of firms by country. The age distribution of firms in Kenya is strikingly different from the other three countries. The figure clearly shows that Kenyan firms are, on average, older than firms in Ethiopia and Ghana. One potential reason for such difference could be because industrialization in Ethiopia and Ghana 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.

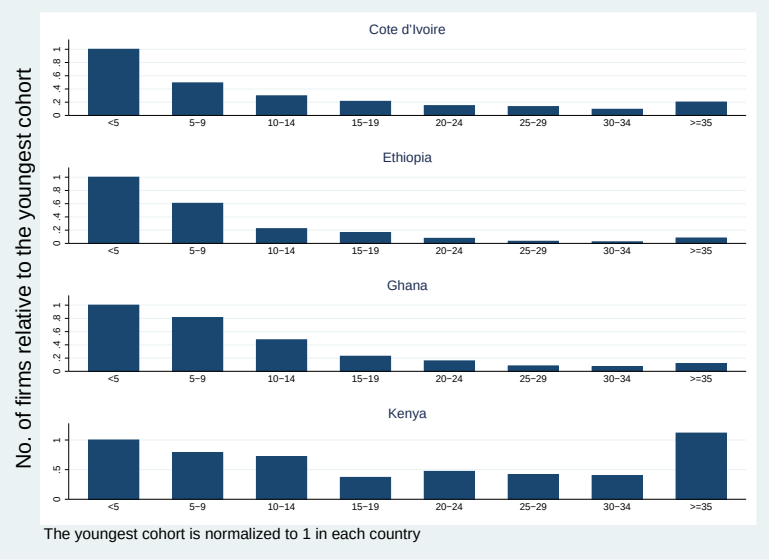
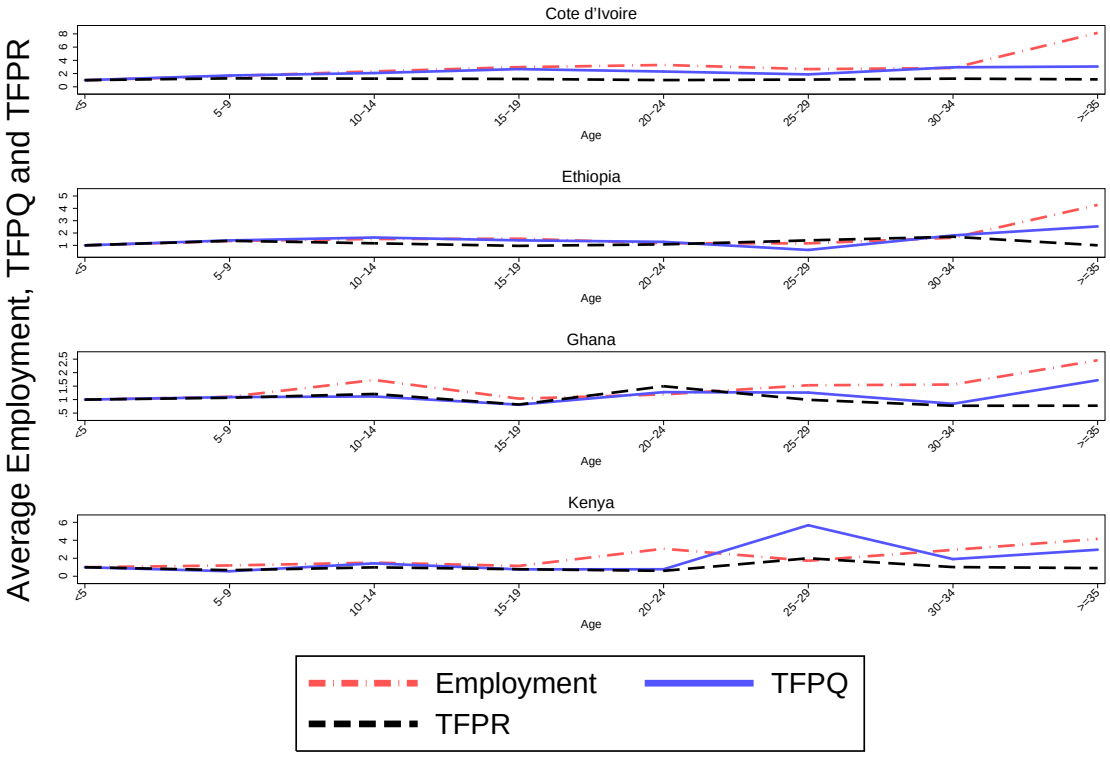


Figure 6: Number of Establishments by Birth Cohort

To understand whether firms become larger and improve their productivity as they age, Figure 7 presents the average employment and productivity of firms across different age cohorts.[15] The figure provides preliminary evidence that firms have experienced slow employment and productivity growth over their life cycle, albeit some differences across countries. This implies that entrants do not seem to invest in productivity enhancing activities over their life cycle.

[15]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.

Figure 7: 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 in our sample countries. The figures shows that TFPR steadily increases with establishment age (although declining for the oldest cohort) in Ethiopia, suggesting that older firms, on average, face bigger distortions. Older Ethiopian firms are thus smaller than they would be in a frictionless economy. In contrast, TFPR seems to be decreasing with firm's age in Kenya. There is no apparent relationship between productivity dynamics and TFPR variation. This patter differs somewhat from earlier work that concluded that TFPR rises with firm age in developing countries (Hsieh and Klenow, 2014).

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 groups of firms in a cross-section is

may be a 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 a panel dataset in Africa.[16]

7 A Comparison with Survey Data

Our strategy to measure and quantify the costs of misallocation was taken directly from the literature. In return to relying on strong assumptions, the methodology provides a clear benchmark of efficiency with which to confront the data and is relatively simple to apply. The real limitation is 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 there are significant deviations in the coverage of the full spectrum of firms in the ES for Ghana, where we find that large firms are over-represented relative to the Census. In Kenya, on the other hand, we find that the two distributions match up 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 attempt 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 counting with a database that properly accounts for the real distribution of value added shares in the economy.

7.1 Firm-Size Distribution: Survey vs Census

To give some background to the analysis, the ES is briefly described as follows. The ES is an ongoing project of the World Bank to collect establishment-level data from several countries, particularly from low and middle income countries.[17] 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. Two rounds of surveys were conducted in each of our sample countries.

To ensure the proper sample representation, the surveys rely on a stratified sampling technique. Three levels of stratification were 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 is stratified into three size strata: small (5 to 19 employees), medium (20 to 99 employees), and large (more than 99 employees). The degree of industry stratification depends on the size of the economy. In 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

[16] Although there are some studies in Africa that examine productivity dynamics over the life cycle of firms using panel data Van Biesebroeck (2005), they rely on revenue-based measures of productivity. As a result, the dynamics of "productivity" over the life cycle may be misleading.

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

to value added, employment and number of establishments. The various combinations of these strata generate the cells for each industrysizeregion. Notice the lack of 4-digit stratification, feature to which we shall return in the subsection below.

As a first look at the data, we assess the comparability between the manufacturing censuses and ES using the Quantile-Quantile (QQ) plot. Figure 8 plots the quantiles of the size distribution of firms in the ES against the quantiles based on manufacturing census data. The size quantiles are given in a logarithm of employment. 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 indicate that the firm size distribution in the two datasets are different.[18]

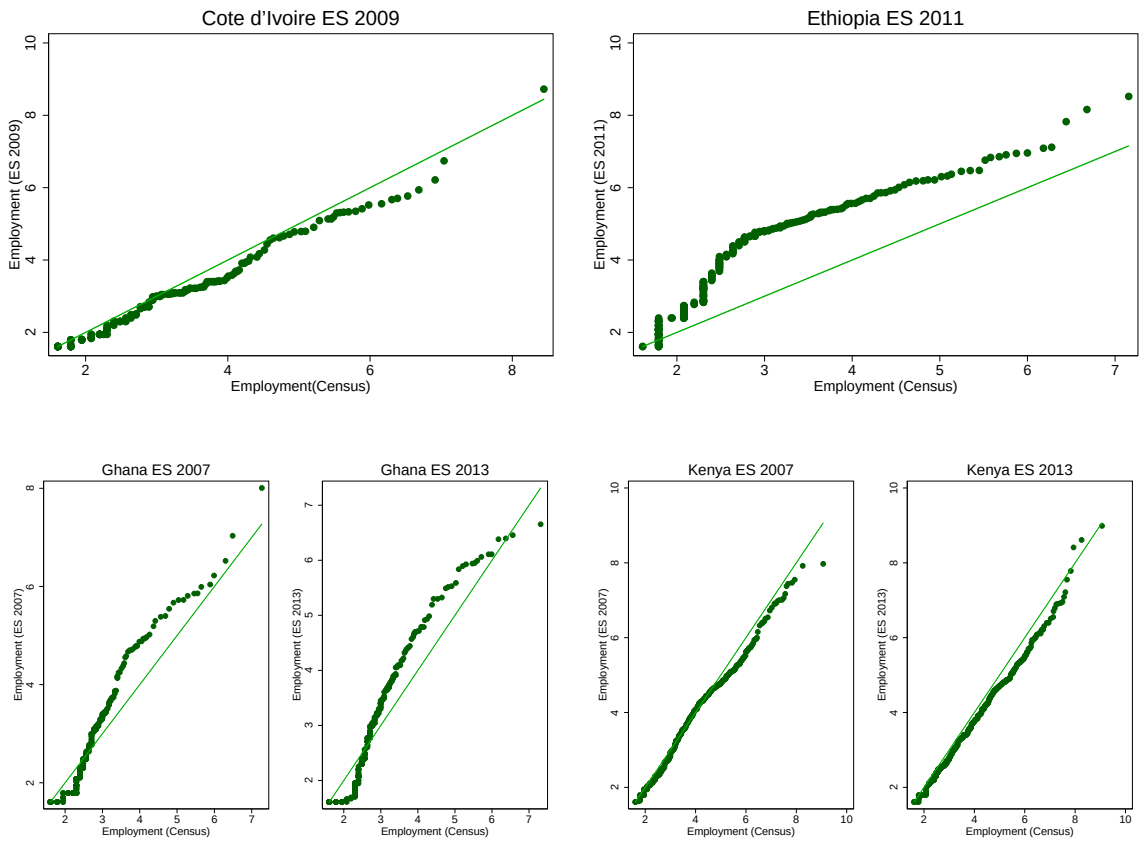


Figure 8: QQ plot of the enterprise censuses vs surveys

A visual comparison of the QQ plots shows that the distribution based on the ES and the census data look different in all the countries except for Kenya.[19] The top panel of 8 plots the quantile of size distribution 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 a the 2003 National Industrial Census of Ghana. A visual comparison

[18]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.

[19]To make it comparable with the ES, firms employing fewer than 5 workers are dropped in our sample.

shows a clear difference in firm size distribution between the two datasets. For the case of Kenya, a comparison of the ES (for the years 2007 and 2013) against the 2010 Census of Business Establishments (CBE) reveals that the size distributions of firms in the two datasets track each other quite closely. This can be explained by the fact that, unlike in the other countries, the CBE is actually being used to create the sampling frame in Kenya. [20]

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

7.2 Extent and Cost of Misallocation: Survey vs Census

We turn now 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.[21]

There are a number of challenges involved in making the analysis of misallocation in the ES comparable to that in the Census. First, the surveys for the four countries under study are not built to ensure representativeness of in terms of disaggregated sectoral coverage. As mentioned above, there is stratification across two broad categories, manufacturing and services, in the case of Ethiopia, 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 Census. Under the assumption that Census-based weights are closer to the true ones, the experiments allow us to assess the quantitative significance of the weak 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 receive no coverage at all in the surveys. To gain comparability in face of this difficulty, we restrict the sample of firms in the Census to those belonging to industries that are covered both in the Census and the ES, re-weighting valued added shares accordingly.

[20] Obviously, we do not expect the sample to resemble our census due to the structure of the sampling procedure. Large establishments are in typically oversampled in the ES relative to the random sampling of firms in each country. To further explore the comparability of the two datasets, we compare the size distribution in our census data with the sampling frames used to draw samples in the ES. We find that the sampling frame significantly underestimates small firms in Ethiopia and Ghana.

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

Table 4: Dispersion of TFPR and TFPQ based on the Enterprise Surveys

	Kenya				Ghana			
	TFPR (Census wgts)	TFPR(ES wgts)	TFPQ (Census wgts)	TFPQ(ES wgts)	TFPR (Census wgts)	TFPR (ES wgts)	TFPQ (Census wgts)	TFPR(ES wgts)
	2013	2013	2013	2013	2007	2007	2007	2007
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. $Census - wgts$ stand for value added shares inputed from the Census, while $ES - wgts$ are the weights implied by the sample of firms in the enterprise surveys.

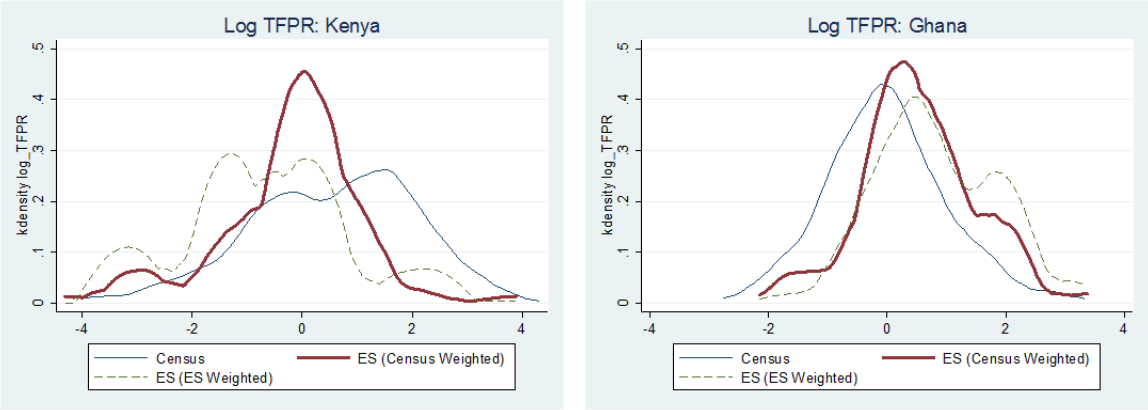


Figure 9: Distribution of TFPR : Census, ES with Census weights, and ES with survey Weights

We can see that when weighting sectors as in the Census, 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 ES's own weights. A visual representation of the same conclusion can be observed in figure 9, which illustrates the distributions of TFPR from the ES with census weights, the ES with survey weights, and the Census. The figure not only validates the conclusion from the table that the dispersion in the distribution of distortions is lowered when weighting industries according to Census-based value added shares, it also shows that the survey based distribution is even less dispersed than the Census one.

Table 5: Potential TFP Gains with Different Industrial Weights

	Census		Enterprise Surveys		
	Baseline	Partial	ES	Full Census	Partial Census
Ghana	75.7	71.1	146.6	32.8	54.3
Kenya	162.6	184.2	86.5	16.7	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 columns "Full Census" and "Partial Census" refer to TFP gains across firms in the ES where industries are weighted based on the full and partial censuses, respectively.

Finally, table 5 reports the counterfactual gains in aggregate manufacturing resulting from reversing distortions in the the three types of data that we have been comparing: census, ES with census weights, and ES with survey weights. In the case of the Census, we report the baseline results introduced above together with the gains corresponding to the case where we restrict to the subset of industries that overlap with the industries in the ES.

The table conveys a clear message: once industries are weighted as in the census, and hence once we correct for biases in the sectoral distribution of production in the survey, gains from withdrawing distortions are significantly muted (column 4 vs column 2). They are less than half the census-based gains in the case of Kenya, and are reduced by 25% in the case of Ghana. The gains from the ES using its own implied weights are expectedly larger.

8 The Underlying Sources of Misallocation

The results presented above clearly revealed that resource misallocation is quite large in our sample countries. Thus improving the allocation of resources is a critical element in order to boost manufacturing productivity in these countries. To offer specific suggestions on how these countries can improve their productivity by reducing allocative inefficiency, it is important to identify the specific factors that have contributed to the observed misallocation. Nevertheless, identifying the specific policies or institutions that may have contributed to such misallocation is notoriously difficult. In principle, many factors – observable and unobservable – may reasonably contribute to resource misallocation across firms. For example access to finance, tax rates and regulatory requirements may favor particular firms because of political connections or family ties.[22] Identifying specific distortions is perhaps more difficult in Africa since the region is often characterized by a high cost of doing business. While our census data do not allow us to pin down the reasons behind the substantial level of resource misallocation in our sample countries, we believe that this pattern is associated to the heterogeneous business environment faced by firms. Our goal in this section is to uncover the potential underlying sources of misallocation by examining the role of different business environment bottlenecks experienced by firms. To this end we merge our data with the ES data, which provide various measures of business climate indicators.

[22] Hsieh and Klenow (2009) argue that the substantial domination of SOEs and cumbersome licensing requirements contribute to misallocation of resources in China and India, respectively.

Institutions The ES database contains both perception as well as quantitative information regarding the costs of doing business experienced by firms for a large number of countries. The perception indicators are often used to examine the effects of the business environment, but present a number of possible limitations. The main concern is that perception data are subject to measurement errors since they are likely to be affected by observed and unobserved firm and country specific factors. For example, they might simply reflect "individual differences in the degree of optimism or pessimism of the managers" and/or experience or performance of the establishment (Aterido et al., 2011). In view of this, we prefer quantitative measures, where managers are asked to specify the specific costs incurred when doing business, over perception data for our analysis.[23]

We construct an index of the quality of institutions based on the objective measures from the ES.

Financial friction is often thought to be an important source of misallocation, particularly in countries with poorly-functioning financial market. It can severely harm aggregate TFP by preventing the optimal adjustment of factor inputs. A recent study by Buera et al. (2011) has shown that a substantial portion of the variation in aggregate productivity across countries may be accounted for by resource misallocation due to imperfect financial markets. The ES dataset contains a number of questions in regard to access to finance. Specifically, the survey asked firms to indicate whether the establishment has 'access to finance' as well as the actual 'cost of financing'.[24] We define the quality of the financial institution as the ease for establishments to get external financing. More specifically, we measure the financial friction as the percentage of establishments in the each region that do not have a line of credit or loan from a financial institution.

Another possible driver of misallocation is uneven implementation of regulations which allows unproductive firms to enter and survive easily. The ES dataset contains a large number of measures of the extent of regulation and red-tape induced costs. We use the share of *senior managers' time that is used in dealing with government officials* as our measure of regulation (Red-tape), as used in (Hallward-Driemeier et al., 2010; Li et al., 2011).

It is also plausible that the quality of infrastructure may have a differential effect on the operation of firms within industries. Poor-quality infrastructure is often considered to be a major bottleneck for performance of firms in SSA countries. However, the effects of poor infrastructure are *not uniform* across establishments. For example, the same extent of power outages may cause less damage to large firms because they might insure themselves against outages by purchasing generators or otherwise substituting away from electricity (Aterido et al., 2011; Allcott et al., 2015). We measure the extent of infrastructure bottlenecks by the proportion of annual sales lost due to power outages (*Electricity*).

Finally, the high level of resource misallocation could also reflect that firms in our sample countries face severe corruption costs. The ES contains information on the occurrence of bribe requests as well as the amount of the informal payments to 'get things done' with regard to customs, taxes, licenses, regulations, other public services.[25] To measure the extent of corruption, we use the average percentage of sales spent on informal payments made to get things done.

[23]Note that Kalemli-Ozcan and Sorensen (2012) use subjective firm responses as measures of the business environment to examine the cost of capital misallocation in Africa.

[24]The specific questions are "Does this establishment currently have a line of credit or loan from a financial institution? and What is the rate of interest of this most recent line of credit or loan?", respectively.

[25]The survey questions are: In any of these inspections was a gift or informal payment requested? If so, what percent of total annual sales is paid in informal payments?

Empirical Specification To investigate the role of institution on the process of resource allocation, we map the measures of business climate from the ES to our census data. Since there is no firm-specific policy variable in our data, we first construct policy variables from the ES by taking the averages of survey responses of firms located in the same region. The underlying assumption of this approach is that policies vary across regions within a country, which is plausible since firms facing the same *de jure* policy are likely to face different policy implementation across regions (Acemoglu and Dell, 2010; Hallward-Driemeier et al., 2010).[26] The estimation equation is then given by:

$$y_{isrc} = \beta_0 x_{ic} + \beta_1 BE_{rc} + D_c + D_s + \epsilon_{isrc} \tag{14}$$

where y_{isrc} is firm-specific measure of distortion of firm i in industry s region r and country c. D_c and D_s are country and industry dummies, respectively. x_{ic} is a vector of firm characteristics that may be correlated with distortions (age and size). The policy variables (BE) are region-average of the respective measures of business environment. For example, 'Finance' measures the region-average of fraction of firms with no access to short-term finance. Corruption – the region-average of losses due to informal payments. Electricity - average of losses due to electrical outages in each region. Regulation – the region-average of the fraction of time that the senior managers spent dealing with government regulations.

The results of this regression are reported in Table 6. In a frictionless world, $TFPR_{si}$ should be equalized across all firms within industries, and we would expect all the coefficients of the policy variables to be not significant if these policies are orthogonal to other factors that may possibly affect $TFPR$. To the extent there is a positive and significant coefficient of the policy variables, this can be taken as evidence that the business environment affects idiosyncratic distortions.

Although it cannot be interpreted as causal evidence, the results in table 6 shows that business environment indicators are found to be significantly correlated with firm-specific distortions.[27] In particular, our results show that lack of access to short-term finance is associated with a higher level of capital and output distortions, after controlling for firm and industry differences. Business regulations, measured as the fraction of time that the senior managers spent dealing with government regulations, is also positively correlated with capital and 'output' distortions, indicating that regulatory red-tape cause a higher capital and 'output' wedge. The effect of access to electricity on τ_K is negative, suggesting that losses due to electricity generate a higher labor distortion relative to capital distortion. This result is puzzling because one would expect lack of electricity to affect capital more than labor. In addition, informal payments are associated with higher output distortions. Overall, and although there is a lack of variability in our data that can facilitate identification of the causal effects, the results suggest that the business environment is an important factor explaining misallocation in the sample countries.

Although we attempted to make connection between various business environment measures and resource misallocation, we are nonetheless aware that establishing causal relationship would require firm-specific policy variation, hence, this constitutes a profitable area for future research.

[26] By regressing firm-specific measures of business environment onto regional dummies, we find that the policies vary significantly across regions.

[27] Note that the number of observations decreases because the ES only covers establishments in the major regions of the sample countries. Thus, establishments located in small regions are not included in the analysis.

Table 6: Idiosyncratic distortions and business environment

	(1) TFPR		(2) τ_k		(3) τ_y	
Finance	0.90***	(0.04)	1.88***	(0.05)	0.20***	(0.03)
Electricity	-0.05***	(0.00)	-0.02***	(0.00)	-0.04***	(0.00)
Corruption	0.06***	(0.01)	0.01	(0.01)	0.05***	(0.01)
Red-tape	0.03***	(0.00)	0.05***	(0.01)	0.01*	(0.00)
Industry FE	Yes		Yes		Yes	
Firm controls	Yes		Yes		Yes	
Observations	8037		8037		8037	
R^2	0.631		0.648		0.237	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

9 Sensitivity Analysis

This section provides a sensitivity analysis to assess the robustness of our main findings reported in Table 3. 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 using wage bill. The reallocation gains would be modestly larger in Côte d'Ivoire (33.2 vs 31.4), Ethiopia (77.97 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 gains from reallocation continue to be the largest in Kenya.

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 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 four countries.

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 of resources from the least

productive establishments to the most productive ones.

Finally, in our benchmark analysis we include all establishments regardless of their size. As explained before our census covers all establishments employing 10 workers and a representative sample of firms were taken from establishments with less than 10 workers in Ethiopia and Ghana while the Kenyan census covers all manufacturing establishments in the country. One may argue that Kenyan census may not be comparable to the Ivorian, Ethiopian or Ghanaian censuses in covering the smallest establishments. To examine the extent to which this finding is an artifact of the Kenyan dataset that has sparse coverage of small firms, as a final 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 but the qualitative result remains unchanged.

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 implies that our finding that resource misallocation is the highest in Kenya and the least in Côte d'Ivoire is robust to alternative assumptions regarding the measures of labor inputs, elasticity of capital and outliers. However, the figure that emerges from comparing Ethiopia and Ghana is rather mixed, the relative ranking changes depending on the alternative assumptions.

10 Concluding Remarks

This paper has examined the effects of resource misallocation induced by firm-specific distortions on aggregate manufacturing productivity using comprehensive and comparable data on manufacturing firms in four Sub-Saharan Africa countriess - Côte d'Ivoire, Ethiopia, Ghana and Kenya.

Our main results are as follows. First, we found evidence that firm-level distortions have a quantitatively sizable detrimental impact on aggregate productivity, through the misallocation of resources away from more efficient to less productive ones, in all four countries we study. The counterfactual exercises imply a substantial productivity gain from the removal of distortions in Kenya, with a range of estimates from 162.6 to 194.6, depending on the model assumptions. The potential productivity gains are also large for Ghana (with range from 66.6 to 82.0 percent) and Ethiopia (with a range from 75.7 to 85.1 percent). For Côte d'Ivoire the gains are from 31.4 to 44.7 percent, much smaller than the other three countries. These results are robust to alternative parameter values that we use to measure the distortions.

Our results also suggest that distortions are positively correlated with firm-level productivity in all

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 in the output market. The misallocation due to factor market friction has a fairly modest effect on more productive firms.

We also find evidence that the measured distortions are correlated with various measures of business environment, and suggest that these are likely to play an important role explaining the pervasive resource misallocation. These findings suggest that paradoxically, while industrialization and productivity growth in manufacturing are important policy objectives in these countries, the misallocation induced by uneven regulations and poor business environment are undermining a larger contribution of manufacturing in these economies. Improving the business environment should, therefore, be a priority for policy also from an industrialization point of view.

Our analysis has abstracted from many factors which may be worth exploring further. First, our analysis covers firms in the manufacturing sector, ignoring non-manufacturing sectors. Distortions affecting firms in the manufacturing sector may have potential economy-wide implications though linkages in the input-output network with other sectors. An interesting future research area will be to assess the extent of misallocation in a multi-sector framework by accounting for all the potential linkages between sectors. Second, although we attempted to make a connection between various business environment measures and resource misallocation, establishing this relationship with robustness requires firm-specific policy variation of the cost of doing business, which constitutes a profitable area for future research.

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APPENDIX

A Tables and Figures

Table A1: Definition of Variables and Parameters

Variables	Definition
Production variables	
GVP	Value of annual gross output.
PY	Total value of production minus intermediate inputs.
WL	Wages and salaries plus fringe benefits..
K	Capital stock is defined as the book value of fixed assets.
M	Annual consumption of intermediate inputs - materials, utilities and purchased services.
Other firm covariates	
L	Total number of paid and unpaid workers plus proprietors.
Age	Years since the establishment started its operation.
Ownership	Private and government-owned firms.
Location	Establishment located in the capital (Addis Ababa, Accra, Nairobi) or outside from capital.
Parameters	
α_s	The capital share in the corresponding 4-digit US industry.
σ	Elasticity of substitution, set at 3 in the baseline calculation.
R	The rental rate of capital, set at 10%.

Table A2: Data Sources.

Country	Provider	Size Threshold	Year	# Observations
Côte d'Ivoire	National Statistics Institute (INS): Registrar of Companies for the modern enterprise sectors.	*Census* of all registered firms.	2003-2012	Raw data: 6,746
Ethiopia	Central Statistical Agency (CSA): Large and Medium Scale Manufacturing and Electricity Industries Survey	*Census* of firms employing more than 10 workers.	2011	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.	2011	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.	2003	Raw data: 3,302

Continued on next page

Table A2 – continued from previous page

Country	Provider and Survey Type	Size Cutoff	Year	Observations/Year
Kenya	Kenya National Bureau of Statistics (KNBS)- Census of Industrial Sector.	Census of all formal firms.	2010	Raw data: 2,089