Can the Service Sector Lead Structural Transformation in Africa? Evidence from Côte d'Ivoire

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Abstract

Standard models of structural transformation of developing economies typically see an increase in manufacturing as a necessary phase of economic development. Meanwhile, many African countries are bypassing manufacturing and moving directly toward a service sector economy, which has concerned many observers, especially about the labor and productivity growth effects. Can the service sector lead structural transformation in an African economy through productivity and labor force growth? We answer this question with firm-level panel data from Côte d'Ivoire. Using proxy variable estimates of total factor we show that it is possible to produce credible estimates of service sector productivity and estimate labor movements across firms of different productivity levels. Our results show that TFP is 6.5% higher on average in services than in manufacturing and that high-productivity firms in services hire more workers overall especially unskilled workers than low-productivity firms. Overall the results suggest that in Côte d'Ivoire the service sector is leading structural transformation and GDP growth. We draw conclusions about what this means for development policy in Africa.

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1 Introduction

The service sector is vital to the growth of African economies, often representing about 55% of the economy. (UNCTAD, 2019) It is the fastest growing sector across the continent, as African countries go from agricultural societies to service ones mostly bypassing the industrialization stage seen elsewhere in the world. Yet the service sector worldwide is characterized as notoriously having low and slow productivity growth (Lagakos (2016)) due to low technology investment (Parente and Prescott (1994, 1999); Herrendorf and Teixeira (2011)), low competition(Schmitz (2005)), and misallocation of resources between firms (Restuccia and Rogerson (2008); Hsieh and Klenow (2009)). Can the service sector be the engine of growth and structural transformation in Africa?

Typical models of structural change in the service sector means that input factors, such as labor, are reallocated to the sector with lower productivity, leading to Baumol's cost disease (Baumol (1967), Duernecker et al. (2017)). In a developed country context, Moro (2015) argues that the rise of the service sector decreases economic growth in the United States and Gordon (1996) shows that productivity growth in the United States stagnated during the period from 1973 to 1989 in part due to the slowdown of productivity growth in the service sector. Similar slowdown patterns also appear in European countries. Lagakos (2016) shows that across many countries the productivity in the retail industry is lower due to the large share of a traditional less innovative segment. Sorbe et al. (2018) estimate multi-factor productivity in OECD countries and show that the service sector has lower productivity than the manufacturing sector. These studies focus on developed countries or countries that are following a traditional structural change path of manufacturing then services. Our research focuses on the structural transformation path of a developing African country, Côte d'Ivoire, that represents a new type of development path.

Low-income countries in Africa, such as Côte d'Ivoire, are following a unique economic growth and development path in which the economy transforms from a low productivity agricultural sector directly to the service sector. This bypasses the industrialization stage seen in the structural transformation paths of developed countries and East Asian countries. A large number of studies have already shown that industrialization plays an important role in economic growth and long-term poverty reduction through the sector's superior employment and productivity growth rates (Buera & Kaboski (2012), Kniivilä (2007), Herrendorf et al. (2014)) A common refrain in policy and academic circles is that African countries cannot grow their economies long-term without industrialization (see e.g., Rodrik (2016)).

We use micro-level data from Côte d'Ivoire to estimate total factor productivity (TFP), and employment changes in the manufacturing, agricultural and service sectors. We first demonstrate that it is feasible to estimate productivity in the service sector in a way similar to what is commonly done in the manufacturing sector using proxy variable techniques. The specificity of using high-quality firm-level data from a single country allows us to employ modern productivity estimation techniques that account for potential endogeneity and also provide estimates of employment by firm and sub-sector. With TFP estimated, we analyze the productivity patterns and demonstrate the differences in the three sectors. In order to test how TFP relates to the structural transformation of the economy, we then analyze employment changes across sectors, sub-sectors, and firms by their productivity levels. This allows us to test the correlation between TFP and employment growth across sectors and firms. In contrast to a literature that typically uses only broad categories of labor, our work also disaggregates labor into skilled and unskilled workers. This disaggregation allows us to test differential employment effects of structural transformation for both skilled and unskilled labor.

The theoretical setup for our estimates demonstrates that the proxy variable techniques can estimate service sector productivity using external labor/consultants as a proxy variable. Our empirical results then show that productivity estimates for the service sector in Côte d'Ivoire are on average 5% greater than those in the manufacturing sector. The distribution of productivity across firms in the service sector is also more concentrated, lower variance, than in the manufacturing sector. We demonstrate that the estimates are robust to alternative methods for estimating TFP and data assumptions. We then show that employment growth, especially among unskilled workers, in service industries is fastest among the top firms in the productivity distribution. In contrast, we find little evidence of the same sort of employment dynamism in manufacturing industries, with employment growth spread out across the productivity distribution and not stronger for either unskilled workers or more productive firms. While our results suggest no Baumol disease effects, we do show evidence that improved productivity in services may be related to Lucas' (1978) span of control theory.

This work makes substantive contributions to four literatures. First, we make empirical and methodological contributions to the literature on structural transformations of economies (Duarte & Restuccia (2010), Ngai & Pissarides (2007), McMillan & Rodrik (2011)). Specifically, our work is similar in spirit to Herrendorf et al. (2022) who test productivity across multiple sectors across multiple economies, but ours is done within a single country. Our work makes a methodological contribution by showing that with appropriate micro-level data, one can use proxy-variable techniques to address endogeneity in TFP estimates and that this is possible in the service sector.[1] Empirically, we add to the structural change literature with estimates at the sector, sub-sector, and firm level of how employment growth happens across the productivity spectrum.

Secondly, our work contributes to the productivity estimation literature, especially in the service sector (e.g., Lagakos (2016), Li & Prescott (2009), Joppe & Li (2016)). We show that one can appropri-

[1] Most of the structural change literature uses value added per worker as a measure of TFP, which, while easy to calculate from macro data across countries, is likely to suffer from endogeneity issues as a measure of TFP. Value added per worker also elides the potential measurement issues in services that we address in this work.

ately measure service sector output with value-added while using external labor as a proxy variable for productivity estimation. These methods improve considerably on the older existing literature that estimates service sector productivity using DEA and stochastic frontiers. Our methodology also improves on more recent work in service sector productivity using value-added per worker.

Much of the literature on structural transformation in Africa and elsewhere uses labor productivity instead of total factor productivity. For example, De Vries et al. (2015) study value added per worker across 11 Sub-Saharan African countries and McMillan and Rodrik (2011) use labor productivity to show structural transformation in both African and Latin American economies. The TFP estimated in our work using proxy variable techniques takes the potential endogeneity of inputs such as labor, capital, human capital, and intermediate inputs into account, which is often not considered in the labor productivity studies.

Third, we contribute to the literature on structural transformation and development of African economies, by providing estimates of the relative productivity and employment growth of services and manufacturing. Although the service sector has become the largest sector in most African economies, productivity changes in this sector are still understudied and poorly understood. Only a few works have studied service-sector productivity in African countries. Diao et al. (2018) and Ellis et al. (2017) use value-added to measure productivity in Tanzania's service sector. Spray and Wolf (2017) study labor productivity in service-related industries. Yet productivity in the service sector is rarely carefully measured and discussed because the detailed firm-level data in African countries are hard to achieve and there has been no consensus on how to estimate the service-sector productivity. In addition the literature rarely shows how productivity might create new hiring opportunities, which is a key requirement of translating productivity growth into structural change.

Finally, we contribute to the literature on structural transformation patterns by differentiating labor hiring across types. Several studies have already shown that skilled workers and unskilled workers are imperfect substitutes in both developing countries and developed countries (Card (2009), Mello (2008), Acemoglu & Autor (2011)). Some studies have also analyzed structural change based on different worker types in developed countries with a focus on the skilled worker side (Buera et al. (2022), Hendricks (2010), Caselli and Coleman (2001)). On the other hand, few studies identify differences between skilled and unskilled workers in developing countries where unskilled workers dominate and are arguably the most important worker type for structural transformation and equitable growth. By analyzing differences between skilled workers and unskilled workers' reallocation across firms and sectors in Côte d'Ivoire, we provide a deep insight into the special structural transformation path of African countries.

Our results, based on micro-level estimation of productivity growth across manufacturing and service sectors call into question a lot of the orthodoxy of African development. In contrast to the literature and large numbers of development professionals who see manufacturing growth as the only way to the structural transformation of African economies and the growth of services as a nefarious development that will doom economies, our work shows the potential of service sector growth in both productivity and employment growth.

The remainder of the paper is organized as follows. Section 2 discusses the heterogeneity in the service sector. Section 3 explains the data and methods we use to estimate the productivity. Section 4 estimates service sector productivity. Section 5 analyzes the productivity outcomes. Section 6 studies the structural transformation across sectors and firms including employment growth. Section 7 concludes the discussions above.

2 Service Sector Productivity

2.1 Inputs and Outputs

A large, older literature focused primarily on Europe an the US has estimated service productivity across many sub-sectors. These works, summarized in Table 1, usually focus on one specific service industry such as the banking industry, transport industry, hotel industry, etc. Here we summarize the inputs and outputs used to estimate productivity in those industries. We build our case for using a standard production function models used in manufacturing on the fact that the inputs and outputs used to estimate service productivity in these sectoral studies are similar to those used in the manufacturing sector.

In the CIV data, we have comprehensive data in 9 service industries: Health and Social Services, Finance and Insurance, Rental Building and Management, Education and Research, Personal Beauty, Restaurant, Legal Service and Training, Transport and Communication, and Commerce. Table 1 reviews the inputs and outputs from studies in those industries. It is evident that the inputs and outputs commonly used to estimate TFP are the same in most of those industries.[2] The main inputs evident are capital, labor, and human capital, and the main output is value-added. Despite the large literature, there remains a concern in using capital and labor as inputs and value-added as output in the Service Sector which is the potential large heterogeneity in inputs and outputs. In Section 2.3, we discuss potential heterogeneity problems and show that it is feasible to use the same inputs and outputs as in the manufacturing sector in the service sector context.

Table 1: Literature Review

[2] The exceptions are Health and Social Service and the Education and Research Industries, which are non-market industries (Herrendorf et al. (2022)) where value-added is an imperfect measure of output.

Industry	Paper	Input and Output
Banking	Sealey & Lindley (1977), Berger & Humphrey (1992, 1997), Wheelock & Wilson (1999), Drake & Hall(2003), Isik & Hassan (2003), Casu et al.(2004)	Inputs are labor and capital. Output can be deposits, net revenue, or value-added.
Banking	Grifell-Tatjé & Lovell (1997)	Inputs are the number of employees, non-labor operating expense, and a capital cost input.
Banking	Johnes et al. (2014)	Fixed assets as represent capital input. General and administration expenses as a proxy for labor input.
Transport	Gordon(1992)	Output is value-added. Inputs are labor and capital.
Railway	Oum et al.(1999)	Output is an aggregate output quantity index. Inputs are capital (physical quantity) and labor.
Port	Gonzalez & Trujillo (2009)	Outputs are cargo or income. Inputs are labor and capital
Telephone Service	Sichel (2001)	Bills from telephone service as output. Capital especially the equipment, and labor as inputs.
Telecommunication	Li & Xu (2004)	Value-added as an output. Labor and capital employed as inputs.
Telecommunication	Oniki et al. (1994), Yoon (1999), Rushdi (2000), Lam & Lam (2005)	Revenues as an output. Capital and labor as inputs.
Restaurant & Hotel	Smeral(2009)	The growth in the value-added comes from the labor input and capital service.
Restaurant & Hotel	Campos-Soria et al.(2005), Smeral (2009)	Human capital factor has a positive influence on the service quality and productivity.
Tourism	Borooah (1999), King & McVey (2006), Parilla et al (2007)	Physica capital investment increase the growth in tourist sector.

Commerce	Ortiz-Buonafina (1992), Dubelaar et al (2002)	Sales or value added as outputs. capital and labor as inputs
Commerce	Leadbeater (2001), Scarbrough & Swan (2001), Higón et al. (2010)	Skilled workers are determinants of retail industry
Commerce	Higón et al. (2010))	Capital is important

∗ In literature estimating service productivity across sub-sectors, they usually focus on one specific service industry such as the banking industry, transport industry, hotel industry, etc. The inputs and outputs that they use to estimate the service productivity are similar to those used in the manufacturing sector, and we can proceed to employ standard production models of manufacturing in the service industries.

2.2 The Model

The large literature described in Table 1 demonstrates that it is possible to accurately measure service sector productivity. That literature shows that labor (skilled workers and unskilled workers) and capital are the main inputs and value-added is the best measure of output in most service industries. We can therefore build a Cobb-Douglas production function for service sector productivity estimation, analogous to manufacturing productivity estimation, as follows:

$$Y_{it} = A_{it} H_{it}^{\alpha} L_{it}^{\beta} K_{it}^{1-\alpha-\beta} \tag{1}$$

where Y_{it} is the value added of output of firm i in time t, A_{it} is total factor productivity, H_{it} is skilled worker input, L_{it} is unskilled worker input, and K_{it} is capital input.

In contrast to standard practice in manufacturing estimation, in our production function, we divide the labor into two types: the skilled worker and the unskilled worker. As suggested in the literature, they are imperfect substitutions for each other. According to Card(2009), the elasticity of substitution between skilled workers and unskilled workers in the US is between 1.5 to 2.5. Mello (2008) shows that the elasticity of substitution between skilled workers and unskilled workers is 2.2 in Chile and 1.9 in the Philippines.

In the service sector, technology innovation improves the efficiency of resources used in the firms and can also increase output quality[3]. If we assume we have a perfectly competitive market and that changes in markups would pass through to the price thoroughly, observable price changes would show the quality changes in the service sector. An increase in quality would raise the markup of

[3]For example, adding an electronic payment system in a restaurant increases production efficiency and also improves the quality of service to customers. These quality improving effects are likely also present in manufacturing, but remain largely ignored in the literature.

the product (Bellone et al. (2016)) and thus increase the price. Then it is feasible for us to use the monetary value of output, which we can observe from the firm-level data set, to estimate value added-based TFP.

One concern is that the market in some services sub-sectors might not be perfectly competitive and then price incorporates both productivity differences and market power (Francis et al. (2020)). In Section 4.4, we test for whether market concentration, our best available measure of market power, changes our productivity estimates and find that concentration has little effect on productivity. More specifically, there is a negative but insignificant correlation between the estimated productivity level and the Herfindahl-Hirschman Index for domestic firms. Then we further look at the relationship between the productivity and number of firms as a further measure of concentration. The coefficient is positive but close to zero.

2.3 Heterogeneity of Services

2.3.1 Heterogeneity in Outputs

A key stumbling block for researchers trying to estimate productivity in services is the heterogeneity in outputs, especially the valuation of intangible assets and variation in product types. The outputs in the service sector are often customized and can be intangible products (Tether & Hipp(2002)). For example, legal services might provide different advice to different consumers based on the consumers' backgrounds, and the advice itself is intangible. Because of the special characteristics of the outputs, it is often hard for the service industries to create industry standards. In addition, the value of the outputs is often decided by the consumers, not just the producers (Karmarkar & Pitbladdo (1995), Ojasalo (2003)).[4]

There are also potentially large differences between sub-sectors within services. Finance and banking are different products than restaurants and commerce. This heterogeneity in products may make service sector productivity estimation more challenging than manufacturing. The literature on manufacturing productivity estimation has for the most part assumed that the industry produces homogeneous products (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Ackerberg et al, 2015).[5] We accommodate this heterogeneity in the service sector by estimating our TFP models by individual sub-sectors so that for example financial service firms are compared only to other financial service firms.

[4]The prices of the same dish in different restaurants may vary because of the consumers' differential valuations.

[5]It is worth noting that typical TFP estimates in manufacturing also come from heterogeneous sub-industries, ranging from mining to car manufacturing to electronics to bakeries.

2.3.2 Heterogeneity in Inputs

In addition to the heterogeneity in outputs, services also potentially have high levels of heterogeneity in inputs, especially labor. Labor input is likely more important in the service sector compared with the manufacturing sector because the service sector is more personnel-intensive. (Rutkauskas & Paulavičienė, 2005). At the same time, heterogeneity in labor inputs in Africa is not unique to the service sector. According to Bassi et al. (2023), there are large levels of heterogeneity across firms in manufacturing due to the lack of labor specialization in Uganda. Below we show that the input heterogeneity in the service sector is no larger than the input heterogeneity in the manufacturing sector, which allows us to argue that the service productivity we estimated is comparable to the manufacturing productivity.[6] In the model we estimate, we therefore use labor (skilled workers and unskilled workers) and capital as the primary inputs. External service and material inputs serve as the proxy variable. Therefore, we show all the inputs that are used to estimate productivity in Table 2.

In order to test the relative heterogeneity of input shares in services relative to manufacturing, we show in the CIV data the value share, input value divided by total expenditure, of the inputs we used in the production function. Table 2 shows the mean value shares, standard deviation, and coefficient of variation of the input shares in agriculture, manufacturing, and service. In agriculture, capital accounts for the largest proposition because the agriculture firms in our data are large plantations. In the manufacturing sector, material input is the most important input and the mean value of the share is about 39%, followed by capital and external service. In the service sector, on the other hand, external service input has the highest share and the mean value is around 40%. The shares of skilled workers and unskilled workers are higher than the other two sectors. This is consistent with estimates across the world showing that the service sector is personnel-intensive.

While we focus on the heterogeneity in the service sector, we should also consider that there is heterogeneity in the manufacturing sector as well (Cantner & Krüger (2008), Abraham et al (2010), Elshennawy & Bouaddi(2021)). Although production processes and products in the manufacturing sectors are more standardized, it does not necessarily mean that the income shares are always the same across firms within the industries. Large firms and small firms may have different efficiencies in using the resources and thus make different decisions in capital usage and labor hiring. In the traditional productivity estimation literature, we have accepted the assumption that the income shares are the same across the firms. This would give us the constant values for the income shares from the regression.

In order to proceed with our service sector productivity estimations using the same methods as man-

[6] In the Appendix, we further show the input share comparison across sub-sectors. The results are similar in the manufacturing sub-sectors and the service sub-sectors.

ufacturing productivity estimation, what we want to prove is that the heterogeneity in income shares in the service sector is not meaningfully higher than that in the manufacturing sector. From Table 2, we can see that the standard deviations and the coefficient of variation of the inputs are close to each other in the three sectors, which means that the input variability in each sector is similar. From the sector-level comparison, we do not find that the heterogeneity in inputs in the service sector is larger than that in the manufacturing sector. In the Appendix, we further investigate the heterogeneity in the income share of inputs in each service industry. We can see that the standard deviations in most service industries are not very big, indicating that the heterogeneity in the service industry is smaller than expected and generally smaller than in manufacturing.

Table 2: Inputs Share Comparison Across Sectors

Sector	Inputs	Obs	Mean	Std. dev.	CV
Agriculture	Skilled worker	1,330	0.0963718	0.1469733	1.525
	Unskilled worker	1,330	0.0923565	0.141863	1.536
	Capital	1,330	0.3771598	0.3156895	0.837
	External Service	1,330	0.2614375	0.2632593	1.007
	Material	1,330	0.1726744	0.2605995	1.509
Manufacturing	Skilled worker	9,586	0.1005161	0.1400962	1.394
	Unskilled worker	9,586	0.0756511	0.1198514	1.584
	Capital	9,586	0.2419685	0.2553786	1.055
	External Service	9,586	0.1906013	0.1989653	1.044
	Material	9,586	0.3912649	0.2968555	0.759
Service	Skilled worker	68,801	0.1621908	0.2010422	1.240
	Unskilled worker	68,801	0.1119439	0.1798793	1.607
	Capital	68,801	0.2402663	0.2706904	1.127
	External Service	68,801	0.3995419	0.2444577	0.612
	Material	68,801	0.0860568	0.1781215	2.070

$*$ We show the mean value shares, standard deviation, and coefficient of variation of the input shares in agriculture, manufacturing, and service.

$**$ In the manufacturing sector, material input is the most important input and the mean value of the share is about 39%, followed by capital and external service.

$***$ In the service sector, on the other hand, external service input has the highest share and the mean value is around 40%. The shares of skilled workers and unskilled workers are higher than the other two sectors.

$****$ we can see that the standard deviations and the coefficient of variation of the inputs are close to each other in the three sectors, which means that the input variability in each sector is similar.

3 Productivity Estimation data and methods

3.1 Data

The Côte d'Ivoire firm-level data (CIV data) covers the registered firms from the agricultural sector, the manufacturing sector, the service sector, the construction sector, and the extraction sector in Côte d'Ivoire from 2003 to 2014. The original data has 91,630 firm-year observations. The data contains information on sales (domestic and exported), inputs, employment (skilled workers and unskilled workers), ownership status, and operating costs of all formal agricultural, manufacturing, service, and trade establishments in the country. The records are a census of all formally registered public enterprises, private domestic firms, and foreign firms in the country. Due to the data limitation, researchers usually use the survey data in African countries where only the larger firms (with more than 5 workers) are studied. However, in our data, we have more than 50% firms with less than 5 workers. The data set provides us with more information about the small firms that have been not studied carefully before.

The input variables that we use in the estimation are capital (K), skilled labor (H), unskilled labor (L), and intermediate inputs (material (M) in the manufacturing sector and external service (E) in the service sector. The output variable is value-added output (Y)[7]. To convert the variables into real values, we use the World Bank's GDP deflator for Côte d'Ivoire, setting 2003 as the base year.

To estimate the productivity (A) from the production function statistically, we first need to take the log of both the dependent variable (Y) and explanatory variables (K, H, L, M, and L).[8] Besides, there are some firms with 0 inputs or value-added outputs but are still operating in the market. Dropping those 0-value firms will create selection bias in the model, especially in our dynamic estimation methods where a full history of firms is required. To deal with the problem, we use log(X+1) instead of directly taking the log of the variables.[9]

Specifically, we use total sales to subtract intermediate inputs (intermediate materials for the agriculture and the manufacturing sectors, and external service for the service sector) and get value-added. In these data the definition of skilled and unskilled workers depends on the both education level and the categories of employment. [10]

[7]Value-added is a better output variable in our research. In the MrEst method we use, intermediate materials enter into the proxy variable policy function and are subtracted from the production function.

[8]The model requires the log transition. Other transformation methods, such as inverse hyperbolic sine transformation is inconsistent with the model that the estimation method is based on.

[9]Since the values of those inputs and output are pretty large compared to the value of 1, adding 1 to the original value does not change the shape of the distribution of variables.

[10]According to the local wage category documents and Monson's study (1980), skilled workers include senior managers, middle managers, and technicians, while unskilled workers are workers and apprentices.

3.2 Estimation Methods

Our review of the literature on productivity estimation in the service sector shows that most papers use older non-parametric (DEA) and parametric (SFA) methods. Both methods are not robust to endogeneity concerns and suffer from known biases.[11] Modern TFP estimation has four different common estimators for TFP: the OP method (Olley & Pakes, 1996), the LP method (Levinsohn & Petrin, 2003), the ACF method (Ackerberg et al., 2015), and the MrEst method (Rovigatti & Mollisi, 2018). Those methods are typically used to estimate manufacturing productivity based on a production function with a "proxy variable" approach to deal with the potential endogeneity issues. The proxy variable for the manufacturing industry is typically the intermediate material inputs, a variant of which is what we use in our estimation.

The production function for firms in the service sector in our estimate is similar to the production function typically estimated in the manufacturing sector. From our literature review, we have already shown that although skilled workers contribute more to firms' output in the service sector than unskilled workers and capital, all inputs are needed in the production process. The difference comes from the proxy variable. The intermediate goods for firms in the manufacturing sector are materials, energy, etc., while for the service sector we choose external service goods as the intermediate input consumed by firms to produce their final service goods.[12] Service firms need to consume external professional services such as consultants to support their operations. The consultants, especially those highly-educated consultants are also the inputs in the service sector (Sarvary (1999), Nachum (1999), Bessant & Rush (1995)). Instead of using intermediate material alone as the proxy variable, we add the external service to the intermediate material and create a new proxy variable that can be used in all three sectors.

To show the practicality of the new proxy variable, we go back to the CIV data. Table 2 shows that manufacturing firms consume more intermediate material and the share is as high as 39%. The share of external labor is far lower. In the service sector, the share of external services (40%) is higher than the share of intermediate materials (8%).

Another advantage of using the new proxy variable is that there are fewer zeros in both the service and manufacturing sectors. Manufacturing firms need more material inputs, while fewer external services are needed. Different from the manufacturing sector, service firms' demand for intermediate inputs is smaller and some firms do not report purchasing intermediate inputs at all. As a result, there are a lot of zeros in the intermediate input variable in the service sector. External service, on the

[11] The DEA method can be affected by sample size which creates a bias in comparisons between estimates (Zhang & Bartels (1998)). As we need to compare productivity across sectors, industries, and firms, the econometric TFP method makes the productivity outcomes more comparable. The DEA method also has a low tolerance for random errors (Berger & Humphery (1997), Drake & Hall (2003)). The SFA ignores the endogeneity problem of firm manager choices when faced with technological change. (Greene (2005), Amsler et al. (2016), Griffiths & Hajargasht (2016), Kumbhakar et al. (2020))

[12] In the Appendix, we develop the theory to prove that using external service goods as the proxy variable is theoretically sound under profit maximization.

other hand, is frequently consumed by service firms in our data. From Table 3, we can see that the proportion of positive entries for external service is 97.5% in the service sector, while the figure for intermediate material is only 57.8 %. By using the new proxy variable, we avoid a sample selection problem in the service sector.

Table 3: Zeros in Proxy Variables

Sector	External Service	Material
Manufacturing	97.9%	80.9%
Service	97.5%	57.8%

∗ There are fewer zeros in external service in the service sector. The proportion of positive entries for external service is as high as 97.5% in the service sector, while the figure for the intermediate material is only 57.8 %.

An important concern in estimating service sector productivity with the "proxy variable" approach is that service firms often produce products based on customers' needs and the quality of output is determined by consumer experience with the firm. As a result, information, especially experience from previous years, is a vital input in service firms' production process. [13] Thus, it is important to include longevity information in the production function if we want to estimate service-sector TFP. The estimates from the OP method, the LP method, and the ACF method are not able to capture this characteristic.[14] Wooldridge's (2009) productivity estimator uses the lagged state variables and free variables as instruments for themselves and serial dependence in idiosyncratice shocks in a productivity estimation. The lagged variables in the service firms provide us with extra information likely correlated with consumers' demand and experience that we do not observe directly from the data. They also help with potential omitted variable bias by allowing for serial correlation in the idiosyncratic shocks. Therefore, we believe that the Wooldridge method is a better choice in the service sector TFP estimate.

Applying the Wooldridge Method, however, can be costly because adding a lag in the production estimation means losing the observations in the first year for each firm. There are 21,887 firms in the service sector in the CIV data and the loss would be about 1/3 of the total observations. To avoid the loss, we use the MrEst method developed by (Rovigatti & Mollisi, 2018) that uses the proxy variable approach while applying the Blundell and Bond (1998) dynamic panel-data instruments [15] in the Wooldridge GMM framework (2009).

[13]The CIV data produces estimates that are suggestive of this experience effect in the entry and exit of firms. According to our estimates, newly founded firms have a far higher probability of shutting down in one year and older firms are more likely to survive in the market.

[14]In the Appendix, we show the outcomes of the 4 productivity estimation methods. The differences between those methods are not very large, except for the ACF method.

[15]Another reason to use the Dynamic Panel Method is that the data set we have has "large N, small T". Dynamic instruments are useful in the estimation of this kind of panel data set.

4 Productivity Estimation Results

Using the MrEst method, we first estimate the parameters of the production function by the 7 sub-sectors in the service sector. They are Finance and Insurance, Rental Building and Management, Transport and Communication, Personal Beauty, Restaurant, Training Legal Service, and Commerce. To form the panel data, we eliminate some firms with missing years in the data. The final data we use in the service sector accounts for 63% of the original data. Table 4 shows the estimation outcomes of each service industry.

In Table 4, we can see that the coefficients on skilled workers in 5 sub-sectors (Transport and Communication, Rental Building and Management, Personal Beauty, Restaurant, and Training Legal Service) are the largest among the three inputs, which means that these are skilled service sub-sectors. Commerce (including Retail and Wholesale) is the sector with more contribution from unskilled workers. In the commerce industry, unskilled workers are a more important input (0.534) compared with both skilled workers (0.327) and capital (0.106). On the other hand, capital inputs such as machines, equipment, land, etc. are perhaps not as important in the service sector compared with the manufacturing sector (Li & Prescott (2009)). Overall, from the regression outcomes across the service industries, we verify the argument that the service sector is personnel-intensive. Meanwhile, the coefficients vary a bit across the sub-sectors.

Table 5 shows the estimation of the production function for manufacturing industries.[16] The manufacturing industries in our estimation are Editing and Printing, Food Products, Wood Products, Detergents, Plastic and Rubber, Metallurgy, and Agro-chemicals and Fiber. They account for 63% of the firm data in the manufacturing sector. Similarly, the skilled worker coefficients are the largest in most industries, though the coefficient for capital input is largest in the Agrochemical and Fiber Industries.

[16]To meet the requirements in the MrEst Methods that the industry needs to have a positive definite weight matrix, we eliminate some industries. The eliminated industries are those with relatively few firms.

Table 4: Estimates of Production Function Parameters (Service Sector)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Finance and Insurance	Transport and Communication	Rental Building and Management	Personal Beauty	Restaurant	Training Legal Service	Commerce
Skilled	0.403***	0.300***	0.316***	0.451***	0.449***	0.519***	0.327***
	(4.63)	(7.11)	(4.10)	(5.85)	(7.43)	(18.30)	(12.08)
Unskilled	0.285***	0.254***	0.164**	0.285***	0.351***	0.265***	0.534***
	(3.84)	(8.65)	(2.73)	(5.44)	(7.48)	(15.16)	(24.47)
Capital	0.466*	0.146**	0.303**	0.0828	0.0327	0.117***	0.106***
	(2.20)	(2.94)	(2.79)	(0.69)	(0.39)	(4.99)	(5.74)
N	1011	3843	1256	223	1453	10531	25646

$*$ t statistics in parentheses

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

$***$ the coefficients on skilled workers in 5 sub-sectors (Transport and Communication, Rental Building and Management, Personal Beauty, Restaurant, and Training Legal Service) are the largest among the three inputs, which means that these are skilled service sub-sectors.

$****$ The coefficient on the unskilled workers in the Commerce sub-sector is the largest, indicating that the unskilled workers are the most important input.

Table 5: Estimates of Production Function Parameters (Manufacturing Sector)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Editing and Printing	Food Products	Wood Products	Detergents	Plastic and Rubber	Metallurgy	Agrochemical and Fiber
Skilled	0.645***	0.747***	0.571***	0.461*	0.431***	0.915***	0.185
	(6.69)	(4.99)	(6.72)	(2.12)	(3.89)	(5.49)	(0.95)
Unskilled	0.350***	0.561***	0.548***	0.0772	0.162*	0.370***	0.204
	(4.08)	(4.68)	(5.33)	(0.82)	(2.40)	(4.27)	(1.69)
Capital	0.129*	-0.0736	-0.00500	0.749	0.136	0.169	0.483**
	(2.28)	(-0.67)	(-0.03)	(1.73)	(0.80)	(1.76)	(2.94)
N	1377	1851	826	278	651	874	223

* t statistics in parentheses

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

* * * he skilled worker coefficients are the largest in most industries, though the coefficient for capital input is largest in the Agrochemical and Fiber Industries.

For completeness, we also estimate the productivity in the agriculture sector.[17] There are only 4 sub-sectors in the agriculture sector with fewer firm records, therefore, we treat the agriculture sector as a whole. The regression outcome is shown in Table 7. Skilled workers have the largest coefficients and contribute most to the agricultural output.

[17] In the Appendix, we show that the agriculture firms recorded in the data set are those large plantation farms. The average farm size is larger than both manufacturing firms and service firms. The small farms that makeup 95+% of agriculture in the country are not included.

Table 6: Estimates of Production Function Parameters (Agriculture Sector)

	Agriculture Plantation
Skilled	0.939***
	(4.31)
Unskilled	0.623***
	(4.82)
Capital	0.0402
	(0.10)
N	1115

$*$ t statistics in parentheses

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

$***$ Skilled workers have the largest coefficients and contribute most to the agricultural output.

When discussing the estimation methods and outcomes, there are two concerns. One concern is that the market power may cause bias in the estimation of productivity outcomes. In the Appendix, we implement a robustness check for market power. First, we measure the market power using the Herfindahl-Hirschman Index of the 5 largest firms in each subsector each year. Then we fix the industry and year effects and run the regression of productivity estimated by the MrEst Method on the index. We find that the market power has no effect on productivity outcomes.

Another concern is that there are other proxy methods (such as OP, LP, and ACF methods) that can be used to estimate productivity. Besides, labor productivity (value added per worker) is prevalent in structural change papers. In the Appendix, we show the productivity estimation outcomes using 4 different econometric TFP estimation methods and value-added per worker. The 5 methods are the Olley & Pakes method (OP method), the Levinsohn & Petrin method (LP method), the Ackerberg, Caves & Frazer Method (ACF method), and the Labor Productivity method (value added per worker). We find that the mean productivity value is the largest in the service sector in the MrEst Method, the LP method, the LP with ACF method, and the Labor Productivity method. The OP method and the OP with ACF method, on the other hand, has the highest productivity in the agriculture sector or the manufacturing sector. More importantly, in our structural transformation analysis, the rank of firm's productivity is an important factor that affect people's reallocation. Therefore, we further check the firms' rank based on their productivity estimated by different methods. We find that the MrEst productivity highly correlates with the OP, the LP, the ACF, and the labor productivity methods.

5 Productivity Analysis

5.1 Productivity Outcomes

With the estimation outcomes, we can calculate the total factor productivity of each firm in each year. In Table 7, we show averages across sectors, which demonstrate that the service sector has the highest mean productivity, followed by the manufacturing sector. The agriculture sector has the lowest mean value. The mean value of service productivity (14.844) is 6.5% higher than the mean value of manufacturing productivity (13.943). Besides, the standard deviation is also the smallest in the service sector, which indicates that the productivity of service firms is more concentrated.

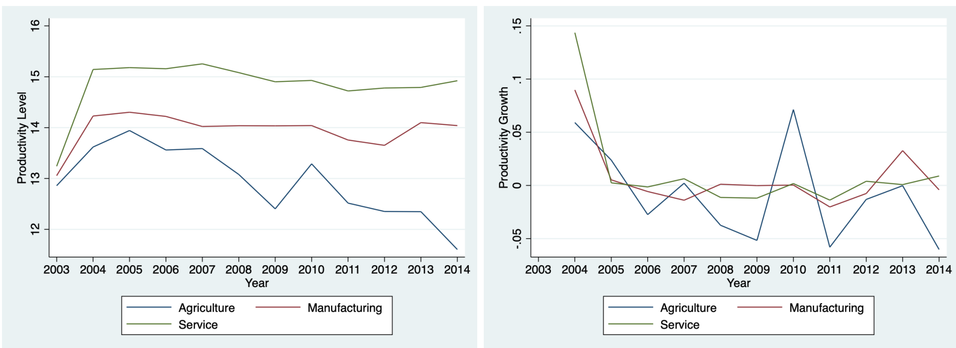
Table 7: Mean Value

Method	Sector	Mean	Std. dev	Observations
MrEst	Agriculture	12.811	5.333	1,166
	Manufacturing	13.943	4.448	7,189
	Service	**14.844**	**3.204**	48,264

∗ The service sector has the highest mean productivity, followed by the manufacturing sector. The agriculture sector has the lowest mean value. The mean value of service productivity is 6.5% higher than the mean value of manufacturing productivity. The standard deviation in the service sector is also the smallest, indicating that the productivity of service firms is more concentrated.

Figure 1 shows the productivity level and productivity growth rate across sectors between 2003 and 2014. We can see that the average productivity level in the service sector is always the highest, followed by manufacturing and agriculture[18]. In contrast, the growth rates in all three sectors fluctuate around 0, with no distinct patterns and no clear productivity growth winners.

Figure 1: Productivity Comparison



(**a**) Productivity Level (**b**) Productivity Growth Rate

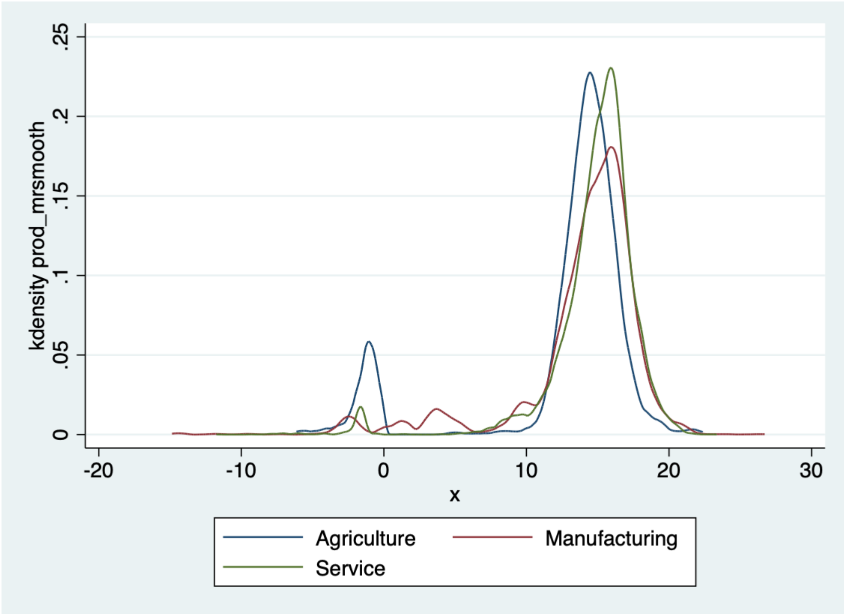
Note: In Figure 1(a), the average productivity level in the service sector is the highest most of the time, followed by manufacturing and service. In Figure 1(b), the growth rates in all three sectors fluctuate around 0.

Figure 2 plots the productivity distributions of the agricultural, manufacturing, and service sectors.

[18]The agriculture firms we estimate are those large farms with high productivity. Therefore, the productivity estimated in agriculture is more upward biased than the other two sectors.

The distribution of service sector productivity is to the right of both the agriculture productivity, while the manufacturing distribution overlaps the service sector. There are more extreme values at both the left and right tails of the manufacturing sector.

Figure 2: Productivity Distribution of Service Sector and Manufacturing Sector



Note: The distribution of service sector productivity is to the right of the agriculture productivity, while the manufacturing distribution overlaps the service sector.

We can understand more of these distributions by investigating the 90-10 percentile gaps in productivity. When we do so in Table 8, we see that the service sector has the lowest productivity gap, followed by manufacturing, with agriculture having the highest gap. Table 7 shows that the standard deviation is the smallest in the service sector, followed by the manufacturing sector. The service productivity gap is always the smallest among all three sectors.

Table 8: 90-10 Percentile Productivity Gaps

	Aggregate	Agriculture	Manufacturing	Service
Top 10%	18.546	17.691	18.656	18.557
Bottom 10%	7.030	-1.596	2.788	8.002
Gap	2.638	-11.085	6.692	**2.319**

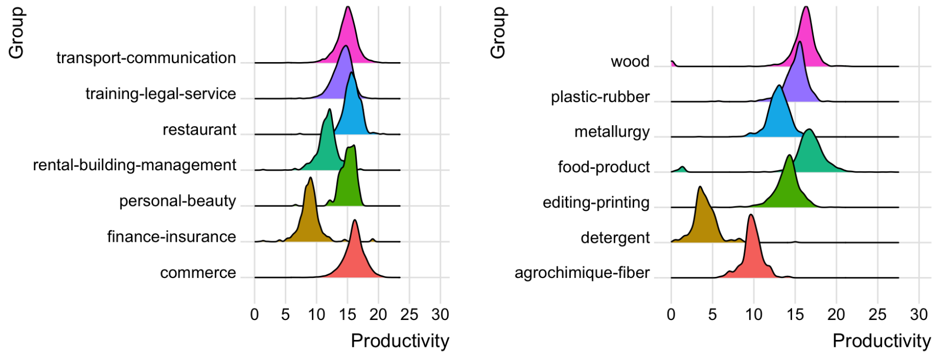
∗ The service sector has the lowest productivity gap among the three sectors.

The service sector has higher average productivity and lower dispersion than the manufacturing sector. There are two likely explanations for the higher dispersion level in the manufacturing sector than in the service sector. First, the productivity values in the manufacturing sub-sectors are different from each other. Second, the productivity values are quite dispersed inside each sub-sector within manufacturing. In the following section, we further decompose the distribution by sub-sectors to test these differences.

5.2 Productivity Distribution Decomposition

In Figure 3, we show the productivity distributions in the 7 service sub-sectors (3(a)) and 7 manufacturing sub-sectors (3(b)).[19] The productivity distributions of the service industries are closer to each other compared with the manufacturing industries. The main part of the service sub-sector distribution ranges between 5 to 20, while the main body of the manufacturing sub-sector distribution ranges between less than 0 to almost 20. Therefore, the service sub-sector productivity values are more concentrated than manufacturing.

Figure 3: Ridge Distribution of Industry



(a) Distribution of the Service Industries **(b)** Distribution of the Manufacturing Industries

Note: Figure 3(a) plots the productivity distributions in the 7 service sub-sectors. The productivity distributions are more concentrated and range between 5 to 20. Figure 3(b) shows the productivity distributions in 7 manufacturing sub-sectors. The distributions are more dispersed and range between less than 0 to almost 20.

At the same time, the productivity distribution inside each manufacturing sub-sector is more dispersed. The Wood Industry and the Food Product industry have lower kurtosis and wider ranges, implying that there are plenty of heterogeneities in firm-level productivity in these manufacturing industries. These two findings imply that the manufacturing sector is more dispersed than the service sector both across sub-sectors and within sub-sectors.

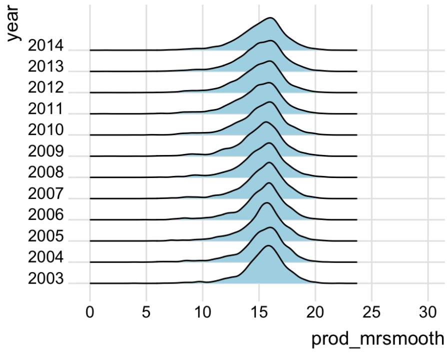
Then we further show the decomposition of the productivity distribution in three sectors across the years of our dataset in Figure 4. We can see that the distribution of the three sectors all become more dispersed over time. The range of the manufacturing sector is always larger than the other 2 sectors in all 12 years.

Overall, we find that the productivity in the service sub-sectors is more concentrated than in manufacturing, which is consistent with the previous conclusions about average levels. Also, the higher level of dispersion both across and within manufacturing sub-sectors explains why the manufacturing sector is more dispersed. These conclusions about the differences in the distribution of produc-

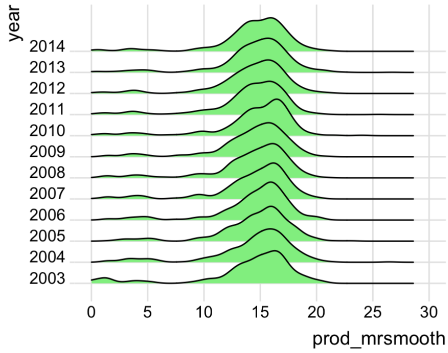
[19]Since we estimate the agriculture productivity as a whole, we cannot decompose the agriculture sub-sectors. We focus on the manufacturing sub-sectors and the service sub-sectors.

tivity within sectors do not change if these changes across years as in Figure 4.

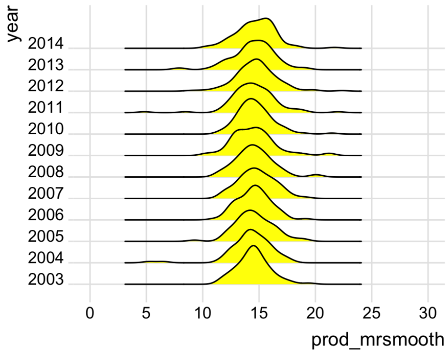
Figure 4: Ridge Distribution by Year



(a) Year Distribution of the Service Industries



(b) Year Distribution of the Manufacturing Industries



(c) Year Distribution of the Agriculture Industries

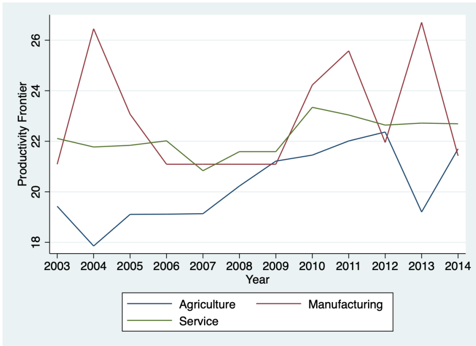
Note: We decompose the productivity distribution in three sectors over time. The distribution of the three sectors all become more dispersed over time. The range of the manufacturing sector is always larger than the other 2 sectors in all 12 years

5.3 Productivity Frontier

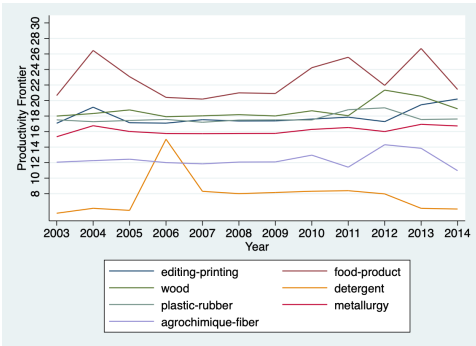
Now we have verified that the service sector has higher average productivity and a lower productivity dispersion level within sub-sectors and across sectors, we focus on another question: does the service sector have a higher absolute productivity level? The mean productivity value in the service sector is indeed higher. Yet, we can argue that a higher average productivity value does not necessarily lead to a higher productivity frontier. If the productivity frontier appears in the manufacturing sector or the agriculture sector, we then need to be careful about what makes the mean value and the maximum value in different sectors.

Figure 5(a) shows the productivity frontier in three sectors. The frontiers of three sectors entangle with each other over time and it's hard to tell which sector dominates. However, if we further look at the productivity frontier by sub-sector as in Figures 5b and 5c, the productivity frontier in the manufacturing sector comes from a single industry, the Food Production sector: the brown line in Figure 5(b). The productivity frontiers are dispersed to each other in manufacturing, ranging from below 8 to above 25. Comparing the distribution of the manufacturing sub-sectors in Figure 5(b) to the distribution of the service sub-sectors in Figure 5(c), we can see that service sub-sectors have relatively higher and more concentrated productivity frontier. Thus, the productivity frontier benefit of the manufacturing sector comes from a single sub-sector, Food Production, otherwise the sub-sectors in services dominate the productivity frontier in manufacturing.

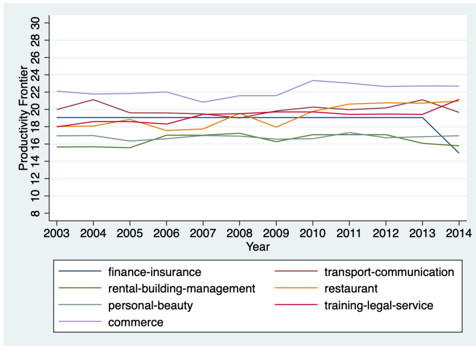
Figure 5: Productivity Frontier



(a) Productivity Frontier in Three Sectors



(b) Productivity Frontier in Manufacturing Industry



(c) Productivity Frontier in Service Industry

Note: The frontiers of three sectors entangle with each other over time and it's hard to tell which sector dominates. Comparing the distribution of the manufacturing sub-sectors in Figure 5(b) to the distribution of the service sub-sectors in Figure 5(c), we can see that service sub-sectors have relatively higher and more concentrated productivity frontier. Thus, the productivity frontier benefit of the manufacturing sector comes from a single sub-sector, Food Production, otherwise the sub-sectors in services dominate the productivity frontier in manufacturing.

To sum up, although the manufacturing sector has the highest productivity frontier, the sub-sector productivity frontiers in most manufacturing industries are lower than in the service industries. This explains the higher average productivity in the service sector.

6 Productivity and Employment

6.1 Sector-level Labor Reallocation

Having estimated productivity in agriculture, manufacturing, and service, we next study structural transformation based on the movements of labor to those sectors and how it relates to their relative productivity. We do so at both the sector and the firm level. If the transformation of labor is efficient, we expect to see that labor moves from low-productivity activities to high-productivity activities, both within and across sectors.

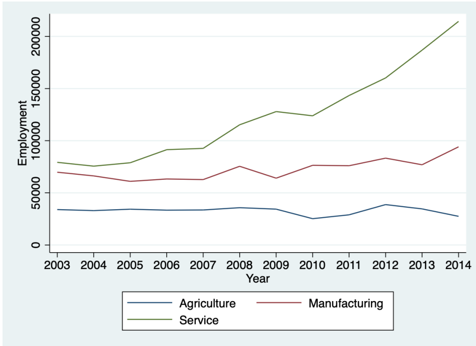
The productivity level is always higher in the service sector than in manufacturing. In response to the higher service sector productivity, we also find that the total employment in the service sector is higher during the time period we study, Figure 6(a). The gap between the employment value in the service sector and the manufacturing sector is smaller at the beginning and that gap shows significant growth over time.

We then divide the total employment into skilled workers and unskilled workers, results of which are shown in Figures 6(b) and 6(c). The number of skilled workers is larger in the service sector than in the manufacturing sector and the gap widens over time. The number of unskilled workers, on the other hand, was smaller in the service sector in 2003 and surpassed the manufacturing sector in 2005 and has continued to grow. Over the study period from 2003 to 2014, the number of workers in the service sector increases much more than that in the manufacturing sector. This is consistent with there being productivity increasing labor reallocation, with the more productive sector doing more hiring than the less productive sector.

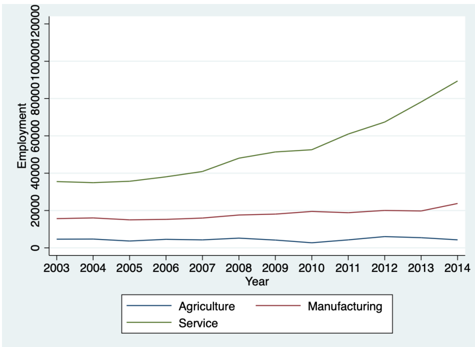
The labor growth rate in Figure 7(a) shows that labor growth in the service sector is mostly positive. The growth rates in manufacturing and agriculture, on the other hand, fluctuates around 0. The findings are the similar in the skilled labor growth(Figure 7(b)) and the unskilled labor growth rate (Figure 7(c)).

Similar patterns are also found if we investigate the employment value shares. In Figure 8, we show that the employment share in the service sector increases and the ratios decrease in both the manufacturing sector and the agriculture sector. The value employment share is always larger in the service sector. The increase in the unskilled worker share is faster than the increase in the skilled worker share in the service sector. Accordingly, the speed of decline in the unskilled worker share is larger than for skilled workers in manufacturing and agriculture. This implies that there is a substantial reallocation of unskilled workers to the service sector both in absolute numbers and when taking into account shares in employment over the time period of our study. From Figure 1(b), we can see that the productivity growth rates in the manufacturing sector and the service sector are

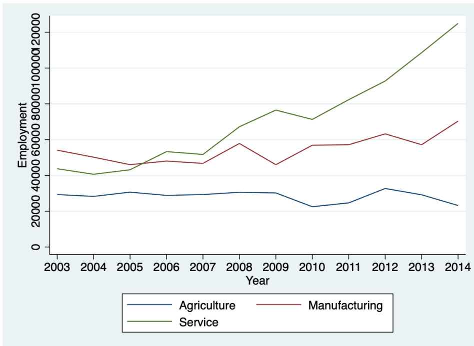
Figure 6: Labor Hired Over Time



(a) Labor



(b) Skilled Labor



(c) Unskilled Labor

Note: The figures show the aggregate labor, skilled labor, and unskilled labor employment in three sectors. In Figure 6(a), the total employment in the service sector is higher from 2003 to 2014. In Figure 6(b), the number of skilled workers is larger in the service sector than in the other two sectors and the gap widens over time. Figure 6(c) shows the similar patterns.

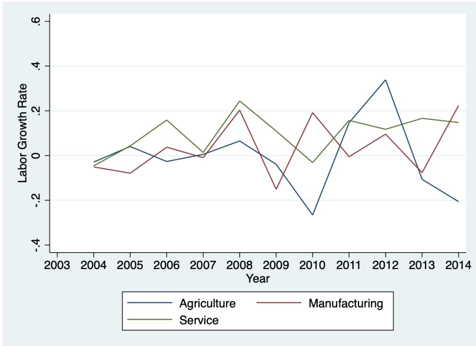
similar. Therefore, the changes in the employment values and the employment shares averages are not associated with the productivity growth rate.

To sum up, more workers move to the service sector regardless of their type and the share of workers in the service sector increases over the period. The changes in the number of workers and the ratio of employment are closely correlated with the change in the productivity level. That is, the service sector has a higher productivity level and attracts more workers, implying in aggregate the reallocation of labor is efficient. As for the growth rate, there is no obvious evidence to show whether workers move to the sector with higher or lower productivity growth rates. Because of this inconclusive result, we cannot find evidence for or against Baumol's disease at the sector level.

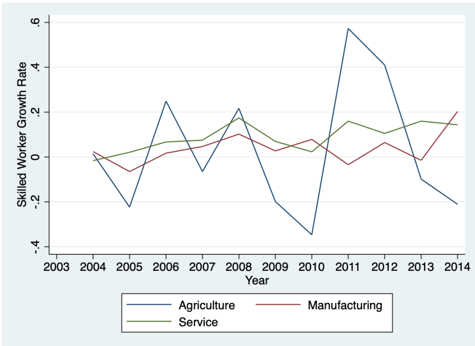
6.2 Firm-level Labor Reallocation by Sectors

Like most structural transformation studies we have now analyzed labor reallocation from less productive sectors to more productive sectors. This leaves the question of whether structural transformation leads to workers moving from the less-productive firms within a sector to the more-productive firms in the sector. If workers are hired by less-productive firms within a sector, they might be at a

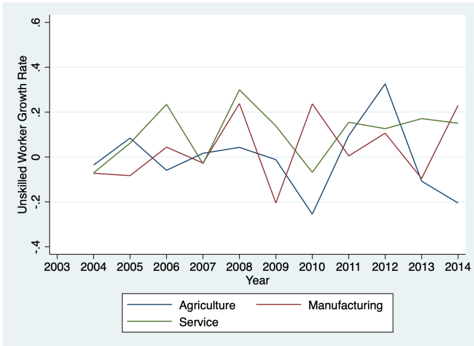
Figure 7: Labor Growth Over Time



(a) Labor



(b) Skilled Labor



(c) Unskilled Labor

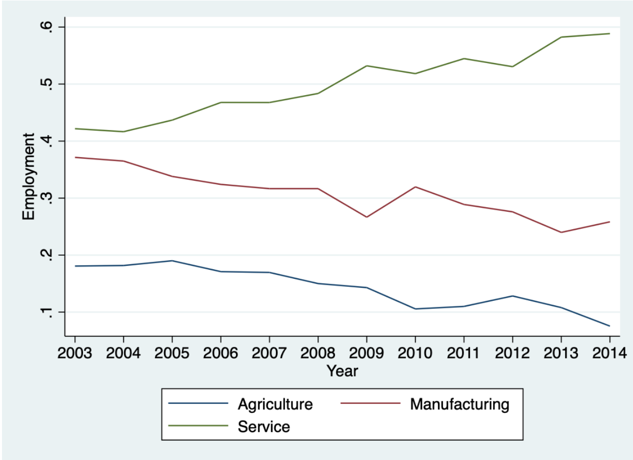
Note: The figures show the growth rate of aggregate labor, skilled labor, and unskilled labor from 2003 to 2014. Figure 7(a) shows that the labor growth in the service sector is mostly positive. Similarly, in Figures 7(b) and 7(c), the growth rates in the service sector are positive. The growth rates in the agriculture sector and the manufacturing sector fluctuate around 0 over time.

lower productivity level than their previous firms in their old sector, even if they are moving to the less productive sector. If this is the case, the reallocation of workers does not help in the economic growth. Therefore, we next investigate the differential reallocation of labor across firms in the service sector and manufacturing sector by firm productivity level.

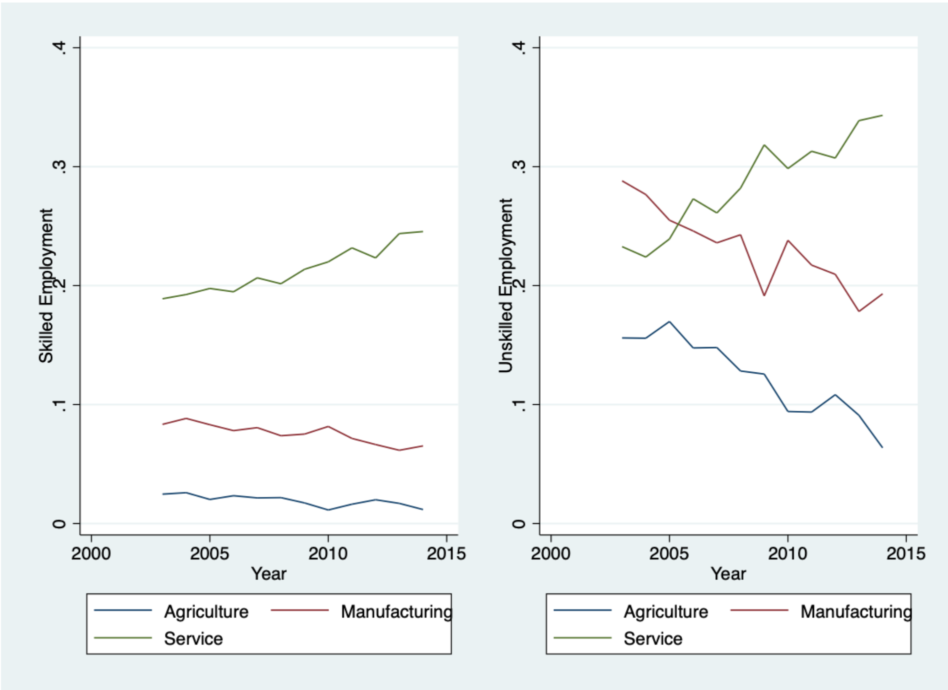
To demonstrate labor reallocation at the firm level, we use a cumulative distribution graph similar to the Lorenz curve used for inequality. The X-axis shows the cumulative firm proportions by productivity. We rank the firms based on their productivity level, instead of ranking people based on income levels as in a standard Lorenz curve. The Y-axis shows the cumulative labor growth rate across all the firms. That is if we add in a new firm, the labor growth rate of this new firm would be added to the present cumulative labor growth rate. With the cumulative distribution graph, we can see the labor reallocation patterns across firms through the concavity or the convexity of the ”Lorenz curve”. The curvature degree of the curve also provides useful information on relative hiring patterns. A highly convex curve, one with high levels of inequality, suggests workers are reallocating to the most productive firms, which is evidence of productivity-increasing structural change.

Figures 9, 10, and 11 show the reallocation rates for all labor, skilled labor, and unskilled labor at

Figure 8: Employment Share Comparison between the Manufacturing Sector and the Service Sector



(a) Employment Share

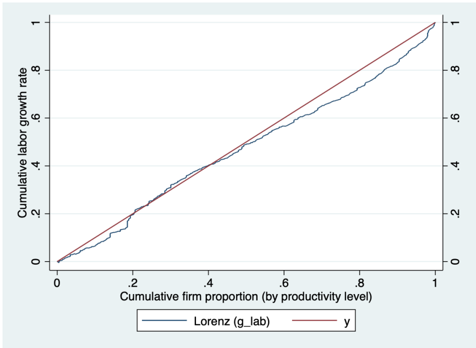


(b) Skilled Employment Share and Unskilled Employment Share

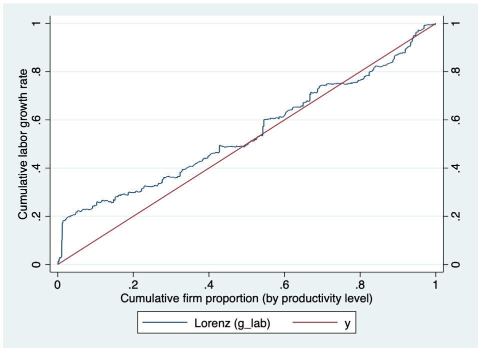
Note: We use employment share instead of employment values to check the changes in employment across sectors. In Figure 8(a), the employment share in the service sector increases, and the ratios decrease in both the manufacturing sector and the agriculture sector. Figures 8(b) and 8(c) show that the increase in the unskilled worker share is faster than the increase in the skilled worker share in the service sector. Accordingly, the speed of decline in the unskilled worker share is larger than for skilled workers in manufacturing and agriculture. This implies that there is a substantial reallocation of unskilled workers to the service sector over the time period of our study.

the sectoral level, showing allocations by firm productivity level. We first investigate the overall labor reallocation in the three sectors in Figure 9. We can see that the blue curve is pretty close to the 45-degree line in the service sector (Figure 9(a)), indicating that the all labor grows equally in different productivity firms. In the manufacturing sector (Figure 9(b)), the curve is also close to the line, though not as close as the service sector. For the agriculture sector, the curve little hiring for the lowest-productivity firms, but then mostly conforms to the other sectors.

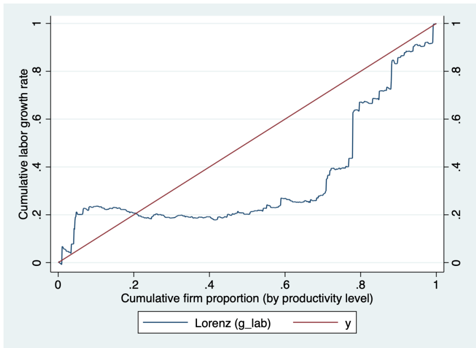
Figure 9: Labor Reallocation in Three Sectors



(a) Service



(b) Manufacturing



(c) Agriculture

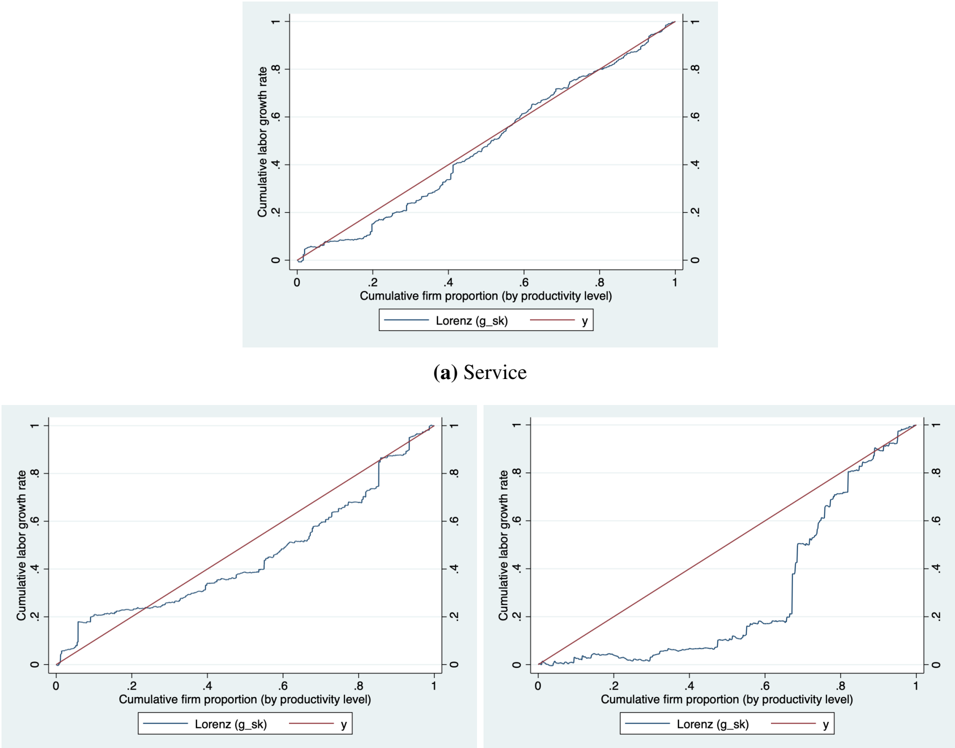
Note: To show the labor reallocation at the firm level, we use a cumulative distribution graph similar to the Lorenz curve. The X-axis shows the cumulative firm proportions. We rank the firms based on their productivity level, instead of ranking people based on income levels as in a standard Lorenz curve. The Y-axis shows the cumulative labor growth rate across all the firms. That is if we add a new firm, the labor growth rate of this new firm would be added to the present cumulative labor growth rate. With the cumulative distribution graph, we can see the labor reallocation patterns across firms through the concavity or the convexity of the ”Lorenz curve”. The curvature degree of the curve also provides useful information on relative hiring patterns.

Figure 9 shows the overall labor reallocation in three sectors. We can see that the blue curve is pretty close to the 45-degree line in the service sector (Figure 9(a)), indicating that the all labor grows equally in different productivity firms. In the manufacturing sector (Figure 9(b)), the curve is also close to the line, though not as close as the service sector. For the agriculture sector, the curve little hiring for the lowest-productivity firms, but then mostly conforms to the other sectors.

Figure 10 shows the reallocation of skilled workers in three sectors. The curves increase around the 45 degree line across different productivity levels. This means that skilled workers have an equal chance to reallocate into firms of all productivity levels in all sectors. Considering that the number of skilled workers in Côte d’Ivoire is relatively smaller, the reallocation of skilled workers does not seem to be the main source of structural transformation patterns in the country.

Finally, we look at the reallocation of unskilled workers in Figure 11. Here we see stronger evidence for productive structural transformation. In the service sector, the cumulative curve ranked by the productivity level is strongly convex (Figure 11(a)) across all productivity levels. The lowest 20% firms witness zero or negative unskilled worker growth, while the top 20% of firms by productivity, on the other hand, hire significantly more unskilled workers. This means that workers

Figure 10: Skilled Labor Reallocation in Three Sectors



(a) Service

(b) Manufacturing

(c) Agriculture

Note: The figures plot the reallocation of skilled workers in three sectors. The curves increase around the red line across different productivity levels. This means that skilled workers have an equal chance to reallocate into firms of all productivity levels in all sectors. Considering that the number of skilled workers in Cˆote d'Ivoire is relatively smaller, the reallocation of skilled workers is not the main source of special structural transformation patterns in the country.

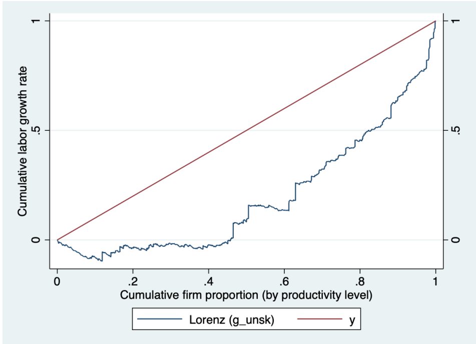
are moving to firms with higher productivity in the service sector. Under the assumption that higher productivity firms pay higher wages, this suggests a correctly functioning labor market and unskilled labor force growth in the most productive firms in the economy.[20] In the manufacturing sector and the agriculture sector, however, the unskilled workers' reallocation patterns are different. In manufacturing, the curve is concave for the lowest 20% firms, indicating that low-productivity firms are hiring unskilled workers. In agriculture, the employment growth is around 0 for the bottom 10% of firms. The growth in agriculture employment comes from medium-sized firms. Among top productivity firms, the curves in both sectors are around the 45 degree line. In both sectors, the unskilled worker growth among the top firms is equal to their proportion in the number of firms.

In relative terms, unskilled workers are more likely to find a job in high-productivity firms in the service sector than in the manufacturing or agricultural sector. To find better-paid jobs, unskilled workers would choose to move to the more productive service sector. This explains why there is a larger increase in unskilled workers than skilled workers in the service sector in both Figure 6 and Figure 8. The total amount of unskilled workers in our CIV data is 1,941,921 workers, which is

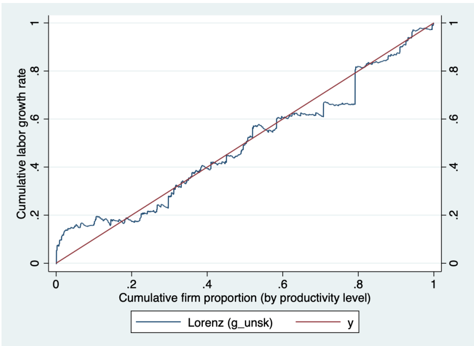
[20] In the Appendix, we show evidence for a positive correlation between productivity and wages.

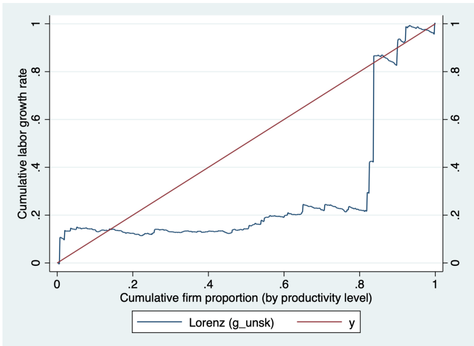
about twice the level of skilled workers (969,249). As a result, unskilled workers appear to be the largest beneficiaries of labor reallocation to the service sector.

Figure 11: Unskilled Labor Reallocation in Three Sectors



(a) Service





(b) Manufacturing

(c) Agriculture

Note: The figures plot the reallocation of unskilled workers in three sectors. In Figure 11(a), the cumulative curve (the blue line) ranked by the productivity level is convex in the service sector. The lowest 20% firms witness zero or negative unskilled worker growth. The top 20% firms, on the other hand, have more unskilled workers reallocated. This means that workers move to firms with higher productivity in the service sector. In the manufacturing sector (Figure 11(b)) and the agriculture sector (Figure 11(c)), however, the unskilled workers' reallocation patterns are different. In both sectors, the curves are concave in the lowest 20% firms, followed by a plateau. Among top productivity firms, the curve is around the line. In both sectors, the least-productive firms have a big unskilled worker growth, and the unskilled worker growth among the top firms is fair.

More labor moving to the service sector, which has higher productivity on average is likely a good phenomenon for economic growth. There are more unskilled workers in Côte d'Ivoire than skilled workers, which is shown in Figure 8(b). As those workers appear to be finding jobs in high-productivity firms in the service sector, this movement should add to overall GDP more than them moving to lower-productivity firms.

6.3 Firm-Level Labor Reallocation by sub-Sector

We have shown that unskilled workers are more likely to move to service firms with higher productivity and that this reallocation pattern is larger in the service than in the manufacturing and agricultural sectors. This pattern and its heterogeneity may be explained by the difference across sub-sectors. High-productivity firms in some service industries might provide more job opportunities to unskilled workers, while some service might not.[21] We therefore test these productivity-employment outcomes across sub-sectors within the service sector.

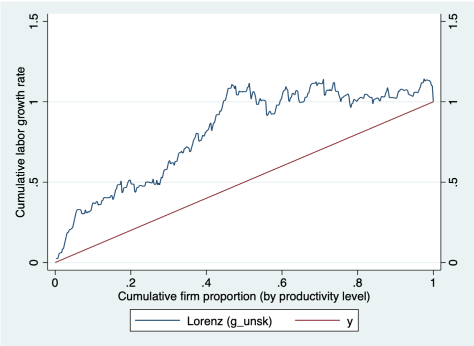
In Figure 12, we test the allocation of unskilled workers by firm productivity within the different sub-sectors of the service industry. In the Training Legal Service industry (12(f)), the top 20% firms are responsible for almost all the labor growth, which means they hire the most job-seeking unskilled workers. In the Restaurant (12e) and the Commerce (12g) sub-sectors, similarly, the top productivity firms hire the most unskilled workers while the low-productivity firms have zero or negative unskilled worker growth rates. Interestingly, the unskilled worker growth rates are zero or negative in high-productivity firms in the Finance and Insurance industries and the unskilled worker growth trends are the opposite of all the other sub-sectors.

In the appendix, we further check the unskilled worker reallocation in the manufacturing industries. The results show that relative to the service sector it is less likely for unskilled workers to find jobs in high-productivity firms in manufacturing sub-sectors except for the Editing and Printing industry. In manufacturing industries such as Detergent, and Plastic and Rubber, the unskilled labor growth rates are pretty close to the 45 degree line, indicating that unskilled workers are no more or less likely to find jobs in high-productivity firms. Overall, we cannot find the strong high productivity high hiring of unskille workers that we find in services in the manufacturing sub-sectors.

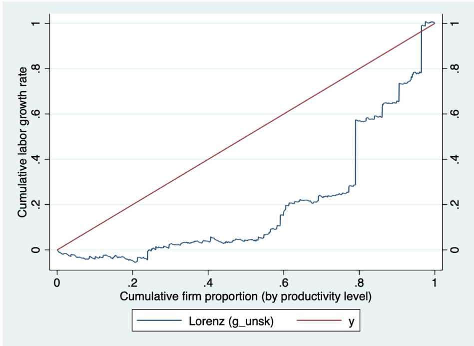
In conclusion, there are two advantages in the service sector that attract workers, especially unskilled workers. The service sector has on average a higher productivity levels than the manufacturing sector. Workers reallocating to the service sector should therefore achieve higher wages. However, high sectoral productivity is not enough, it is that within the service sector the most productive firms are those that are adding the most workers and doing so especially among unskilled workers.

[21]For example, insurance firms might have little motivation to hire unskilled workers. On the other hand, the local retail shops might hire a lot of unskilled workers.

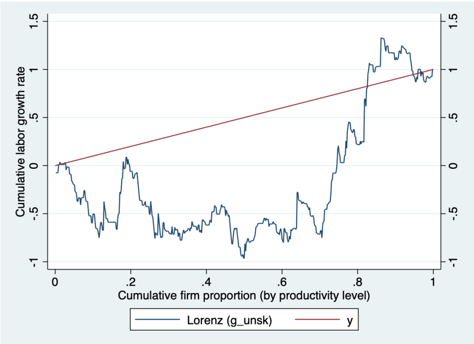
Figure 12: Unskilled Worker Reallocation across Service Industries



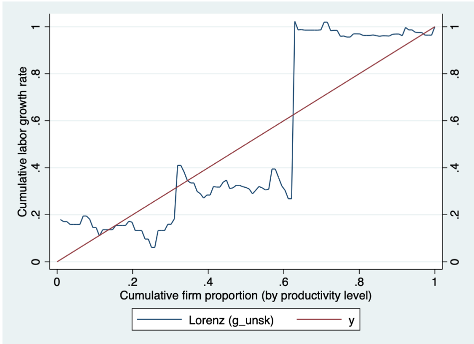
(a) Unskilled Worker Reallocation in the Finance and Insurance Industry (by Productivity Level)



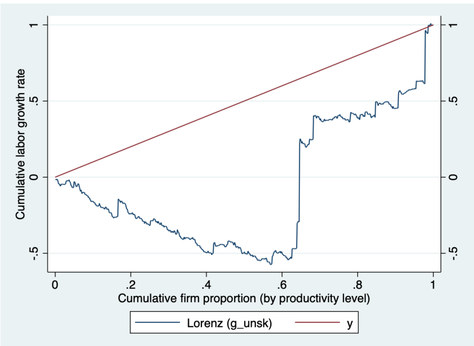
(b) Unskilled Worker Reallocation in the Transport and Communication Industry(by Productivity Level)



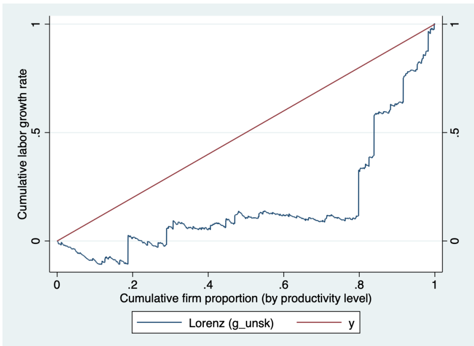
(c) Unskilled Worker Reallocation in the Rental Building and Management Industry (by Productivity Level)



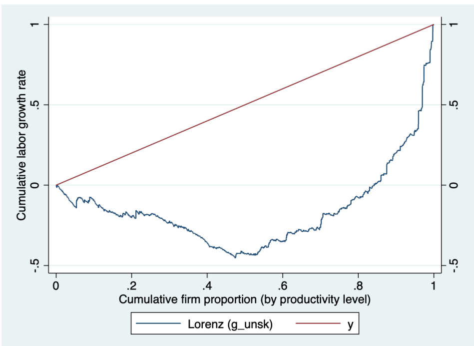
(d) Unskilled Worker Reallocation in the Personal Beauty Industry (by Productivity Level)



(e) Unskilled Worker Reallocation in the Restaurant Industry (by Productivity Level)



(f) Unskilled Worker Reallocation in the Training and Legal Service Industry (by Productivity Level)



(g) Unskilled Worker Reallocation in the Commerce Industry (by Productivity Level)

Note: We further look at the unskilled workers' reallocation pattern at the sub-sector level. In the Training Legal Service industry (Figure 12(f)), the top 20% firms are responsible for almost all the labor growth, which means they hire the most job-seeking unskilled workers. In the Restaurant industry (Figure 12(e)) and the Commerce industry (Figure 12(g)), similarly, the top productivity firms hire the most unskilled workers while the low-productivity firms have zero or negative unskilled worker growth rates. Interestingly, the unskilled worker growth rates are negative in most firms in the Finance and Insurance industries (Figure 12(a)) and the unskilled worker growth trends are the opposite of all the other sub-sectors.

7 Discussion

We have demonstrated that we can measure service sector productivity with existing productivity estimation methods used in manufacturing with some small modifications. Using the MrEst method, we estimate the productivity in agriculture, manufacturing, and service in Côte d'Ivoire so that we are able to compare the productivity values across all three sectors. The productivity estimated from this method is better than labor productivity measure (value added per worker) typically used in the structural change literature. First, the method takes the endogeneity problems into consideration. The inputs capital and labor (both skilled and unskilled) are likely to be positively correlated with productivity. In this case, the labor productivity estimation is biased. Besides, labor productivity takes the skilled workers and unskilled workers as the same inputs even when the contribution of skilled and unskilled workers in the output differs across sectors. The MrEst method used here with differentiated workers captures the differences, which are shown in Tables 5, 6, and 7.

From the estimation outcomes, we show that the service sector in Côte d'Ivoire has the highest average productivity. Income is positively correlated with productivity, and higher income in services attracts more workers to move to the service sector. This explains the special structural transformation pattern in the economy. This finding is consistent with El Abbassi & Sahel's (2023) idea that the service sector has strong potential to enhance economic growth. Although the manufacturing sector has higher productivity and acts as the economic growth engine in many parts of the world, manufacturing in Africa is different from the modern sector we observed in most countries. Bassi et al. (2023) show that the manufacturing firms in Uganda act as a sharing production space for self-employed workers, rather than a productivity increasing unit with specialization. In such a case of modest productivity in manufacturing, it is not surprising to see the service sector being more productive.

One concern is that the service sector suffers from Baumol's disease in which the service sector usually has lower productivity and less productivity growth. A labor reallocation to the service sector would then decrease economic growth. However, our findings show that the service sector has higher productivity than manufacturing and further that unskilled workers move to the most productive firms, which has a positive effect on economic growth and is the opposite of the Baumol disease effect. Meglio and Gallego (2022) also shows that the service sector in Africa could contribute to the productivity and economic growth following Kaldor's laws.

Our results are more consistent with the span of control literature (Lucas (1978)) in which firms are able to increase productivity through improved management and supervision. Our result that the reallocation of skilled and unskilled workers across sectors produces unskilled workers moving to higher-productivity service firms is a finding consistent with the span of control effect. According to

Lucas(1978), given a perfect allocation of inputs among managers, firm sizes would increase as the economy develops as skilled managers are able to manage more unskilled workers. Table A6 in the appendix shows a positive and significant correlation between labor growth and a firm's productivity level in the service sector, while the manufacturing firms do not. When we proxy skilled workers as the managers and investigate the relationship between the unskilled-skilled worker ratio and the productivity level (Table A7), we still find a positive and significant correlation in the service sector. This implies that the productivity in the service sector might actually grow faster if more unskilled workers are hired.

The findings consistent with span of control effects shed light on policies that might help to improve service sector productivity. Recent work in Africa and other developing countries has shown that consumer demand increases the development of nontradable service sectors (Fan et al. (2023), McCullough (2024)). Given the global competition in export-led manufacturing and the seemingly low manufacturing productivity in Africa, the service sector may be a good investment choice. With both skilled and unskilled workers moving into the most productive firms in the service sector and the same effect being muted in manufacturing, the service sector tends to create more employment growth in high productivity firms, which leads to economic growth.

While this work has found potential benefits for structural change, employment and productivity growth from the service sector, there remain concerns that the country may not have enough foreign exchange, which is typically earned by exporting manufacturing products. In the case of Côte d'Ivoire, which is the world's top exporter of cocoa, raw cashews, coffee, and has significant mineral and oil reserves, this may be of less concern than it could be elsewhere. Meanwhile, with higher productivity and more workers reallocation to the service sector, it is possible to develop the tradable service sub-sectors such as Transport and Communication, Tourist, Training and Legal Services, etc. Those tradable services could also attract foreign exchange. But it is worth cautioning against the service sector led path for all countries since other countries without significant foreign exchange earners may not be able to emulate the effects we see in Côte d'Ivoire.

8 Conclusion

In this work, we show that the service sector can be a dynamic and productive part of structural transformation in an African country. Having shown how to estimate service sector productivity using micro-level firm data in Côte d'Ivoire, we have then compared it to manufacturing as a source of structural change. Specifically, we show that in the first two decades of this century, the service sector in Côte d'Ivoire was on average 6.5% more productive than manufacturing firms and that employment growth in the service sector is concentrated in the most productive firms. We demonstrate that this employment growth in services is mostly in the form of unskilled workers rather than the skilled workforce. We further show that the employment growth is due to growth at the most productive firms in most service sub-sectors, which is indicative of a well-functioning labor market and positive structural change.

In terms of methods, this work has shown that one can indeed produce high-quality estimates of service sector productivity with micro-level data that take into account the endogeneity of inputs in the determinants of productivity. The literature on services and structural transformation does not have to content itself with value-added per worker. We have also introduced a way, using Lorenz curves, to visualize and analyze the movements of the workforce across firms as a function of their productivity. Such methods allow us to show the structural transformation process from firm-level labor and productivity data.

There are some important caveats to this work. First, the estimation here, like most in Sub-Saharan Africa concerns formal sector firms and thereby ignores the large informal sector, which is especially important in services. The conclusions presented here may not extend to productivity or employment in the informal sector[22]. Additionally, while we can observe employment, we cannot observe individual worker movements between firms. Third, while Côte d'Ivoire is a key economy in West Africa and has many broad similarities to the other seven former Francophone countries in the CFA zone, the results may not extend to other East or Southern African countries with different economic structures.

The findings in this work on the overall importance of the service sector as an engine of structural transformation in African countries suggest some rethinking of current development policy. Policymakers across Africa would do well to reconsider a manufacturing-first development policy and seek to even out their efforts across both manufacturing and services. If the goal of a government's development policy is to provide employment opportunities for unskilled workers moving out of agriculture and rural areas, the results presented here suggest that helping grow the service sector could do a lot to aid the process of structural transformation. Similarly, donor efforts to stem migration out of African countries with employment generation would do well to consider the service sector an important part of those efforts.

[22] In the Appendix, we discuss the relationship between the formal sector we measure and the unmeasured informal sector. We believe our outcomes are informative and likely representative of the vast majority of the measured GDP in the country.

Appendix

Appendix 1 Input Comparison Across Service Industries

Table A1 Inputs Comparison Across Industries

Industry	Inputs	Obs	Mean	Std. dev.
finance-insurance	Skilled worker	1,799	.1890625	.218229
	Unskilled worker	1,799	.0511664	.1136882
	Capital	1,799	.1959806	.2541626
	Material	1,799	.0594068	.1151054
	External Service	1,799	.5043836	.2924626
personal-beauty	Skilled worker	273	.1724562	.2092477
	Unskilled worker	273	.1609412	.2171439
	Capital	273	.2827994	.2705605
	Material	273	.1284959	.1919526
	External Service	273	.2553073	.194315
rental-building-management	Skilled worker	2,012	.1369513	.2001722
	Unskilled worker	2,012	.0555367	.1314258
	Capital	2,012	.3932801	.3805568
	Material	2,012	.0988445	.1960921
	External Service	2,012	.3153874	.2701094
restaurant	Skilled worker	1,730	.0921355	.1448677
	Unskilled worker	1,730	.1156556	.1736648
	Capital	1,730	.3867122	.360241
	Material	1,730	.2210508	.2484712
	External Service	1,730	.1844459	.1764273
training-legal-service	Skilled worker	14,775	.2039135	.2219859
	Unskilled worker	14,775	.0951138	.176366
	Capital	14,775	.1768119	.2173931
	Material	14,775	.1111459	.2002108
	External Service	14,775	.4130148	.2421112
transport-communication	Skilled worker	4,984	.1822521	.1937735
	Unskilled worker	4,984	.0729528	.1345394
	Capital	4,984	.2649452	.2706698
	Material	4,984	.0715602	.1695443
	External Service	4,984	.4082896	.2479406

commerce	Skilled worker	30,816	.1519084	.1956354
	Unskilled worker	30,816	.1399733	.1937703
	Capital	30,816	.2174205	.2499631
	Material	30,816	.0671833	.1587002
	External Service	30,816	.4235138	.2285429

Appendix 2 Agricultural Farm Size

To show that the recorded farms in our data are large plantation farms, we check the number of workers hired. In Table A2, we show that the average worker hired by farms is 292, while the average manufacturing firm size is 90 and the average service firm size is 30.

Table A2 Average Firm Size

Sector	Mean	Observations
Agriculture	292	1,348
Manufacturing	90	9,668
Service	21	69,577

Appendix 3 Productivity Level and Wage

Our analysis follows from the idea that workers move to the sectors or firms with higher productivity because those sectors or firms have higher wage rates. The argument is based on the standard assumption that wages equal marginal products of labor and are therefore positively correlated with productivity levels. In Table A3 and Table A4, we show the correlation between wage and productivity in the manufacturing sector and the service sector. To avoid variation in both industries and years, we fix the industry effect and years effect.

Table A3 shows that the productivity level is always positively associated with wages for skilled workers, unskilled workers, and overall workers. In the manufacturing sector, the coefficient of productivity is 0.0753 if we regress overall wage on productivity. The coefficients of the productivity level on the skilled worker wages (0.0857) and the unskilled worker wages (0.0641) are also significant. In Table A4, the coefficients of productivity are larger in the overall wage, the skilled worker wage, and the unskilled worker wage in the service sector than in the manufacturing sector. The coefficient for the dependent variable of overall workers' wages is 0.165, higher than that in the manufacturing sector. The coefficient between productivity and skilled workers is 0.192. The coefficient for the unskilled workers is 0.104. Taken together these regressions provide evidence that the wage increases as the productivity level grows.

Table A3 Correlation between Wage and Productivity Level in the Manufacturing Sector

	(1))	(2)	(3)
	Wage	Skilled Worker Wage	Unskilled Worker Wage
Productivity	0.0753***	0.0857***	0.0641***
	(18.35)	(15.29)	(13.22)
Constant	13.06***	13.64***	12.76***
	(219.61)	(169.10)	(180.20)
N	6717	5178	5141

Table A4 Correlation between Wage and Productivity Level in the Service Sector

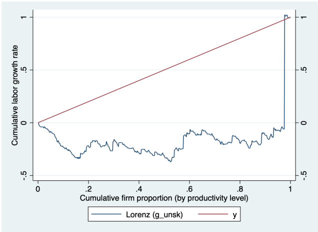
	(1))	(2)	(3)
	Wage	Skilled Worker Wage	Unskilled Worker Wage
Productivity	0.165***	0.192***	0.104***
	(72.18)	(63.02)	(42.69)
Constant	11.73***	11.80***	12.13***
	(337.00)	(252.79)	(324.41)
N	44259	31981	28020

Appendix 4 Reallocation of Unskilled Workers in the Manufacturing Sector

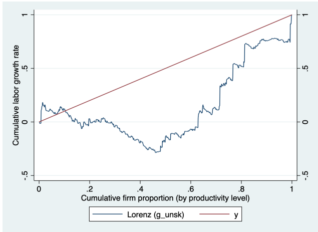
Figure 13 shows the growth rate of unskilled workers in the manufacturing industries. Compared with the service industries, those manufacturing industries do not have an obvious trend showing that higher productivity firms have more unskilled worker growth. It is less likely for unskilled workers to find jobs in high-productivity firms in manufacturing sub-sectors except for the Editing and Printing Industry (13a). In manufacturing industries such as Detergent, and Plastic and Rubber, the unskilled labor growth rates are pretty close to the linear curve, indicating that unskilled workers are less likely to find jobs in high-productivity firms.

Appendix 5 Market Power and Productivity

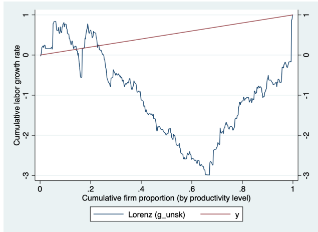
In concerns of the bias caused by the market power, we implement a robustness check for market power. First, we measure the market power using the Herfindahl-Hirschman Index of the 5 largest firms in each subsector each year. Then we fix the industry and year effects and run the regression of productivity estimated by the MrEst Method on the index. We find that the market power has no effect on productivity outcomes.



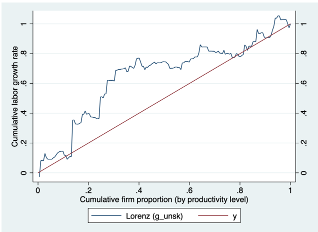
(a) Unskilled Worker Reallocation in the Editing and Printing Industry (by Productivity Level)



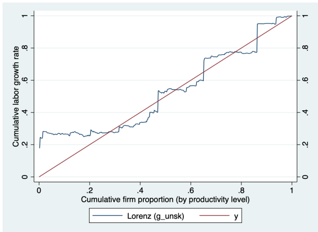
(b) Unskilled Worker Reallocation in the Food Product Industry(by Productivity Level)



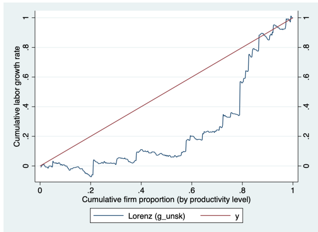
(c) Unskilled Worker Reallocation in the Wood Industry (by Productivity Level)



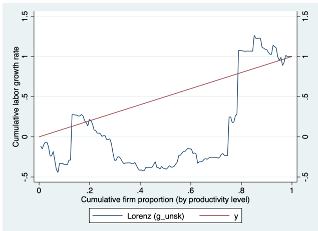
(d) Unskilled Worker Reallocation in the Detergent Industry (by Productivity Level)



(e) Unskilled Worker Reallocation in the Plastic and Rubber Industry (by Productivity Level)



(f) Unskilled Worker Reallocation in the Metallurgy Industry (by Productivity Level)



(g) Unskilled Worker Reallocation in the Agrochimique and Fiber Industry (by Productivity Level)

Figure 13: Unskilled Worker Reallocation across Manufacturing Industries

Table 8 shows the results for the correlation of our productivity estimates with measures of market power: HHI and firm numbers. The coefficient is positive but insignificant. The economic interpretation of the outcome is that the increasing concentration would increase productivity. If market power creates a bias in the productivity estimate, we expect to see that the bigger firms have larger productivity, which is consistent with the regression outcomes we have. Next, we look at the relationship between productivity and the number of firms. The coefficient is positive but close to 0 and statistically insignificant, implying that the productivity of firms is not affected by more firms competing in the market.

Table A5 Productivity and Market Power

	(1))	(2)
	Productivity	Productivity
Productivity	0.233***	0.301
	(5.89)	(1.78)

Constant	-1.119	0.602
	(-1.87)	(0.26)
N	48263	7189
Industry	Yes	Yes
Year	Yes	Yes

Appendix 6 Productivity Estimation Outcomes Using Different Methods

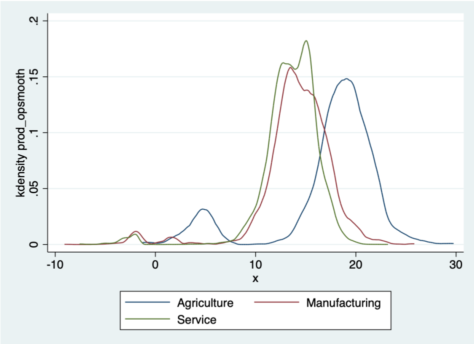
In this section, we show the productivity estimation outcomes using 4 different econometric TFP estimation methods and value-added per worker. The 5 methods are the Olley & Pakes method (OP method), the Levinsohn & Petrin method (LP method), the Ackerberg, Caves & Frazer Method (ACF method), the MrEst Method, and the Labor Productivity method (value added per worker). The ACF method applies a correction to the LP method and the OP method and therefore we have two distributions of the ACF method in Figure 14.

Though the distributions of the productivity are different across the methods. When we look at the mean values of the sectors using different methods in Table A6, we find that the mean productivity value is the largest in the service sector in the MrEst Method, the LP method, the LP with ACF method and the Labor Productivity method. In the other 2 methods, either agriculture or manufacturing has the highest productivity.

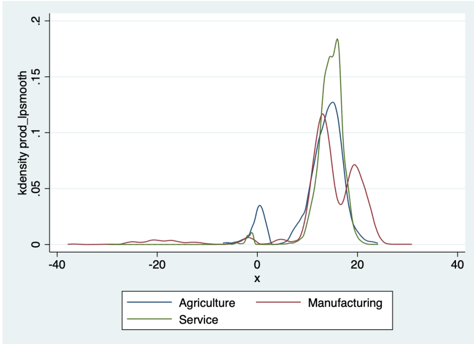
Table A6 Mean Value

Method	Sector	Mean	Observations
MrEst	Agriculture	12.811	1,166
	Manufacturing	13.943	7,189
	Service	14.844	48,264
OP	Agriculture	17.423	1,166
	Manufacturing	14.087	5,516
	Service	13.474	48,251
LP	Agriculture	12.484	1,166
	Manufacturing	13.674	7,189
	Service	14.410	48,264
ACF+OP	Agriculture	12.858	1,166
	Manufacturing	16.284	7,189
	Service	14.439	48,264
ACF+LP	Agriculture	13.975	1,166

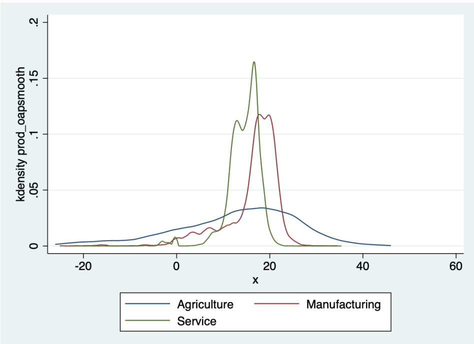
	Manufacturing	13.840	7,189
	Service	16.342	48,264
Labor Prod	Agriculture	15.686	1,014
	Manufacturing	15.462	8,150
	Service	16.147	54,763



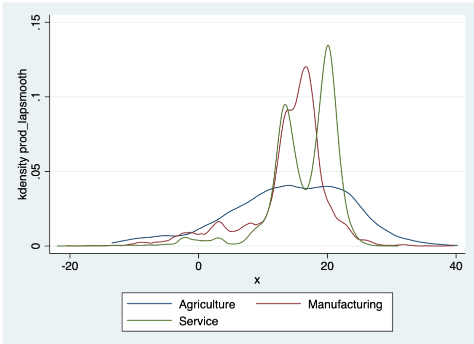
(a) Olley & Pakes Method (OP Method)



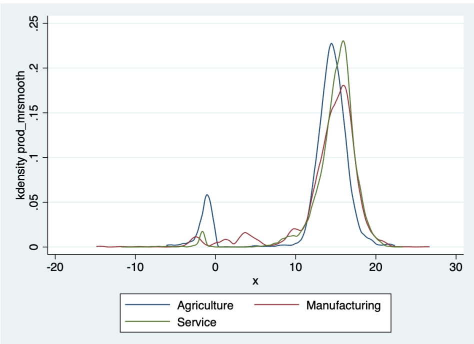
(b) Levinsohn & Petrin Method (LP Method)



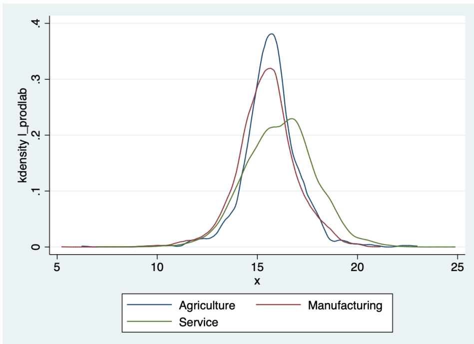
(c) ACF + OP Method



(d) ACF + LP Method



(e) MrEst Method



(f) Labor Productivity Method

Figure 14: Productivity Distribution Using 6 Methods

Appendix 7 Correlation of Firm Ranks

In Section 6, we analyze employment growth based on firm-level productivity. We need to show that the firms' productivity ranks in the different methods discussed above are highly enough correlated so as to not bias our conclusions. If the ranks are not correlated, the conclusions about the employment growth may not be robust. Therefore, we check the firm rank correlation at the aggregate level, the sector level, and the industry level. We find that the correlations between the MrEst Method and the OP method, and between the MrEst method and the LP method are close to 1. The correlation between the MrEst method between the labor productivity method is also high.

Table A7 Correlation of Firm Ranks at the Total Level

	MrEst	OP	LP	Lab-Prod	ACF-OP	ACF-LP
MrEst	1.0000					
OP	0.8159*	1.0000				
LP	0.8743*	0.8537*	1.0000			
Lab-Prod	0.7832*	0.7401*	0.7212*	1.0000		
ACF-OP	0.7787*	0.8812*	0.8707*	0.6040*	1.0000	
ACF-LP	0.7778*	0.8302*	0.8241*	0.7032*	0.8399*	1.0000

Table A8 Correlation of Firm Ranks at the Sector Level

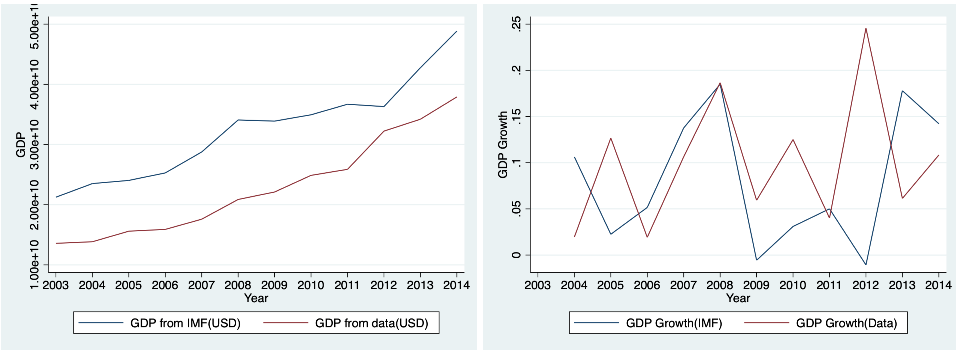
	MrEst	OP	LP	Lab-Prod	ACF-OP	ACF-LP
MrEst	1.0000					
OP	0.9367*	1.0000				
LP	0.9430*	0.9815*	1.0000			
Lab-Prod	0.9129*	0.9068*	0.9249*	1.0000		
ACF-OP	0.8983*	0.9688*	0.9739*	0.8846*	1.0000	
ACF-LP	0.8858*	0.9439*	0.9544*	0.8559*	0.9724*	1.0000

Table A9 Correlation of Firm Ranks at the Industry Level

	MrEst	OP	LP	Lab-Prod	ACF-OP	ACF-LP
MrEst	1.0000					
OP	0.9609*	1.0000				
LP	0.9646*	0.9973*	1.0000			
Lab-Prod	0.9581*	0.9514*	0.9590*	1.0000		
ACF-OP	0.9553*	0.9912*	0.9951*	0.9497*	1.0000	
ACF-LP	0.9500*	0.9596*	0.9733*	0.9481*	0.9812*	1.0000

Appendix 8 Formal Sector and Informal Sector

An important concern about with our data is that we are unable to measure the informal sector since the data set includes formal firms. To see if the data are representative, we create a GDP value using the sales variable from the data set. To get the GDP values, we aggregate the sales value from all



(a) GDP Comparison

(b) GDP Growth Comparison

Figure 15: GDP in CIV

firms in each year. Then we convert the GDP values into real GDP values using the World Bank's GDP deflator, setting 2003 as the base year. Then we use a fixed exchange rate, that is 1 XOF to 0.0016 USD. Finally, we get the GDP that will be used to compare with the real Côte d'Ivoire GDP from the IMF.

Figure 15(a) shows the GDP comparison outcomes. We can see that the GDP we calculated from the data is smaller than the real GDP from the IMF. However, the calculated GDP accounts for about 74% of the real measured GDP on average. The overall trends of the GDP values are both increasing. Therefore, the formal sector we study represents a large part of the GDP for the whole economy.[23]

We further check the wages in the formal sector and informal sector using the LSMS (Enquête Harmonisée sur le Conditions de Vie des Ménages 2018-2019). The income from the informal sector is 78,439 CFA/year on average, while the income in the formal sector is 134,075 CFA/year. We have already shown that wage is positively correlated with productivity. The formal sector has higher productivity than the informal sector. According to the idea that the workers, especially the unskilled workers, would move to the more productive sector over time if the market is well functioned.

Appendix 8 Span of Control

According to Lucas(1978), given a perfect allocation of inputs over managers, firm sizes would increase as the economy develops. In our context, we find that the size of high-productivity service firms increases. More specifically, the number of unskilled workers increases among productive service firms. This pattern is consistent with a span of control effect.

Table A10 shows the correlation between the firm's productivity level and its labor changes. The labor growth in services is both positive and significant, indicating that labor is growing if the firm's

[23]The fact that our census of formal sector firms makes up about three-quarters of the measured GDP may also be indicative of national statistics not measuring the informal sector at all well.

productivity is higher. When we decompose labor into skilled and unskilled, we get the same outcomes: both skilled workers and unskilled workers are more likely to be hired in more productive service firms. However, if we look at manufacturing firms, the coefficients are insignificant, showing that workers are not moving to those higher-productivity manufacturing firms.

Table A10 Labor Growth in Productivity

	Labor Growth		Skilled Labor Growth		Unskilled Labor Growth	
	Service	Manufacturing	Service	Manufacturing	Service	Manufacturing
Productivity	0.0319***	-0.0455	0.0445**	0.0134	0.0788***	-0.0159
	(6.28)	(-1.22)	(4.04)	(0.42)	(7.14)	(-0.36)
Constant	−0.316**	0.784	−0.488*	0.107	−1.104***	0.377
	(-4.07)	(1.49)	(-2.88)	(0.23)	(-6.27)	(0.60)
N	32743	5282	24188	4204	21144	4139
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes

Based on the definition of the span of control, we further construct the unskilled-skilled ratio, which is the number of unskilled workers over the number of skilled workers in the same firm. We proxy the skilled workers as the managers of the firms and the unskilled workers are the inputs. An increase in the ratio indicates that the number of unskilled workers is increasing faster than the number of skilled workers and the firm size is growing. The high-productivity firms tend to have a larger unskilled-skilled ratio. As shown in Table A11, the unskilled-skilled ratio increases when the service firm's productivity is higher, which is consistent with a span of control explanation.

Table A11 Unskilled-Skilled Ratio Changes in Productivity

	Unskilled-Skilled Ratio	
	Service	Manufacturing
Productivity	0.233***	0.301
	(5.89)	(1.78)
Constant	-1.119	0.602
	(-1.87)	(0.26)
N	48263	7189
Industry	Yes	Yes

Year	Yes	Yes

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