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

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Selected Paper prepared for presentation at the 2024 Agricultural & Applied Economics Association Annual Meeting, New Orleans, LA; July 28-30, 2024.

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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 7% higher on average in services than in manufacturing. We further show 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 how we should rethink some of the basis of policy and development theory in Africa.

1 Introduction

The service sector is vital to the growth of African economies, often representing between 30 – 55% of the economy and in some countries two-thirds of the employment (Davis, 2020). It is growing the fastest among sectors, 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)). More specifically, Gordon (1996) argues 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 the productivity in the retail industry is lower due to the large share of a traditional less innovative segment. Sorbe et al.(2011) 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 the countries that are following the traditional development path. Our research focuses on the structural transformation path of the 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 quite special economic growth and development path in which the economy transforms from the 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. (Rodrik (2016))

We use micro-level data from a single African country, Côte d'Ivoire, to estimate total factor productivity (TFP), and employment changes in the manufacturing, agricultural and service sectors. We demonstrate how it is possible 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 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, in order to test the correlations between TFP and employment growth. In contrast to a literature that typically uses only broad categories of labor, our work 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 7% greater than those in the manufacturing sector. The distribution in the service sector is also more concentrated than in the manufacturing sector. We demonstrate that the conclusions are robust to alternative methods for estimating TFP and data assumptions. We then show that employment growth, especially among unskilled workers, in service industries are 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 unskilled workers.

This work makes 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 done at a country level. 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 services.[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 appropriately measure service sector output with value-added and use 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 improve on more recent work in service sector productivity using value-added per worker.

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 manufacturing and services. Although the service sector has become the largest sector in most African economies, productivity changes in this sector are still understud-

[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.

ied 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.

Finally, we contribute to the literature on structural transformation patterns by investigating different labor 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 discussed 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 sector 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.

Much of the literature on structural transformation in Africa and elsewhere uses labor productivity instead of total factor productivity. De Vries et al. (2015) study 11 Sub-Saharan African countries and decompose the aggregate labor to study both the static and dynamic effects. McMillan and Rodrik (2011) use labor productivity to show the structural transformation in both Africa and Latin America. Compared with labor productivity, the TFP estimated in our work using proxy variable techniques takes inputs such as labor, capital, human capital, and intermediate inputs into account.

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 method we used to estimate the productivity. Section 4 estimates the service sector productivity. Section 5 analyzes the productivity outcomes. Section 6 studies the structural transformation across sectors and firms. Section 7 concludes the discussions above.

2 Service Sector Productivity

2.1 Inputs and Outputs

A large, older literature focused on the US and other developed countries 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. If the inputs and outputs used to estimate the service productivity are similar to those used in the manufacturing sector, we can proceed to employ standard production models of manufacturing in the service industries.

From the CIV data, we have comprehensive data in 9 service industries: Health and Social, Finance and Insurance, Rental Building and Management, Education and Research, Personal Beauty, Restaurant, Legal Service and Training, Transport and Communication, and Commerce. From Table 1 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 the value-added.

Table 1: Literature Review

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.

[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 not a relevant measure of output.

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

Despite the large literature described in Table 1, there remain important questions on how to accurately measure service sector productivity. To estimate service sector productivity accurately, we need to answer three questions: (1) How can service sector productivity be determined? (2) What parameters are primary determinants of service sector productivity? (3) How are these parameters related? (Rutkauskas & Paulavičienė (2005)) In this part, we will answer the questions separately.

From the literature, we have shown 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 use a standard Cobb-Douglas production function in service sector productivity estimation with these inputs:

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

where Y_{it} is the output of firm i in time t, A_{it} is the productivity from technology improvement, H_{it} is the skilled worker input, L_{it} is the unskilled worker input, and K_{it} is the capital input.

In the production function, we divide the labor into two types: the skilled worker and the unskilled worker, because 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 the changes in the markup would pass through to the price thoroughly, the price changes would show the quality changes in the service sector. An increase in quality would raise the markup of the product (Bellone et al. (2016)) and thus increase the price. Then it is feasible for us to use monetary output, which we can observe from the firm-level data set, to estimate revenue-based TFP.

One concern is that the market in each service industry is not perfectly competitive and price incorporates both productivity and market power. (Francis et al. (2020)) In Section 5.4, we find that the market power has little effect on

[3]For example, adding an electronic payment system in a restaurant increases production efficiency and also improves the quality of service to customers.

the productivity we estimate. More specifically, there is a negative but insignificant correlation between productivity level and the Herfindahl-Hirschman Index for domestic firms. Then we further look at the relationship between the productivity and number of firms. The coefficient is pretty positive but close to 0.

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, finance consultants 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 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. In manufacturing productivity estimation, researchers assume that the industry produces homogeneous products(Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Ackerberg et al, 2015).[5] We accommodate this heterogeneity by estimating our TFP models by individual sub-sectors so that financial service firms are compared only to other financial service firms.

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 more important in the service sector compared with the manufacturing sector because the service sector is more personnel-intensive. (Rutkauskas & Paulavičienė, 2005). In the model, we are still using labor (skilled workers and unskilled workers) and capital as the inputs. Below we show that the input heterogeneity in the service sector is no larger than the input heterogeneity in the manufacturing sector, we argue that the service productivity we estimated is comparable to the manufacturing productivity.[6]

First, we show in the CIV data the share of the inputs we used in the production function to verify that those inputs

[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.

[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.

appear in the service production process. To get the share values, we divide the input values by the value-added. Table 2 shows the mean value, standard deviation, and p-value of the input shares in the manufacturing sector and the service sector. The P-value is the outcome from the T-test, implying whether the input share is significantly different from 0. In the manufacturing sector, capital input is the most important input and the mean value of the share is about 24.35%, followed by the skilled worker and the unskilled worker. In the service sector, on the other hand, the skilled worker is the most important input and the mean value is 14.93%, higher than the share of skilled workers in the manufacturing sector. This is consistent with the argument that the service sector is personnel-intensive. More specifically, the service sector is skilled-worker-intensive. The contribution of the unskilled worker in the service sector is even lower than the contribution of capital.

Compared with the manufacturing sector, the input shares in the service sector seem to be lower. The low values of contribution do not necessarily imply that labor input and capital input are not important in production. One explanation for this outcome is that markups lower the input shares. (Crouzet & Eberly (2021)) The markups of the outputs are larger in the service sector, while the factor prices remain the same as in the manufacturing sector. Higher markups lead to higher value-added and thus lower input shares.

Table 2: Inputs Share Comparison Across Sectors

Sector	Inputs	Obs	Mean	Std. dev.	P-value (T-test)
Manufacturing	Skilled worker	9515	0.1727	2.3102	0.00
	Unskilled worker	9511	0.1289	2.1777	0.00
	Capital	9490	0.2435	5.7031	0.00
Service	Skilled worker	68,336	0.1493	2.7423	0.00
	Unskilled worker	68,357	0.0493	2.1813	0.00
	Capital	68,371	0.0593	3.5543	0.00

$*$ The table shows the mean value, standard deviation, and p-value of the input shares in the manufacturing sector and the service sector. The P-value is the outcome from the T-test, implying whether the input share is significantly different from 0. In the manufacturing sector, capital input is the most important input and the mean value of the share is about 24.35%, followed by the skilled worker and the unskilled worker. In the service sector, on the other hand, the skilled worker is the most important input and the mean value is 14.93%, higher than the share of skilled workers in the manufacturing sector.

$**$ The standard deviations of the three inputs are close to each other in the two sectors, which means that the input variability in each data set is similar. From the sector-level comparison, we can't get the conclusion that the heterogeneity in the inputs in the service sector is larger than that in the manufacturing sector.

To estimate productivity, we are assuming that the income share of capital $(1-\alpha-\beta)$ and the income share of labor (α and β) in the production function are the same for firms within the industry. However, the firms in the service sector are customizing their inputs and creating potential heterogeneity within the industry. This implies that the capital owners and the labor owners in different firms in the same industry may have different income shares.

When we discuss the heterogeneity in the service sector, we should consider that there is heterogeneity in the manufacturing sector as well.(Cantner & Krüger (2008), Abraham et al (2010), Elshennawy & Bouaddi(2021)) Although producing processes and products in the manufacturing sectors are more standardized, it doesn't necessarily mean that the income shares are always the same across firms within the industries. Big firms and small firms may have different efficiencies in using the resources and thus make different decisions in capital usage and labor hiring. In traditional productivity estimation papers, 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.

What we want to prove is that the heterogeneity in income shares in the service sector is not higher than that in the manufacturing sector. Contrarily, the heterogeneity among the service firms is quite close to the heterogeneity among the manufacturing firms. To show this, we need to do a simple calculation of the income shares. Under perfect competition, the factor earnings are equal to their marginal products. Therefore, the income share of each factor in each firm is:

$$
\begin{aligned}
skilled \quad worker: \qquad & \alpha_i = \frac{H_i \times MPH_i}{Y_i} \\
unskilled \quad worker: \qquad & \beta_i = \frac{L_i \times MPL_i}{Y_i} \\
capital: \qquad & 1-\alpha_i-\beta_i = \frac{K_i \times MPK_i}{Y_i}
\end{aligned}
$$

where MPH_i is the marginal product of skilled workers, MPL_i is the marginal product of unskilled workers, and MPK_i is the marginal product of capital. From the data, we can directly get the earnings of both the skilled workers and unskilled workers, as well as the numbers of skilled workers and unskilled workers hired in each firm. For the capital income share, we don't have return to capital data. We assume that the return to capital is the same across different firms as the capital can move freely. Therefore, we can compare the cross-sector heterogeneity in income shares of the inputs by looking at the shares of inputs.

From Table 2, we can see that the standard deviations of the three inputs are close to each other in the two sectors, which means that the input variability in each data set is similar. [7] From the sector-level comparison, we can't get the

[7] We do not calculate the coefficients of variation here because the mean values of the input shares in both sectors are close to 0. However, we further check the minimum value and the maximum value for each input share in the manufacturing sector and the service sector. We find that the minimum values and the maximum values are close in different sectors.

conclusion that the heterogeneity in the inputs in the service sector is larger than that in the manufacturing sector. In the Appendix, we further look at 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.

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 capture 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 (Y)[8]. 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 run the regression, we take the log transformation of all variables, that is $log(X+1)$.

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. Besides, the definition of skilled and unskilled workers depends on the both education level and the categories. [9]

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

[8] 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.

[9] 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.

from known biases. [10] 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 intermediate material, 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 the intermediate goods in the service sector are external service goods[11] consumed by firms to produce their final service goods. Service firms need to consume external professional services such as consultancy 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))

To show the practicality of the external service variable, we go back to the CIV data. Table 3 shows that manufacturing firms consume more intermediate material and the share is as high as 203.41%. The share of external labor is far lower. In the service sector, the share of external services (53.52%) is higher than the share of intermediate materials (30.35%). Service firms use more external services to produce the outputs.

[10] 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))

[11] In the Appendix, we prove that using external service goods as the proxy variable holds theoretically.

Table 3: Proxy Variable Comparison Across Sectors

Sector	Inputs	Obs	Mean	Std. dev.
Manufacturing	Material	9,489	2.0341	9.3355
	External Service	9,515	0.4135	5.0982
Service	Material	68,385	0.3035	4.7779
	External Service	68,337	0.5352	7.2555

$*$ The table shows the practicality of the external service variable. Manufacturing firms consume more intermediate material and the share is as high as 203.41%. The share of external labor is far lower. In the service sector, the share of external services (53.52%) is higher than the share of intermediate materials (30.35%). Service firms use more external services to produce the outputs.

Another advantage of using the external service as the proxy variable is that there are fewer zeros in external service in the service sector. Different from the manufacturing sector, service firms' demand for intermediate inputs is smaller and some firms do not report purchasing intermediate inputs. As a result, there are a lot of zeros in the intermediate input variable in the service sector. External service, on the other hand, is frequently consumed by service firms in our data. From Table 4, we can see that 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 %. By using the external service, we avoid a sample selection problem in the service sector.

Table 4: 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. [12] Thus, it is important to include longevity information in the production function if we want to

[12]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.

estimate the service-sector TFP. The estimation from the OP method, the LP method, and the ACF method may not be precise enough to capture this characteristic.[13] Wooldridge (2009) uses the lagged state variables and free variables as instruments for endogenous shocks in a productivity estimation. The lagged variables in the service firms can provide us with extra information likely correlated with consumers' demand and experience that we do not observe directly from the data. 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 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 [14] in the Wooldridge GMM framework (2009).

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.[15] 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 62% of the original data. Table 5 shows the estimation outcomes of each service industry.

In Table 5, we can see that the coefficients on the skilled workers in 5 sub-sectors (Finance and Insurance, Rental Building and Management, Personal Beauty, Restaurant, and Training Legal Service) are the largest among the three inputs. This means that skilled workers are the most important input in most service sub-sectors, which is consistent with the idea that the service sector is more skilled-worker-intensive.

The coefficients of the unskilled workers are smaller, but always significant across the different service industries. In the commerce industry, unskilled workers are a far more important input (0.349) compared with both skilled workers (0.0879) and capital (0.0834). This is because retail sales (such as local shops) that do not require higher skills or more capital dominate the commerce industry. The coefficients of capital are also smaller. In industries such as Finance and Insurance and Personal Beauty, the capital coefficients are insignificant. Capital inputs such as machines, equipment, land, etc. are perhaps not as important in the service sector compared with the manufacturing sector (Li & Prescott

[13] 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.

[14] 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.

[15] In the appendix we show results for estimating with the other 3 common proxy variable techniques. The estimates of TFP are remarkably similar across the different estimates.

(2009)). Yet, the Transport and Communication industry and the Rental Building and Management Industry have larger capital coefficients. This finding is consistent with the special characteristics of these two sub-sectors. [16]

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 6 shows the estimation of the production function for manufacturing industries.[17] The manufacturing industries in our estimation are Editing and Printing, Food Products, Wood Products, Canned Food Preparation, Detergents, Grain and Flour, Plastic and Rubber, Metallurgy, and Agro-chemicals and Fiber. They account for 74% of the firms in the manufacturing sector. The coefficients for capital input are larger in manufacturing industries, though the skilled worker coefficients are similarly sized to services.

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Fin	Trans	Build	Beauty	Rest	Legal	Comm
Skilled	0.248^{***}	0.179^{***}	0.347^{***}	0.369^{***}	0.315^{***}	0.396^{***}	0.0879^{***}
	(4.32)	(5.12)	(4.45)	(5.79)	(5.66)	(17.40)	(3.89)
Unskilled	0.113^{*}	0.192^{***}	0.115^{*}	0.214^{***}	0.281^{***}	0.236^{***}	0.349^{***}
	(2.36)	(8.52)	(2.08)	(4.32)	(6.85)	(17.71)	(19.78)
Capital	0.112	0.149^{***}	0.182^{**}	0.0321	0.151^{**}	0.124^{***}	0.0834^{***}
	(1.85)	(4.30)	(2.64)	(0.35)	(2.82)	(6.12)	(6.15)
N	973	3779	1219	222	1431	10290	25168

$*$ t statistics in parentheses

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

$***$ The coefficients on the skilled workers in 5 sub-sectors (Finance and Insurance, Rental Building and Management, Personal Beauty, Restaurant, and Training Legal Service) are the largest among the three inputs. This means that skilled workers are the most important input in most service sub-sectors.

$****$ The coefficients on the unskilled workers in the Transport and Commerce sub-sectors are the largest, indicating that the unskilled workers are the most important input.

[16] The equipment such as trucks or cars is important to run the Transport and Communication business and a building is a necessity in the Rental Building and Management industry.

[17] 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 6: Estimates of Production Function Parameters (Manufacturing Sector)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Edit	Food	Wood	Canned	Det	Grain	Plastic	Meta	Agro
Skilled	0.551***	0.333***	0.394***	0.369*	0.130	0.360***	0.426***	0.567***	0.273***
	(8.12)	(3.65)	(8.72)	(2.56)	(1.12)	(7.29)	(4.67)	(7.49)	(3.77)
Unskilled	0.222***	0.0341	0.339***	0.0505	0.0720	0.307***	0.0762	0.321***	-0.0638
	(3.81)	(0.57)	(7.42)	(0.49)	(1.47)	(6.76)	(1.79)	(6.92)	(-1.22)
Capital	0.0593	0.187	0.191*	-0.165	0.399***	0.0479*	0.121	0.115	0.333**
	(1.21)	(1.42)	(2.21)	(-1.41)	(3.59)	(2.05)	(1.04)	(1.59)	(2.95)
N	978	246	711	202	254	1205	584	630	187

∗ *t* statistics in parentheses

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

∗ ∗ ∗ The coefficients for capital input are larger in manufacturing industries, though the skilled worker coefficients are similarly sized to services.

For completeness, we also estimate the productivity in the agriculture sector.[18] There are only 4 sub-sectors in the agriculture sector with fewer firm records. If we estimate the productivity by sub-sector, the sample will be too small to reach a result. Therefore, we treat the agriculture sector as a whole. The regression outcome is shown in Table 7. Unskilled workers have the largest coefficients and contribute most to the agricultural output.

[18]The agriculture firms recorded in the data set are those large farms. The small farms are not included.

Table 7: Estimates of Production Function Parameters (Agriculture Sector)

	Agriculture
Skilled	0.280***
	(4.91)
Unskilled	0.304***
	(7.34)
Capital	0.0751
	(1.25)
N	535

∗ *t* statistics in parentheses

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

∗∗∗ Unskilled workers have the largest coefficients and contribute most to the agricultural output.

5 Productivity Analysis

5.1 Productivity Outcomes

With the estimation outcomes, we estimate the total factor productivity of each firm. In Table 8, the service sector has the highest mean productivity, followed by the agriculture sector. The manufacturing sector has the lowest mean value. The agriculture records come from big farms or agricultural companies. The mean value of service productivity (15.54) is 7% higher than the mean value of manufacturing productivity (14.49). The service sector has higher average productivity than the manufacturing sector.

Table 8: Mean Value

Method	Sector	Mean	Std. dev	Observations
MrEst	Agriculture	14.534	5.785	1,153
	Manufacturing	14.488	4.053	6,632
	Service	15.543	3.134	46,742

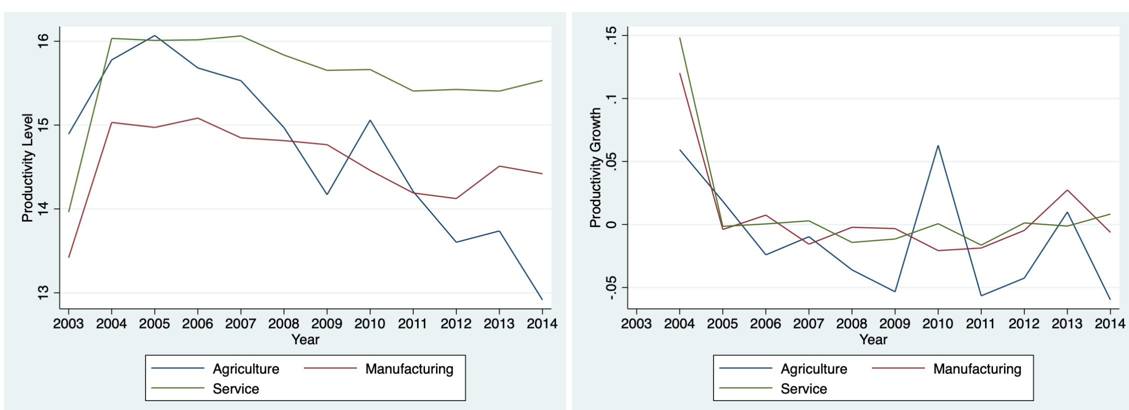
$*$ The service sector has the highest mean productivity, followed by the agriculture sector. The manufacturing sector has the lowest mean value.

$**$ The mean value of service productivity is 7% higher than the mean value of manufacturing productivity.

$***$ High productivity level in agriculture is because the agriculture records come from big farms or agricultural companies.

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 in most of the time. The agriculture sector exceeded the service sector in 2003 and 2005 and kept decreasing after.[19] The growth rates in the service sector and manufacturing sector increase in 2004 and then fluctuate around 0. The agricultural productivity growth rate is below 0 for most of the period.

Figure 1: Productivity Comparison



(a) Productivity Level

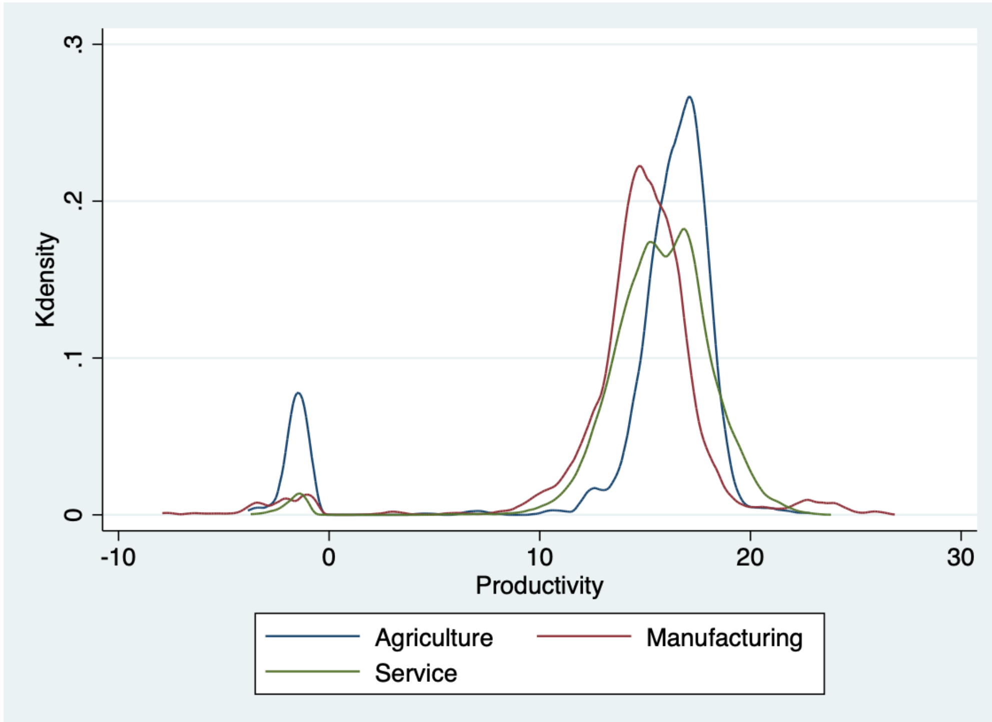
(b) Productivity Growth Rate

Note: In Figure 1(a), the average productivity level in the service sector is the highest most of the time. The agriculture sector exceeded the service sector in 2003 and 2005 and kept decreasing after. In Figure 1(b), the growth rates in the service sector and manufacturing sector increase in 2004 and then fluctuate around 0.

Figure 2 plots the productivity distributions of agriculture, manufacturing, and service. The distribution of service sector productivity is to the right of the manufacturing productivity, while the agricultural distribution is to the left of the service sector. The extreme values in the right tails for all three sectors come from the 0 value-added.

[19]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.

Figure 2: Productivity Distribution of Service Sector and Manufacturing Sector



Note: The distribution of service sector productivity is to the right of the manufacturing productivity, while the agricultural distribution is to the left of the service sector. The extreme values in the right tails for all three sectors come from the 0 value-added.

The distributions in the manufacturing sector and the agriculture sector are more dispersed than in the service sector. In Table 9, we show the 90-10 percentile productivity gaps. The service sector has the lowest productivity gap. Table 8 shows that the standard deviation is the smallest in the service sector, followed by the manufacturing sector. The distribution graph tells a similar story. The manufacturing sector and the service sector have longer left tails and right tails.

Table 9: 90-10 Percentile Productivity Gaps

	Aggregate	Agriculture	Manufacturing	Service
Top 10%	19.616	18.737	19.661	19.581
Bottom 10%	8.744	-1.639	5.734	9.493
Gap	2.243	-11.432	3.429	**2.063**

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

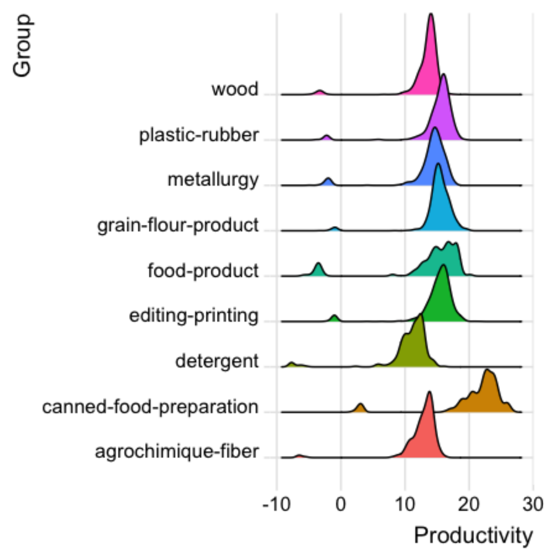
The service sector has higher average productivity and lower dispersion. In this section, we only study the sector-level productivity. There are two explanations for the higher dispersion level in the manufacturing sector than in the service sector. First, the productivity values in the manufacturing sub-sectors are different from each other. Second, the productivity values are quite dispersed inside each sub-sector. In the following part, we further decompose the distribution into sub-sectors.

5.2 Productivity Distribution Decomposition

In Figure 3, we show the productivity distributions in the 7 service sub-sectors (3(a)) and 9 manufacturing sub-sectors (3(b)).[20] 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 10 to 20, while the main body of the manufacturing sub-sector distribution ranges between less than 10 to almost 30. Therefore, the service sub-sectors productivity values are more concentrated.

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 10 to 20. Figure 3(b) shows the productivity distributions in 9 manufacturing sub0sectors. The distributions are more dispersed and range between less than 10 to almost 30.

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

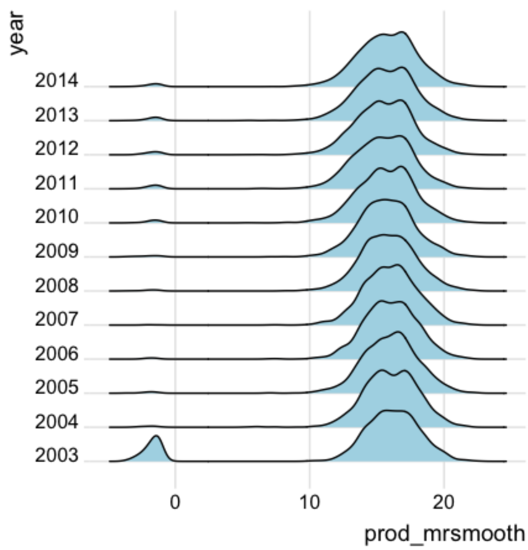
Then we further show the time decomposition of the productivity distribution in three sectors in Figure 4. We can see that the distribution of the three sectors all become more dispersed over time. The range of the manufacturing sector

[20]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.

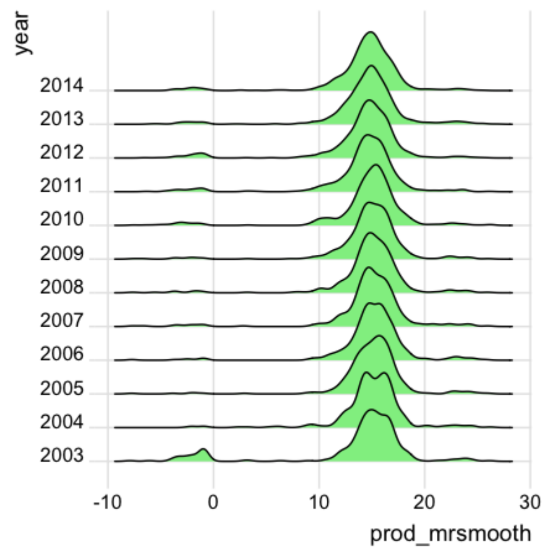
is always larger than the other 2 sectors in all 12 years.

Overall, we find that the productivity in the service sub-sectors is more concentrated, which is consistent with the previous conclusion. Also, the higher level of dispersion both across and within manufacturing sub-sectors explains why the manufacturing sector is more dispersed. Conclusions do not change if we look by years.

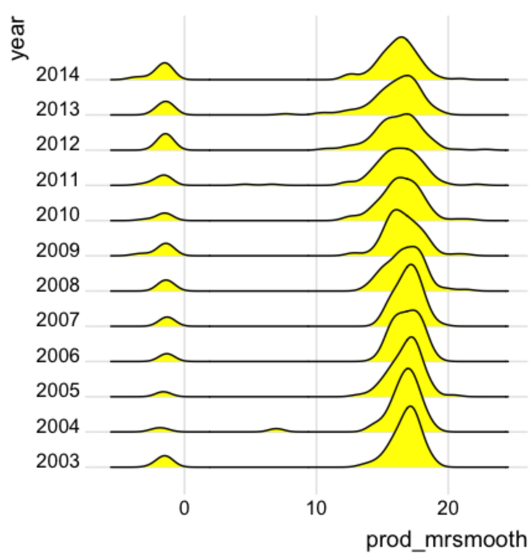
Figure 4: Ridge Distribution by Year



(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 a lower productivity dispersion level by decomposition. Then, we focus on another question: does the service sector have a higher 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. We find that the manufacturing sector has the highest productivity frontier throughout the period. It seems that the idea of investing in the manufacturing sector is supported. However, if we further look at the productivity frontier by sub-sector. The productivity frontier in the manufacturing sector comes from the Canned Food Preparation Industry, which is the yellow line in Figure 5(b). The productivity frontier from this sub-sector is far higher than the other manufacturing sub-sectors. Comparing the rest of the manufacturing sub-sectors in Figure 5(b) to all the service sub-sectors in Figure 5(c), we can see that service sub-sectors have relatively higher productivity frontier. It may be true to invest in the overall productivity frontier, which is the Canned Food Preparation Industry. Yet, investing in manufacturing may not be as good considering the lower productivity levels in most manufacturing sub-sectors.
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.

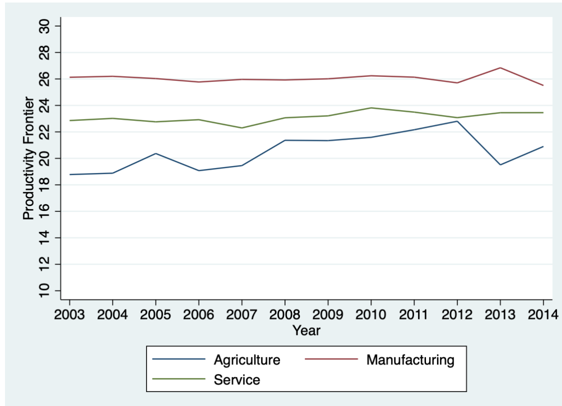
5.4 Productivity and Market Power

When discussing the estimation model, one concern is that the market power may affect the productivity outcomes. In this section, we implement a robustness check on the market power. First, we measure the market power using the Herfindahl-Hirschman Index of the 4 largest firms in each industry each year. Then we fix the industry effect and the year effect and run the regression of productivity estimated by the MrEst Method on the index.

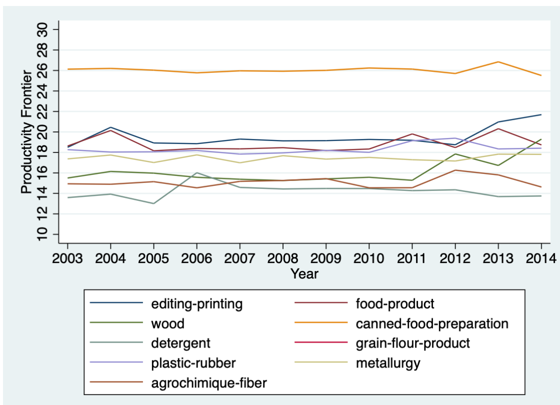
The coefficient is negative but insignificant. The economic interpretation of the outcome is that the increasing concentration would decrease productivity. If the market power creates a bias in the productivity estimate, we expect to see that the bigger firms have larger productivity. Yet, it is the opposite of the regression outcomes we have.

Next, we look at the relationship between productivity and the number of firms. The coefficient is positive but pretty small, implying that the productivity of firms would slightly increase if more firms were competing in the market. This conclusion is consistent with the HHI index regression outcomes. Overall, market power has little or no impact on

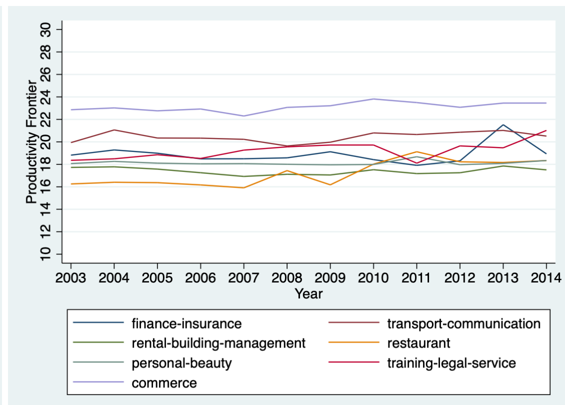
Figure 5: Productivity Frontier



(a) Productivity Frontier in Three Sectors



(b) Productivity Frontier in Manufacturing Industry



(c) Productivity Frontier in Service Industry

Note: We plot the productivity frontier for each sector from 2003 to 2014. In Figure 5(a), the manufacturing sector has the highest productivity frontier throughout the period. However, if we further look at the productivity frontier by sub-sector. The productivity frontier in the manufacturing sector comes from Canned Food Preparation Industry, which is the yellow line in Figure 5(b). The productivity frontier from this sub-sector is far higher than the other manufacturing sub-sectors. Comparing the rest of the manufacturing sub-sectors in Figure 5(b) to all the service sub-sectors in Figure 5(c), we can see that service sub-sectors have relatively higher productivity frontier.

productivity.

Table 10: Productivity and Market Power

	(1) Productivity	(2) Productivity
HHI	-0.690	
	(-1.45)	
Firm Numbers		0.0000311*
		(1.75)
Constant	14.11***	15.20***
	(94.24)	(390.52)
N	10991	47802
Industry	Yes	Yes
Year	Yest	Yest

∗ In the first column, we measure the market power using the Herfindahl-Hirschman Index of the 4 largest firms in each industry each year. The coefficient is negative but insignificant.

∗∗ In the second column, we look at the relationship between productivity and the number of firms. The coefficient is positive but pretty small.

6 Productivity and Employment

6.1 Sector-level Reallocation

Having estimated productivity in agriculture, manufacturing, and service, we next study structural transformation based on the productivity levels and growth in three sectors and the movements of labor to those sectors. We analyze structural transformation 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. We show that labor grows more in high-productivity sectors and high-productivity firms.

The productivity level is always higher in the service sector[21]. In response to the higher service productivity, the total employment in the service sector is higher during the time period we study in Figure 6(a). The gap between the employment value in the service sector and the manufacturing sector is smaller at the beginning and grows larger later.

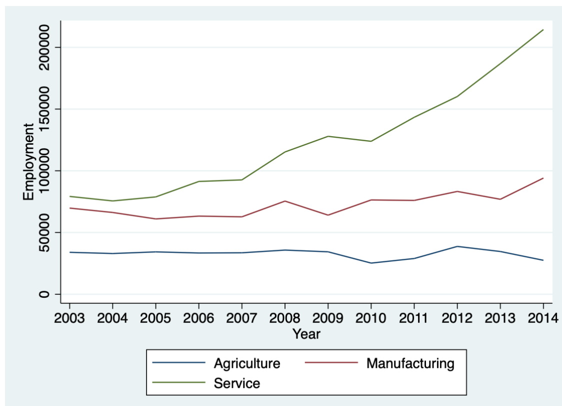
We then divide the total employment into skilled workers and unskilled workers, which is shown in Figures 6(b) and

[21] From the previous analysis, we show that the agriculture sector has higher productivity in two years. However, we believe there is a huge bias in the agriculture data we have as the main population in the country works in the agriculture sector.

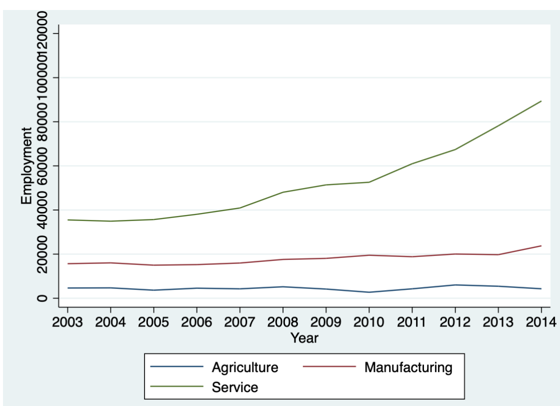
6(c). The number of skilled workers is larger in the service sector than in the manufacturing sector and the gap widens over time. The number of unskilled workers, on the other hand, was smaller in the service sector in 2003 and surpassed the manufacturing sector in 2005. The growth rate of unskilled workers in the service sector is pretty large thereafter. Over the study period from 2003 to 2014, the number of workers in the service sector increases more than that in the manufacturing sector.

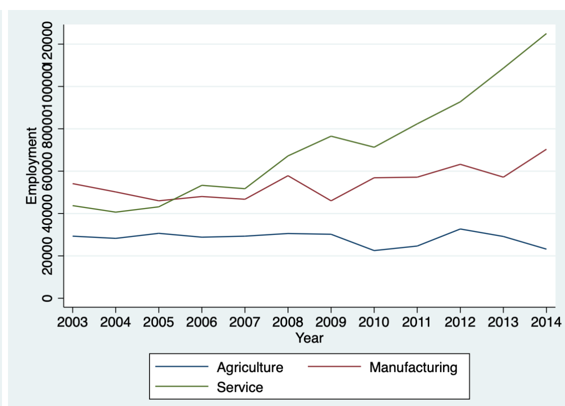
The labor growth rate in Figure 7(a) shows that the labor growth in the service sector is mostly positive. The growth rates in manufacturing and agriculture, on the other hand, fluctuate around 0. The findings are the same in the skilled labor growth(Figure 7(b)) and the unskilled labor growth rate (Figure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

Figure 6: Labor Hired Over Time



(a) Labor





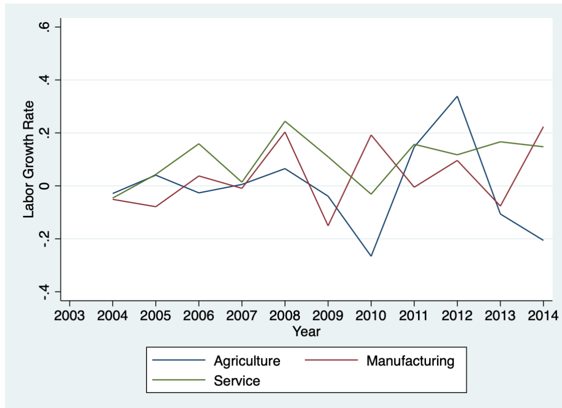
(b) Skilled Labor

(c) Unskilled Labor

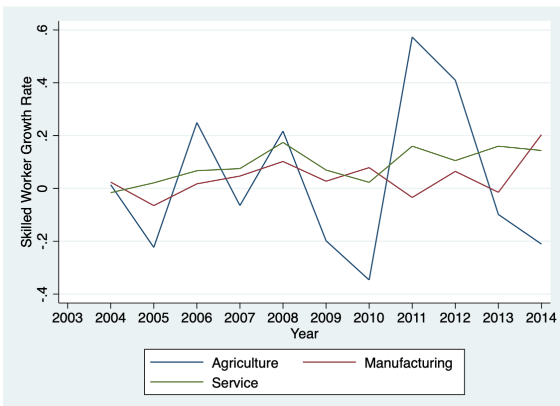
Note: The figures show the aggregate labor, skilled labor, and unskilled labor employment in three sectors. In Figure 6(a), the total employment in the service sector is higher from 2003 to 2014. In Figure 6(b), the number of skilled workers is larger in the service sector than in the other two sectors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

Similar patterns are also found if we investigate the employment share. In Figure 8, we show the share values instead

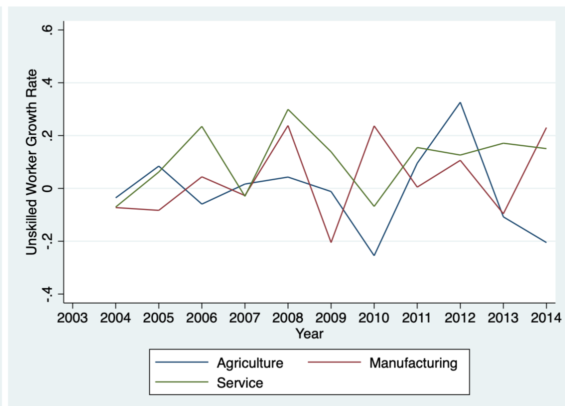
Figure 7: Labor Growth Over Time



(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.

of the employment values. The employment share in the service sector increases and the ratios decrease in both the manufacturing sector and the agriculture sector. The value 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 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 similar. Therefore, the changes in the employment values and the employment shares means are not associated with the productivity growth rate.

To sum up, more workers move to the service sector regardless of their type. 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. The reallocation of labor is efficient. As for the growth rate, there is no obvious evidence to show whether the workers move to the sector with higher or lower productivity growth rates. We cannot reach a conclusion about Baumol's disease at the sector level.

6.2 Firm-level Labor Reallocation by Sectors

Most structural transformation studies focus on 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 lower productivity level than their previous firms in their old sector. If this is the case, the reallocation 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.

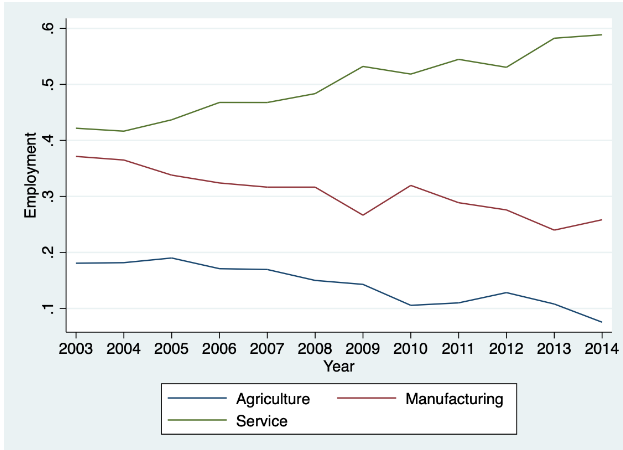
To show the labor reallocation at the firm level, we use a cumulative distribution graph similar to the Lorenz curve. The X-axis shows the cumulative firm proportions. We rank the firms based on their productivity level, instead of ranking people based on income levels as in a standard Lorenz curve. The Y-axis shows the cumulative labor growth rate across all the firms. That is if we add 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.

Figure 9, Figure 10, and Figure 11 show the reallocation rates for labor, skilled labor, and unskilled labor at the sectoral level, showing allocations by productivity level. We first look at the overall labor reallocation in three sectors, that is Figure 9. We can see that the blue curve is pretty close to the red line in the service sector (Figure 9(a)), indicating that the 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 is concave all along, showing that labor reallocates to lower-productivity firms.

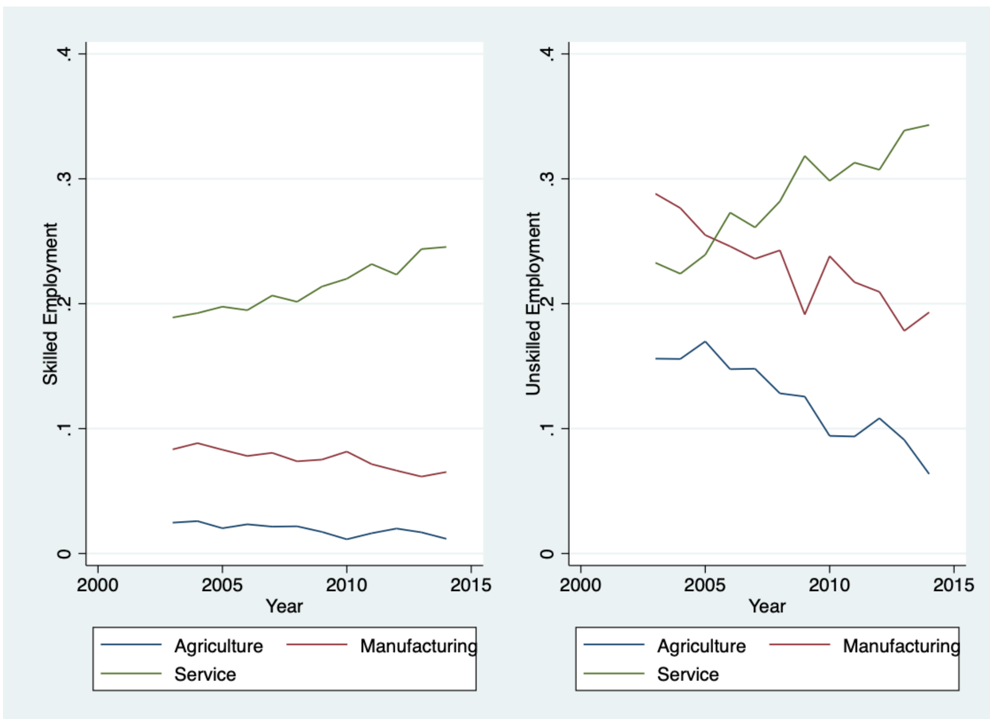
Figure 10 shows the reallocation of skilled workers in three sectors. The curves increase around the red line across different productivity levels. This means that skilled workers have an equal chance to reallocate into firms of all productivity levels in all sectors. Considering that the number of skilled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

Finally, we look at the reallocation of unskilled workers, which is in Figure 11. We observe that the cumulative

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



(a) Employment Share

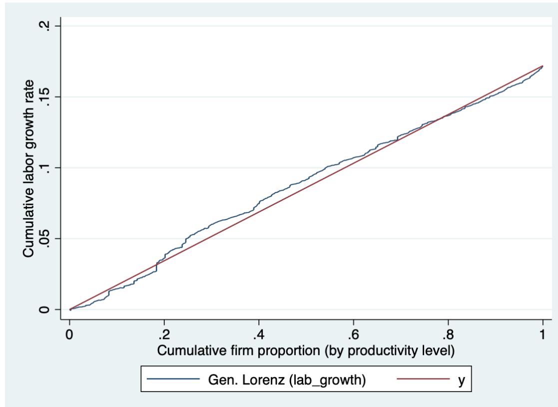


(b) Skilled Employment Share and Unskilled Employment Share

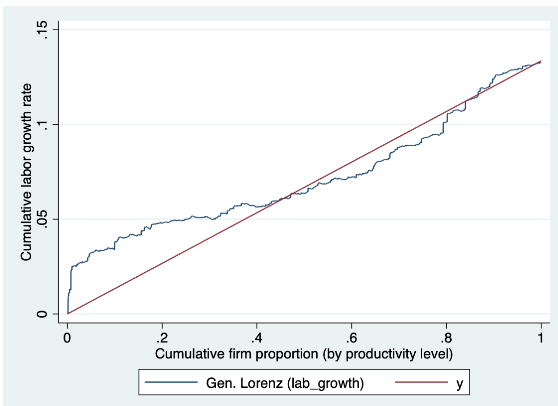
Note: We use employment share instead of employment values to check the changes in employment across sectors. In Figure 8(a), the employment share in the service sector increases, and the ratios decrease in both the manufacturing sector and the agriculture sector. Figures 8(b) and 8(c) show that the 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.

curve ranked by the productivity level is convex in the service sector (Figure 11(a)) across all productivity levels. The lowest 20% firms witness zero or negative unskilled worker growth. The top 20% firms, on the other hand, have

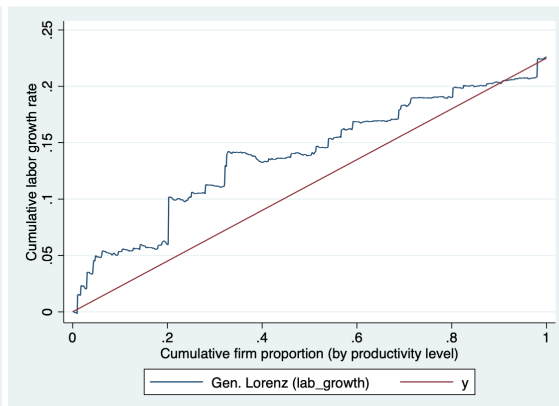
Figure 9: Labor Reallocation in Three Sectors



(a) Service



(b) Manufacturing



(c) Agriculture

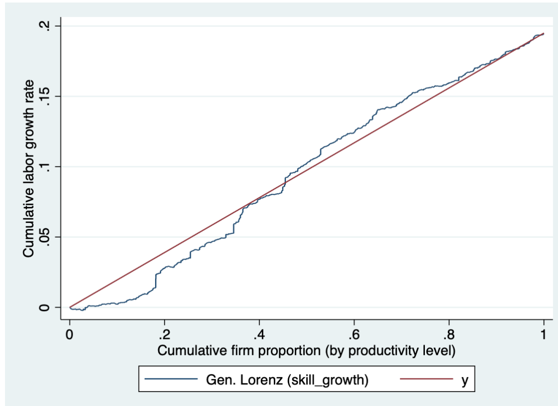
Note: To show the labor reallocation at the firm level, we use a cumulative distribution graph similar to the Lorenz curve. The X-axis shows the cumulative firm proportions. We rank the firms based on their productivity level, instead of ranking people based on income levels as in a standard Lorenz curve. 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. In Figure 9(a), the blue curve is pretty close to the red line in the service sector, indicating that the labor grows equally in different productivity firms. In Figure 9(b), the blue line in the manufacturing sector is also close to the line, though not as close as the service sector. For the agriculture sector in Figure 9(c), the curve is concave all along, showing that labor reallocates to lower-productivity firms

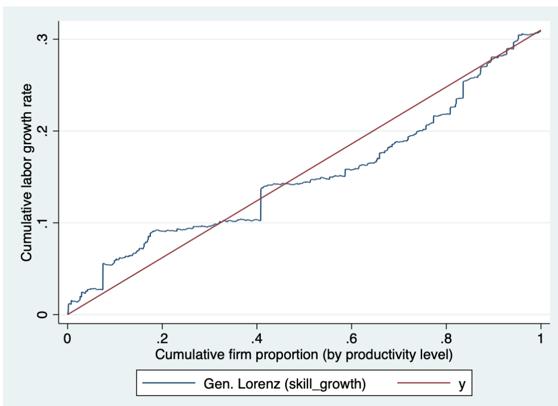
more unskilled workers reallocated. This means that workers move to firms with higher productivity in the service sector. Under the assumption that higher productivity firms pay higher wages, this suggests a correctly functioning labor market and labor force growth in the most productive firms in the economy.[22] In the manufacturing sector and the agriculture sector, 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

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

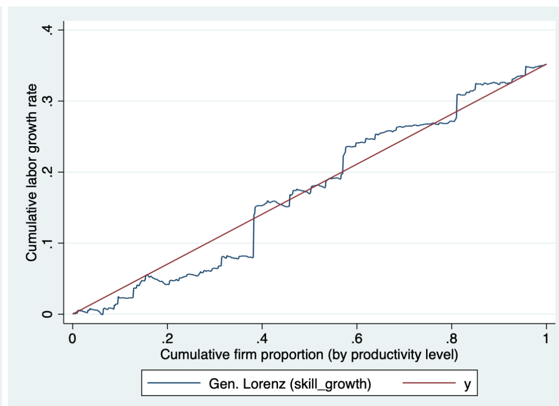
Figure 10: Skilled Labor Reallocation in Three Sectors



(a) Service



(b) Manufacturing



(c) Agriculture

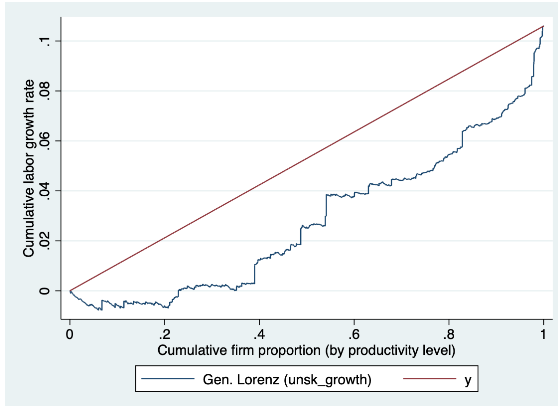
Note: The figures plot the reallocation of skilled workers in three sectors. The curves increase around the red line across different productivity levels. This means that skilled workers have an equal chance to reallocate into firms of all productivity levels in all sectors. Considering that the number 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.

among the top firms is fair.

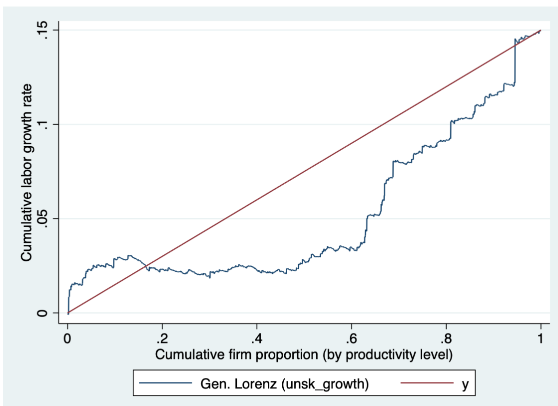
In relative terms, unskilled workers are more likely to find a job in high-productivity firms in the service sector than in the manufacturing sector and the agriculture sector. To find better-paid jobs, unskilled workers would choose to move to the service sector. This explains why there is a larger 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 CIV data is 1,941,921 workers, which is about twice the level of skilled workers (969,249). As a result, unskilled workers appear to be the largest beneficiaries of reallocation to the service sector.

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

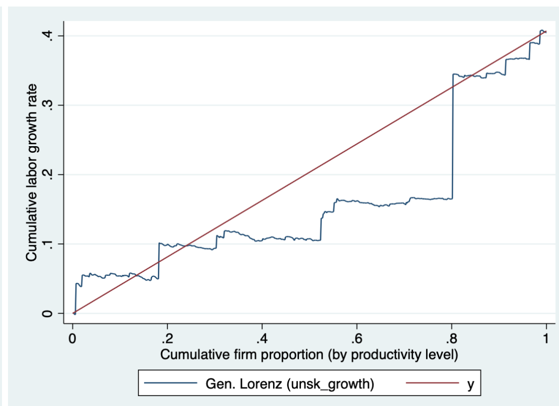
Figure 11: Unskilled Labor Reallocation in Three Sectors



(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.

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 services than in the manufacturing sector and the agriculture sector. However, the pattern is not as obvious as we expected. This may be explained by the difference across sub-sectors. High-productivity firms in some service industries tend to provide more job opportunities to unskilled workers, while some service industries don't.[23] Unskilled workers choose to go to these industries and get jobs in productive firms.

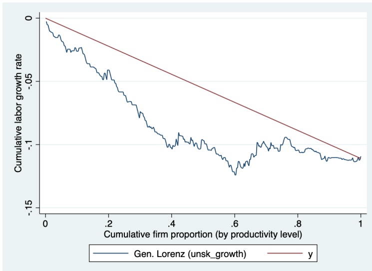
To check our arguments, we dig into the unskilled workers' reallocation pattern at the sub-sector level. In Figure 12, we answer the question of where the unskilled workers go to the sub-sectors where it is easier to find jobs in high-productivity firms. In the Training Legal Service industry, the top 20% firms are responsible for almost all the labor growth, which means they hire the most job-seeking unskilled workers. In the Restaurant industry and the Commerce industry, 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 and the unskilled worker growth trends are the opposite of all the other sub-sectors.

We further check the unskilled worker reallocation in the manufacturing industries (See Appendix). 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 Canned Food Preparation, 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. Overall, we cannot find similar patterns in the manufacturing sub-sectors.

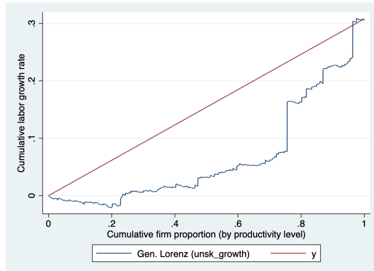
In conclusion, two advantages in the service sector attract workers, especially unskilled workers. The service sector has on average a higher productivity level than the manufacturing sector. Workers reallocating to the service sector achieve higher wages. However, high sectoral productivity is not enough, 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.

[23] For example, insurance firms have no motivation to hire unskilled workers. On the other hand, the local retail shops would want to hire unskilled workers.

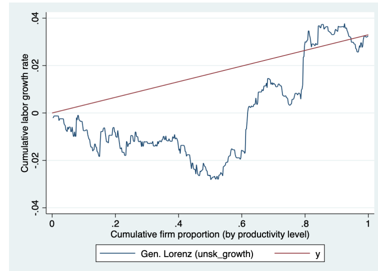
Figure 12: Unskilled Worker Reallocation across Service Industries



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

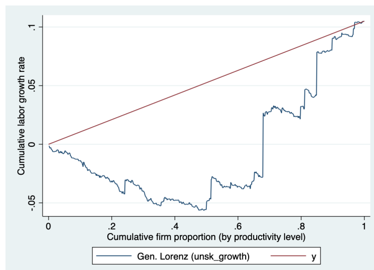


(b) Unskilled Worker Reallocation in the Transport and Communication Industry(by Productivity Level)

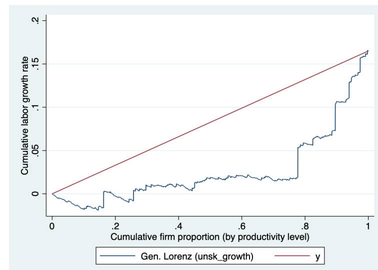


(c) Unskilled Worker Reallocation in the Rental Building and Management Industry (by Productivity Level)

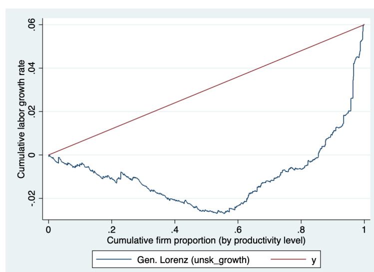
(d) Unskilled Worker Reallocation in the Personal Beauty Industry (by Productivity Level)



(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 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 dynamism. Specifically, we show that in the first two decades of this century, the service sector in Côte d'Ivoire was on average 7% 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.

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 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[24]. 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.

[24] In the Appendix, we discuss a bit about the relationship between the formal sector we have and the informal sector we don't have. We believe our outcomes are informative.

Appendix

Appendix 1 Inputs Comparison Across Service Industries

Table A1 Inputs Comparison Across Industries

Industry	Inputs	Obs	Mean	Std. dev.
association-culture-sport	Skilled worker	505	0.4161	3.6403
	Unskilled worker	504	0.0073	0.8928
	Capital	503	-0.3709	4.177
education-research	Skilled worker	5,768	0.2675	2.6240
	Unskilled worker	5,769	0.1068	1.7467
	Capital	5,773	0.0977	3.6728
energy-water	Skilled worker	179	0.0666	1.5397
	Unskilled worker	178	-0.0787	3.7492
	Capital	178	-0.1567	2.4272
finance-insurance	Skilled worker	1,785	0.1094	3.5732
	Unskilled worker	1,790	0.0579	1.5679
	Capital	1,789	-.0354577	4.1914
health-social	Skilled worker	2,782	0.2057	1.3871
	Unskilled worker	2,780	0.1577	1.7697
	Capital	2,775	.4107607	4.5697
personal-beauty	Skilled worker	272	0.1790	2.8600
	Unskilled worker	270	0.2024	1.5347
	Capital	272	0.2654	2.4094
public-administration	Skilled worker	63	1.1844	5.2112
	Unskilled worker	63	0.1059	0.2764
	Capital	63	0.6388	1.9400
rental-building-management	Skilled worker	1,992	0.0590	2.6498
	Unskilled worker	1,997	-0.1077	2.5116
	Capital	1,998	-.0207535	4.9573
rental-car-equipment	Skilled worker	249	0.0643	2.0697
	Unskilled worker	248	-0.0500	0.9636
	Capital	246	-.9001419	9.3902

restaurant	Skilled worker	1,715	0.2648	2.7149
	Unskilled worker	1,720	0.1481	3.0649
	Capital	1,715	0.1799	4.9707
training-legal-service	Skilled worker	14,653	0.1428	3.2998
	Unskilled worker	14,663	0.0122	2.2565
	Capital	14,666	0.0173	4.3436
transport-communication	Skilled worker	4,944	0.2807	2.5900
	Unskilled worker	4,950	0.0583	1.4014
	Capital	4,945	0.0091	3.2509
commerce	Skilled worker	33,413	0.1043	2.5323
	Unskilled worker	33,409	0.0494	2.3048
	Capital	33,432	0.0648	2.6912

Appendix 2

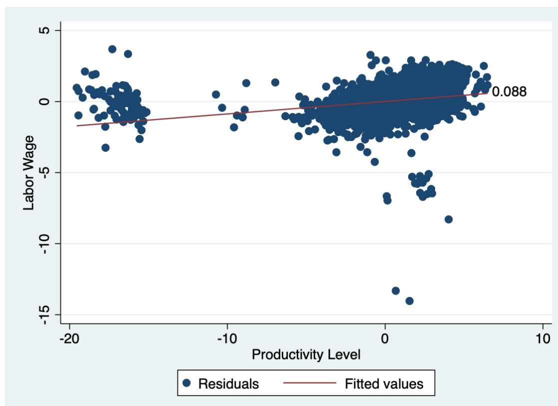
Here we describe how we determine the appropriateness of external labor as a proxy variable in the production process. Theoretically, we need to prove the assumption that the intermediate inputs (external labor) are monotone to the productivity shock. Empirically, we need to show that external labor is a better proxy than the intermediate material in the service sector.

In LP(2003), they assume a perfectly competitive market and the input and output prices are common. In our model, the input prices can be common under perfect competition, but the output price within the industry would be different due to the customization of the products. Therefore, I assume the output prices are decided exogenously instead. The idea that the output prices are exogenous can be explained by the characteristic of the service sector: the output price in the service sector is decided by the interaction between producers and consumers. Consumers' feelings affect the service firms' pricing strategy (Kashyap, R., & Bojanic, D. C. (2000); Malik, M. E., Ghafoor, M. M., & Iqbal, H. K. (2012)). Small firms could charge high prices if consumers think the product is over expectations. With the new price assumption, we prove that the monotone assumption still exists in the service sector.

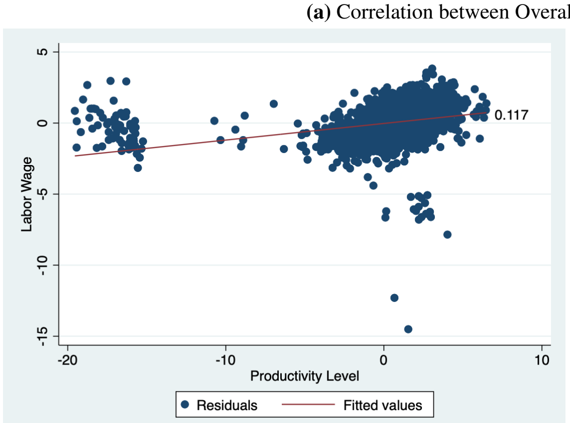
Appendix 3 Productivity Level and Wage

Our previous analysis follows the idea that workers move to the sectors or firms with higher productivity because those sectors or firms have higher wage rates. The argument holds when the wages are positively correlated with the productivity level. In Figure 13 and Figure 14, we plot the correlation between wage and productivity in the manufacturing sector and the service sector. To avoid the variation from both industries and years, we fix the industry effect and years effect and use the residual values to plot the correlation.

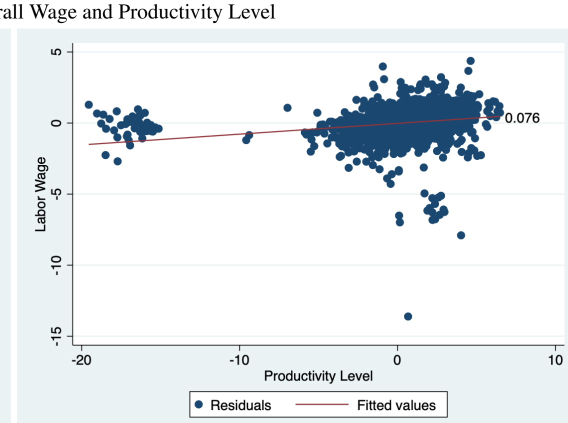
Figure 13 shows that the productivity level is always positively associated with wages for skilled workers, unskilled workers, and overall workers. In the manufacturing sector, the coefficient of productivity is 0.088 if we regress overall wage on the productivity and it is significant at 5%. The coefficients of the productivity level on the skilled worker wages (0.117) and the unskilled worker wages (0.076) are also significant. In Figure 14, 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 0.183, higher than that in the manufacturing sector. The coefficient between productivity and skilled workers is 0.216. The coefficient for the unskilled workers is 0.107. Therefore, the wage increases as the productivity level grows.



(a) Correlation between Overall Wage and Productivity Level

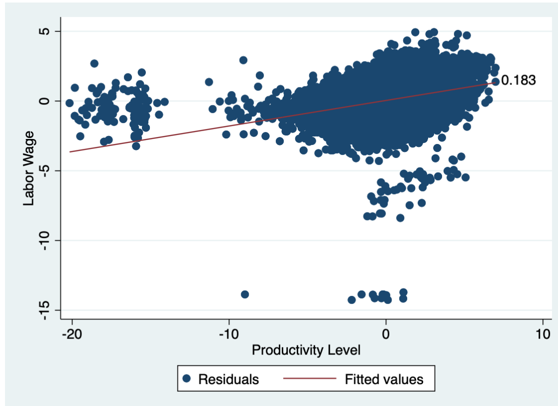


(b) Correlation between Skilled Worker Wage and Productivity Level



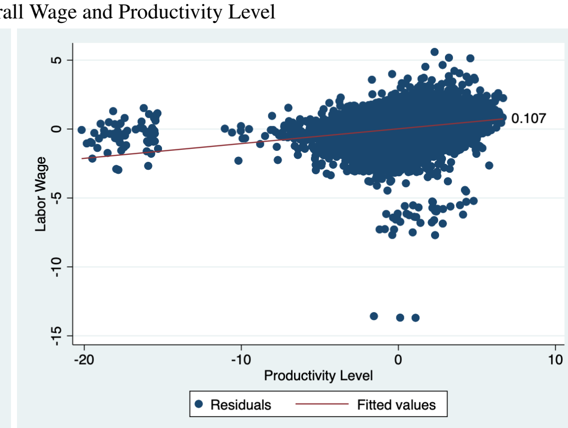
(c) Correlation between Unskilled Worker Wage and Productivity Level

Figure 13: Correlation between Wage and Productivity Level in the Manufacturing Sector



(a) Correlation between Overall Wage and Productivity Level

(b) Correlation between Skilled Worker Wage and Productivity Level



(c) Correlation between Unskilled Worker Wage and Productivity Level

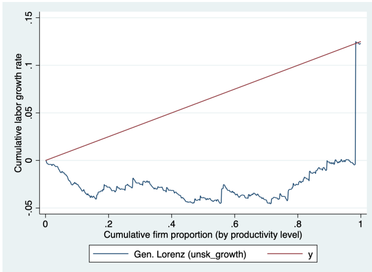
Figure 14: Correlation between Wage and Productivity Level in the Service Sector

Appendix 4 Reallocation of Unskilled Workers in the Manufacturing Sector

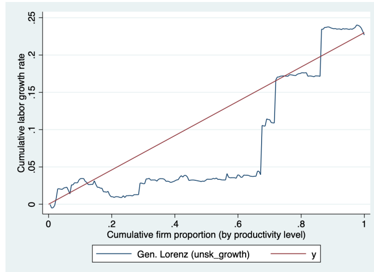
Figure 15 shows the growth rate of unskilled workers in the manufacturing industries. Compared with the service industries, those manufacturing industries do not have an obvious trend showing that higher productivity firms have more unskilled worker growth. It is less likely for unskilled workers to find jobs in high-productivity firms in manufacturing sub-sectors except for the Editing and Printing Industry. In manufacturing industries such as Canned Food Preparation, 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 Productivity Estimation Outcomes Using Different Methods

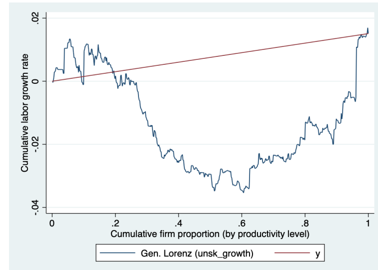
In this part, we show the productivity estimation outcomes using 4 econometric TFP estimation methods. The 5 methods are the Olley & Pakes method (OP method), the Levinsohn & Petrin method (LP method), the Ackerberg, Caves & Frazer Method (ACF method), the MrEst Method, and the Labor Productivity method. 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



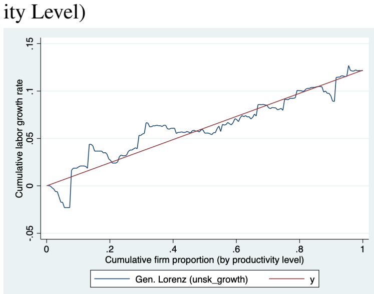
(a) Unskilled Worker Reallocation in the Editing and Printing Industry (by Productivity Level)



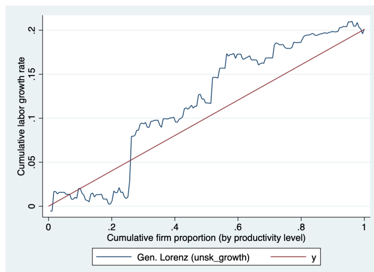
(b) Unskilled Worker Reallocation in the Food Product Industry(by Productivity Level)



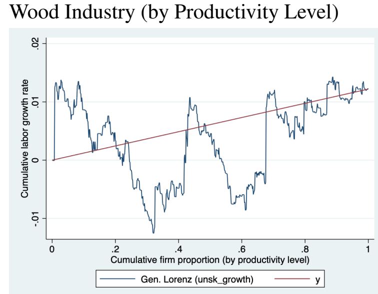
(c) Unskilled Worker Reallocation in the Wood Industry (by Productivity Level)



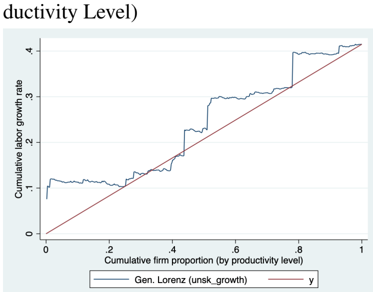
(d) Unskilled Worker Reallocation in the Canned Food Preparation Industry (by Productivity Level)



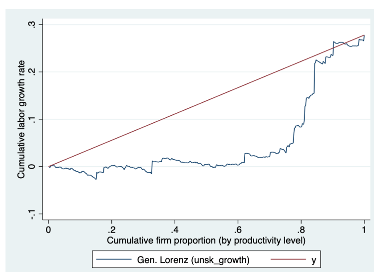
(e) Unskilled Worker Reallocation in the Detergent Industry (by Productivity Level)



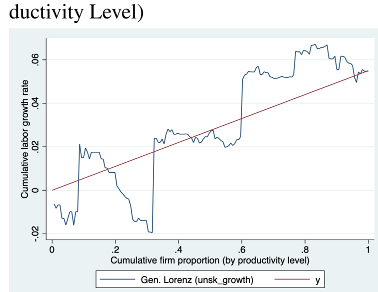
(f) Unskilled Worker Reallocation in the Grain and Flour Product Industry (by Productivity Level)



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



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



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

Figure 15: Unskilled Worker Reallocation across Manufacturing Industries

16.

In Figure 16, the main body distribution of the MrEst method is pretty similar to the LP method and the OP method. The distributions of the two ACF methods have quite different distribution ranges. The MrEst Method has a smaller range and the labor productivity methods provide the smallest distribution range.

Then we further look at the mean values of the sectors using different methods. We find that the service sector always has the largest productivity values except for the ACF+LP method.

Table A2 Mean Value

Method	Sector	Mean	Observations
MrEst	Agriculture	14.534	1,153
	Manufacturing	14.488	6,632
	Service	15.543	46,742
OP	Agriculture	13.959	1,153
	Manufacturing	11.405	6,653
	Service	15.321	46,742
LP	Agriculture	13.956	1,153
	Manufacturing	11.386	6,653
	Service	15.312	46,742
ACF+OP	Agriculture	8.676	1,158
	Manufacturing	4.942	6,702
	Service	9.778	46,973
ACF+LP	Agriculture	8.677	1,158
	Manufacturing	10.342	6,684
	Service	9.681	46,973
Labor Prod	Agriculture	3.55e+07	1,175
	Manufacturing	1.66e+07	8,903
	Service	5.33e+07	61,644

Appendix 6 Correlation of Firm Ranks

In Section 6, we analyze the employment growth based on firm-level productivity. We need to show that the firms' productivity ranks in the different methods discussed above are highly correlated. If the ranks are not correlated, the conclusions about the employment growth will be meaningless. 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 0. The correlation between the MrEst method between the labor productivity method is also high.

Table A3 Correlation of Firm Ranks at the Total Level

	MrEst	OP	LP	Lab-Prod	ACF-OP	ACF-LP
MrEst	1.0000					

OP	0.9782*	1.0000				
LP	0.9782*	0.9998*	1.0000			
Lab-Prod	0.8301*	0.7977*	0.7978*	1.0000		
ACF-OP	0.7155*	0.7416*	0.7405*	0.6502*	1.0000	
ACF-LP	0.7642*	0.7413*	0.7401*	0.6813*	0.9391*	1.0000

Table A4 Correlation of Firm Ranks at the Sector Level

	MrEst	OP	LP	Lab-Prod	ACF-OP	ACF-LP
MrEst	1.0000					
OP	0.9967*	1.0000				
LP	0.9967*	1.0000*	1.0000			
Lab-Prod	0.7080*	0.7070*	0.7075*	1.0000		
ACF-OP	0.8706*	0.8708*	0.8699*	0.5989*	1.0000	
ACF-LP	0.8959*	0.8919*	0.8912*	0.5978*	0.9873*	1.0000

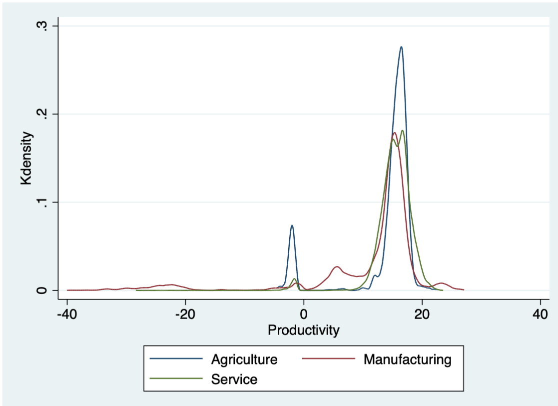
Table A5 Correlation of Firm Ranks at the Industry Level

	MrEst	OP	LP	Lab-Prod	ACF-OP	ACF-LP
MrEst	1.0000					
OP	0.9999*	1.0000				
LP	0.9999*	1.0000*	1.0000			
Lab-Prod	0.8144*	0.8114*	0.8114*	1.0000		
ACF-OP	0.9008*	0.9039*	0.9041*	0.7523*	1.0000	
ACF-LP	0.9010*	0.9041*	0.9043*	0.7522*	0.9999*	1.0000

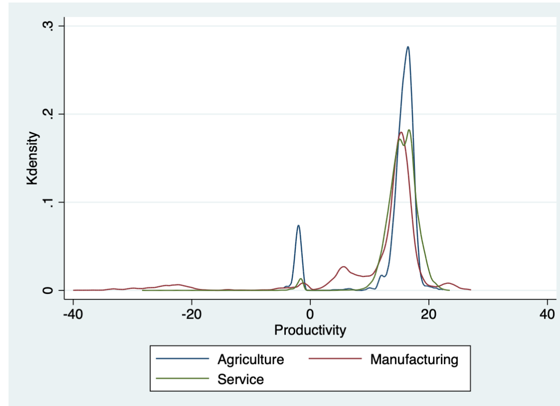
Appendix 7 Formal Sector and Informal Sector

One concern about our data is that we ignore the informal sector as 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 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.

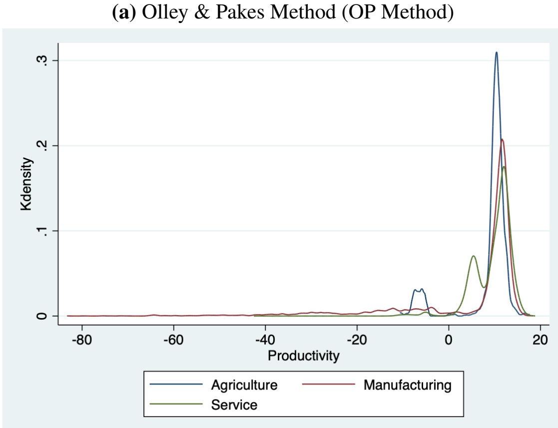
Figure 17(a) shows the GDP comparison outcomes. We can see that the GDP we calculated from the data is smaller



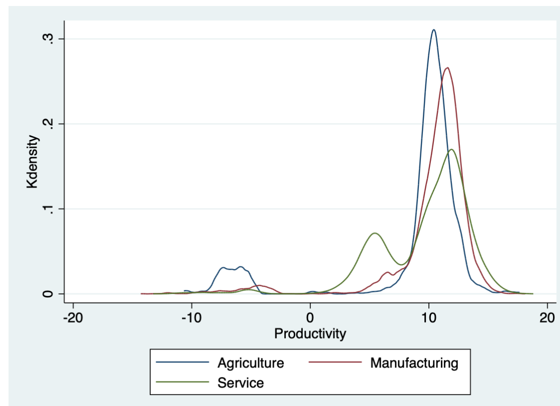
(a) Olley & Pakes Method (OP Method)



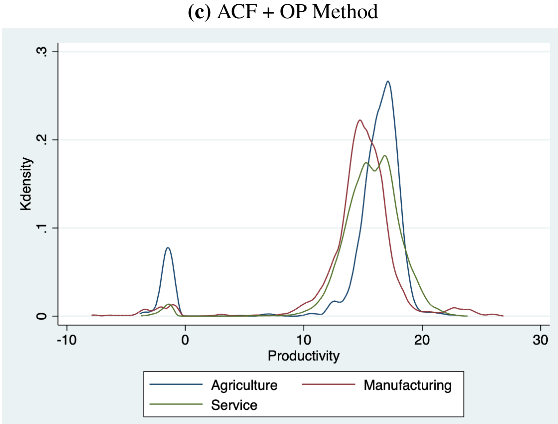
(b) Levinsohn & Petrin Method (LP Method)



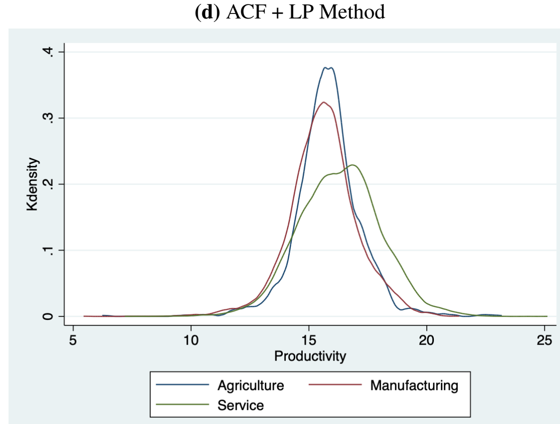
(c) ACF + OP Method



(d) ACF + LP Method



(e) MrEst Method

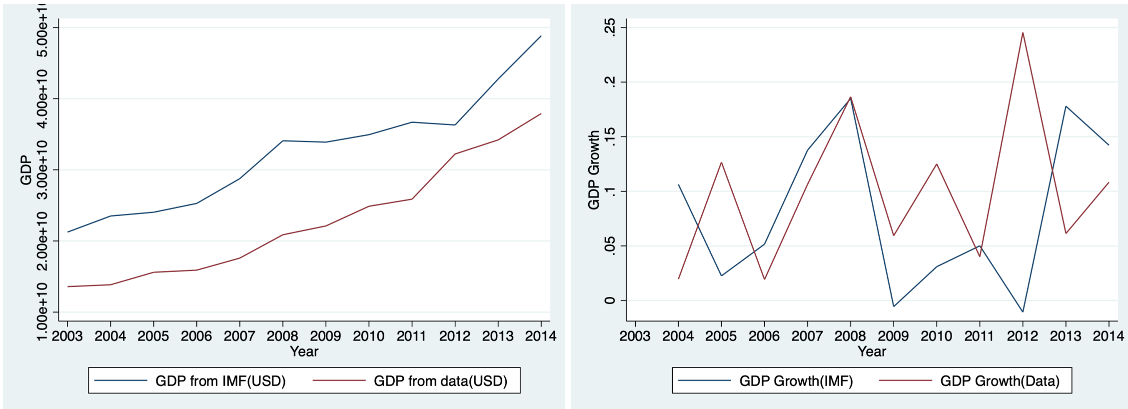


(f) Labor Productivity Method

Figure 16: Productivity Distribution Using 6 Methods

than the real GDP from the IMF. However, the calculated GDP accounts for about 74% of the real GDP on average. The overall trends of the GDP values are both increasing. Therefore, the formal sector we study has explanatory power for the whole economy.

We further check the wages in the formal sector and informal sector using the LSMS (Enquête Harmonisée sur le



(a) GDP Comparison

(b) GDP Growth Comparison

Figure 17: GDP in CIV

Conditions de Vie des Ménages 2018-2019). The income from the informal sector is 78439 on average, while the income in the formal sector is 134075.1. 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.

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