Invited paper presented at the 6th African Conference of Agricultural Economists, September 23-26, 2019, Abuja, Nigeria

Productivity differentials and technology gap in African agriculture: A stochastic metafrontier approach

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Abstract

Increased agricultural productivity is important for development and poverty reduction in Africa. However, productivity levels in African agriculture is very low and strategies for improving them have not produced the desired outcome. Successful productivity improvement strategies are contingent on identifying sources of productivity growth in African agriculture. This paper sought to examine sources of productivity in African agriculture using cross-country panel data. Specifically, a stochastic metafrontier model was employed to decompose efficiency into technical efficiency and technology gap. Generally, the results show an average efficiency of 71%, indicating about 29% shortfall in efficiency in African agriculture. The source of inefficiency is attributable to technological inefficiency rather than technical inefficiency because the empirical estimates show that almost all countries are producing close to the regional frontier. Using the bootstrap truncated regression model, factors such as expenditure on R & D, trade and literacy were determined as having efficiency increasing effects.

Keywords: African agriculture, productivity growth, technology gap, metafrontier, inefficiency

JEL codes: D 24, Q12, Q16

1. Introduction

Historically, agricultural productivity growth has been recognised as the key to overall economic development and poverty reduction in parts of the world, including Africa (World Bank 2004; Alene 2010). Improving agricultural productivity has therefore become a common strategy to improving the poverty status of rural households in Africa. Given rapid productivity gains in technological advances in the Green Revolution in Asia, introduction of new technologies was seen as a panacea for agricultural productivity growth in Africa. However, the Green Revolution failed to achieve the desired outcome in Africa, as was observed in Asia. Despite its poor outcomes, lots of investments are still being made in African agriculture to improve agricultural productivity. It is therefore important to examine productivity and its drivers to inform evidence-based policies in the second Green Revolution anticipated in Africa.

Productivity measurement has long been of interest to economists (Ali & Byerlee 1991; Bravo-Uretha & Pinheiro 1993; Diewert & Lawrence 1999; Thiam et al. 2001). Over the years, economists have examined productivity using production functions with the assumption that all decision making units (DMUs) use common underlying technology (Alem et al. 2019). However, in reality, the underlying production technology and production possibilities could differ because of locational differences and resource endowments (O'Donnell et al. 2008). Specifically, farms in different locations make choices from different sets of possible input and output combinations. Therefore, estimations based on the homogeneity assumption may result in biased efficiency estimates and consequently, wrong policy conclusions (Orea & Kumbhakar 2004). It is therefore important to account for heterogeneity in productivity measurement.

In the production economics literature, a number of methods have been proposed to address heterogeneity issues in the production function estimation. While some researchers make use of cluster algorithms to account for heterogeneity, others use latent class or metafrontier models (Alem et al. 2019). Latent class is based on the assumption that a finite number of groups exist in the data, and uses statistical algorithm to estimate the production frontier for the underlying groups. The metafrontier on the other hand, is based on a priori assumption where physical characteristics are employed to segregate the data for separate model estimations. All the methods used to account for heterogeneity have their advantages and disadvantages. However, the metafrontier approach is the common method for examining heterogeneity in the production frontier literature.

The metafrontier defines a boundary of unrestricted technology set that envelops group frontiers and allows researchers to decompose efficiency into technical efficiency and technology gap ratio. Decomposing efficiency into technical efficiency and technology gap can help policy makers to adopt appropriate strategies to improve agricultural productivity. If the agricultural sector in the various African countries is efficient, then investment in more productive inputs and technology will be an appropriate strategy to improve agricultural productivity. On the other hand, if current input or technology can be used more productively, then the target would be on improving efficiency (Nkamleu 2006).

The original metafrontier model was proposed by Battese and Rao (2002) based on the meta production function idea of Hayami (1969) and Hayami and Ruttan (1970). Battese et al. (2004) extended the metafrontier model into the stochastic framework. The metafrontier is a two-step estimation process. In the Battese et al. (2004) and O'Donnell et al. (2008) stochastic metafrontier model, the first step estimation is conducted using stochastic frontier methods and the second step uses linear programming (LP) methods. However, researchers have identified potential problems with the application of the LP method to construct the metafrontier. For instance, Huang et al. (2014) posit that the LP approach leads to biases in the technology gap estimates. The authors therefore proposed a stochastic metafrontier model where the metafrontier itself is estimated as stochastic.

In this paper, a stochastic metafrontier approach is adopted to examine sources of productivity variations in African agriculture. The stochastic metafrontier approach adopted in this paper deviates from the data envelopment approach utilised Nkamleu (2006) in the study of African agriculture. The approach has the advantage of accounting for noise in both the estimation of the stochastic regional frontiers and the metafrontier. Henningson and Kumbhakar (2009) posit that data from developing economies are usually noisy and therefore, it is important to model such data using stochastic processes.

The data for empirical application come from Food and Agriculture Organization Statistics database. The data comprise production and input information of 19 African countries for the period 1971-2004. Empirical estimates reveal that many African countries are operating close to regional frontiers, however, many of the countries are producing far below the industrial agricultural production technology. Overall, there is inefficiency in agricultural production in African agriculture. Further synthesis based on pre, during and post structural adjustment period in Africa show slight improvement in agricultural productivity during and post structural adjustment period.

The rest of the paper is organised as follows. Section 2 presents methods including empirical models and data used in the empirical application. Section 3 presents the results and discussion and finally the paper concludes in Section 4.

2. Methods

2.1 Stochastic frontier Analysis

The stochastic frontier model incorporates a composed error structure with a two sided symmetric and a one sided component (Aigner et al. 1977, Van den Broeck et al. 1994). The one sided component reflects inefficiency whiles the two sided one captures the random effects outside the control of the production unit as well as measurement errors and other statistical noise typical of empirical relationships. Stochastic frontier Analysis (SFA) may be specified as:

$$y_{it} = f(x_{1it}, x_{2it}, \ldots, x_{nit}; \beta^k) e^{v_{it}^k - u_{it}^k} \tag{1}$$

Where v_{it} is the stochastic random term, which is iid with $(0, \sigma_v^2)$ and u_{it} is the technical inefficiency term, which may assume either half normal, exponential, truncated-normal or gamma distribution (Aigner et al. 1997; Meeusen & Broeck 1977; 1990; Stevenson1990). In this paper, the exponential inefficiency distribution is assumed.

SFA could be estimated using either maximum likelihood (MLE) or Bayesian inference methods. Although the MLE methods are commonly used in the production economics literature (Alem et al. 2010), the Bayesian inference method is adopted in this paper because of the advantage in generating probability statements about unknown parameters and the ease with which statistical inference can be made. The Bayesian approach is based on Bayes theorem. The application of the Bayesian approach in the stochastic frontier analysis was by Van den Broeck et al. (1994). The authors used the posterior model densities and mix of several inefficiency distributions to resolve the uncertainty pertaining to the sampling approach.

2.2 Stochastic metafrontier

The metafrontier enveloping all group frontiers $f_{i(k)}$ is assumed to have a similar functional form where the function is the same for all groups but a different set of parameters. Specifically, the relationship between metafrontier f_i and the group frontier is formulated as

$$f_{i(k)}\left(x_{i(k)}, \beta_{(k)}\right) = f_i\left(x_{i(k)}, \beta^*\right) \quad e^{-U_i{}^M} \tag{2}$$

where $U_i{}^M \geq 0$, implying that $f_i(.) \geq f_{i(k)}\ (.)$.

The metafrontier in (2) was originally implemented using O'Donnell et al. (2008) linear programming approach (LP). However, Huang et al. (2014) noted two key problems associated with estimating the metafrontier as an LP function: 1) it is challenging to statistically interpret the metafrontier parameter estimates; and 2) The LP approach does not account for noise in the metafrontier thus generating biases in the estimates. Instead, Huang et al. (2014) proposed the use of stochastic production function approach in the second step estimation to overcome the set challenges. Estimating the metafrontier as stochastic frontier requires a reformulation of (2) as

$$lnf_{i(k)}\left(x_{i(k)}, \beta_{(k)}\right) = lnf_i\left(x_{i(k)}, \beta^*\right) - U_i{}^M \tag{3}$$

The group frontier is unobservable but its values can be estimated from the first step since the fitted values differ from the true frontier. Hence, (3) can be re-specified as

$$lnf_{i(k)}\left(x_i, \beta_{(k)}\right) = lnf_i(x_i, \beta^*) - U_i{}^M + V_i{}^M \tag{4}$$

where $V_i{}^M$ is the statistical noise denoting deviation between predicted and the true frontier, i.e.

$$ln\hat{f}_{i(k)}\left(x_i, \beta_{(k)}\right) = ln\hat{f}_i(x_i, \beta^*) + V_i^M \tag{5}$$

Equation (5) therefore holds resemblance with typical stochastic frontier model and therefore can be estimated as stochastic. This model, which is described as a stochastic metafrontier regression model was implemented using maximum likelihood methods. However, we extend the model into a Bayesian framework because of the flexibility of imposing regularity conditions and to ensure that consistent standard errors are obtained.

The efficiency of this actual output against the metafrontier output can be decomposed into three components: 1) the meta technology gap or technology gap (MTR), which is the ratio between the group production function to the metafrontier:

$$MTR_i^k = \frac{f_{i(k)}\left(x_i, \beta_{(k)}\right)}{f_i(x_i, \beta^*)} = e^{-U_i{}^M} \leq 1; \tag{6}$$

Therefore, the estimated MTR is computed as follows

$$M\hat{T}R_i^k = \hat{E}\left(e^{-U_i{}^M} | \hat{\varepsilon}_i^M\right) \leq 1 \tag{7}$$

where $\hat{\varepsilon}_i^M = \ ln\hat{f}^k\left(x_i, \beta_{(k)}\right) - ln\hat{f}^M(x_i, \beta^*)$

2) Technical efficiency (TE) as specified in (2) and the metatechnical efficiency (MTE_i^*), which

measures overall technical efficiency of the *i-th* observation relative to the metafrontier. In other words, the MTE compares observed output relative to metafrontier output, adjusted for corresponding random error as specified in (7):

$$MTE_i^* = \frac{Y_{i(k)}}{f_i(x_i,\beta_{(k)})e^{V_i}} = TE_i^k \; x \; MTR_i^k \tag{8}$$

2.3 Model Estimation

Although Cob Douglas functional form is the common production function often applied in empirical literature, the translog functional form is assumed for both the group and metafrontiers because of its flexibility. The Translog functional form may be specified as:

$$\ln y_i = \beta_o + \sum_{j=1}^{m} \beta_{ij} \ln X_{ij} + \frac{1}{2}\sum_{j=1}^{m}\sum_{k=1}^{n} \beta_{jk} ln\, X_{ij}\, lnX_{ik} + v_{i(k)} - u_{i(k)} \tag{9}$$

where: β is a vector of parameters to be estimated; y is output and x is a vector of inputs; $v_{i(k)}$ is the symmetric noise or error term which might be distributed as half-normal or exponential; and $u_{i(k)}$ is a non-negative inefficiency term.

2.3.1 Regional frontier estimation

The regional frontiers were estimated using Bayesian inference approach. The Bayesian inference approach is based on Bayes theorem, which specifies the posterior probability density function (PDF) as proportional to the product of the likelihood function ($L(y|\beta,\sigma)$) and the prior density function ($p(\beta,\sigma)$). Mathematically, the theorem is specified as $p(\beta,\sigma|y) \propto L(y|\beta,\sigma)\, p(\beta,\sigma)$, where; y is the observed data and $p(\beta,\sigma|y)$ is the PDF. Similar to the maximum likelihood estimation, the unknown parameters of interest in the model are vector of coefficients ($\beta's$) and standard deviations (σ) for the noise and inefficiency terms.

The Bayesian approach involves evaluating complex integrals that are analytically intractable (Coelli et al. 2005) and therefore requires simulation techniques to solve. Coelli et al. (2005) noted that the simulation techniques could either be simple Monte Carlo methods that produce independent sample observations or more sophisticated methods that result in chains of correlated observations that have properties of Markov processes (known as Markov Chain Monte Carlo (MCMC) algorithm). There are different algorithms of the MCMC methods including Gibbs sampling and Metropolis-Hastings.

In this paper, following Osiewalski and Steel (1998), the Gibbs sampling algorithm was employed. The MCMC with Gibbs sampling is a technique for obtaining a sample from a full joint distribution of a vector θ by taking random draws from conditional distributions (Osiewalski & Steel 1998; Griffin & Steel 2007). Specifically, we can partition θ into $(\theta_i', \ldots, \theta_p')$ such that sampling from each of the conditional distributions $f(\theta_i' \mid \theta_{1,}', \ldots, \theta_{i-1,}'\theta_{i+1,}', \ldots, \theta_p')$ is straightforward. The Gibbs sampler is then composed of drawing from these distributions in a cyclical manner. More details on the Gibb sampling and other sampling procedures can be obtained from Koop and Steel (2001).

The Bayesian regional frontier estimation uses 2 chains running for 100000 steps with the first 50000 used as burn in, thinning every 15th draw. The priors adopted are similar to those suggested by Griffin and Steel (2007) for the exponentially distributed error structure. For the exponential error structure, $V_{i(k)} = p(v|h) = 2\pi^{-1/2h^{\frac{1}{2}}exp\left\{-\frac{h}{2}\sum_{i=1}^{l} v_i^2\right\}}, where\ h = \frac{1}{\sigma_v^2}$, the prior distribution of the precision parameter, h, is assumed to be gamma with shape and scale set to uninformative priors as specified in Griffin and Steel (2007). The β parameters were assumed to come from a normal multivariate distribution. The estimation of the Bayesian stochastic frontier model requires an assumption of a median prior efficiency value (r-star). Following Van den Broeck et al., 1994, an r-star value of 0.9 was used in the final model estimation. The models were estimated in the R programming software using "appear" package (Hailu 2013).

2.3.2 Metafrontier estimation

Based on Huang et al. (2014) formulation, the metafrontier was constructed using predicted output from the group frontiers. The estimations were implemented in the Bayesian framework in R using 100000 steps with the first 50000 steps used as burn in. The priors adopted here are similar with those used in estimating the regional frontiers. The model was estimated in R programming software using the "appear" package.

2.4 Description of data sources

Panel data on agricultural production for 19 African countries for the period 1971-2004 were accessed from the Food and Agriculture Organization statistics (FAOSTAT). FAOSTAT data is compiled by the Statistics Division of the Food and agriculture Organization. FAOSTAT data has widely been employed in empirical literature (O'Donnell et al. 2008; Mugera and Ojade 2013) and therefore becomes a reliable data source for the problem of study. The site for the FAOSTAT data can be assessed using the URL: **www.fao.org/faostat.**

Following Alene (2010) and Nkamleu (2006), one output and five inputs are considered in the estimation of the models. Agricultural output is measured as the volume of agricultural production in millions of 1999-2001 international dollars. Geary-Khamis method was used to compute the aggregated output for the base year. The aggregated base year figures were then extended to cover the study period from 1971 to 2004. Agricultural land (X1) is measured as the sum of arable land and land under permanent crops and permanent pastures in thousand hectares. The labour input (X2) is defined as the active working population in agriculture for each year in a country. Economically active population in agriculture is defined as all persons engaged or seeking employment in agriculture, forestry, hunting or fishing sector, whether as employers, own-account workers, salaried employees, or unpaid workers (Nkamleu et al. 2006). The machinery input (X3) include total number of wheeled and crawler tractors used in agriculture excluding garden tractors. The fertilizer (X3) input is also measured as the sum of nitrogen, potassium (P_2O_2) and phosphate (K_2O) in tons. Livestock input (X5) is the number of five animals (buffaloes, cattle, pigs, sheep and goats) measured in sheep equivalent. Detailed description of the data can be found in previous studies on agricultural productivity in Africa (Nkamleu 2004; Alene 2010).

The countries are classified into five regions: Western, Eastern, Southern, Northern and Central based on the standard geographical classification (Benin 2016). The Western region consist of eight countries, including: Benin, Burkina Faso, and Côte d'Ivoire, Ghana, Mali, Niger, Nigeria and Senegal. The Eastern region countries comprise Kenya, Ethiopia, Madagascar and Zambia. The Southern region consists of South Africa, Malawi and Botswana. Central region comprises Cameroun, Burundi and Chad and finally, the Northern region comprises Egypt, Mauritania and Morocco.

3. Results and discussion

This study considered five standard geographical classification of regions in Africa: Western, Eastern, Southern, Northern and Central. The results for the selected regional frontier estimation are presented in Table 1. Also, the metafrontier parameter estimates and the performance indicators (technical efficiency, meta technology ratio and meta technical efficiency) are presented in Tables 2-5. Following are detailed discussions of the model estimation results.

3.1 Regional frontier and metafrontier estimates

Using the two-step stochastic metafrontier estimation technique, the technical efficiency of five African regions (Western, Eastern, Southern, Northern and Central) are estimated and compared. The first step, which comprises the estimation of the regional frontiers results in the regional frontier parameter estimates and the regional technical efficiencies. The results of the parameter estimates are presented in Table 1. Results for Western region (Region 1) are located in columns 2-3, while results for Eastern region (Region 2) are in columns 4-5, results for Southern region (Region 3) are presented in columns 4-6, Northern region in columns 8-9 and columns 10-11 for Central region.

Posterior density estimates at the sample mean from the Bayesian stochastic frontier model are similar but vary depending on the region. From the results, we observe that output is most responsive to fertilizer input use than to non-fertilizer input use in Region 1. For Regions 2 and 4, output is most responsive to labour input use in agricultural production (see Table 1a and Table 1b) and Region 3 is more responsive to land input use while Region 5 is more responsive to livestock input. Specifically, for Region 1, the input elasticity estimates are 0.60, -0.29, 0.04, 0.81 and -0.94 for land, labour, tractor, fertilizer and livestock inputs, respectively. The corresponding estimates for Region 2 are 0.25, 0.82, -0.02, -0.21 and 0.32 for land, labour, tractor, fertilizer and livestock inputs, respectively. Similarly, the input elasticity estimates for Region 3 are 0.82, 0.57, 0.36, -0.54 and 0.76 for land, labour, tractor, fertilizer and livestock inputs, respectively. For Regions 4 (5), the input elasticity estimates are 0.20 (-0.70), 1.09 (0.13), 0.09 (0.24), -0.04 (-0.11) and 0.66 (78).

We can infer from the input elasticity estimates that both Regions 1 and 5 experience decreasing returns to scale at the sample mean, while Regions 2-4 exhibits increasing returns to scale at the sample mean. The increasing return to scale experienced by Regions 2-4 show that for these regions, production is at a sub-optimal level and there is more room to increase production. However, for Regions 1 and 5, production is at super optimal level and to increase production, new techniques of production are required. The Gamma values indicate that 79, 67, 75, 79 and 70 percent of the variations of the observed output and the metafrontier output can be attributed to managerial inefficiencies.

Table 1a Parameter estimates of the stochastic frontier model: Exponential inefficiency distribution

	Western region				Eastern region				Southern region			
	Coef.	MCE	2.5%	97.5%	Coef.	MCE	2.5%	97.5%	Coef.	MCE	2.5%	97.5%
Constant	0.78	6.7E-04	0.62	0.94	-0.72	1.2E-03	-0.99	-0.49	0.01	2.7E-03	-0.53	0.60
lnx1	0.60	7.2E-04	0.45	0.78	0.25	8.7E-03	-1.60	2.37	0.82	2.4E-03	-0.88	1.69
lnx2	-0.29	1.7E-03	-0.66	0.14	0.82	2.4E-03	0.29	1.30	0.57	6.3E-03	-0.37	1.79
lnx3	0.04	3.2E-04	-0.03	0.11	-0.02	8.6E-04	-0.22	0.15	0.36	1.0E-03	0.11	0.57
lnx4	0.81	6.3E-04	0.66	0.97	-0.21	2.1E-03	-0.77	0.19	-0.54	4.0E-03	-1.17	0.43
lnx5	-0.94	1.0E-03	-1.18	-0.73	0.32	2.2E-03	-0.23	0.81	0.76	2.2E-03	0.28	1.20
lnx1xlnx1	-0.66	7.3E-04	-0.82	-0.49	1.67	2.5E-02	-3.73	7.43	-0.02	4.8E-03	-0.85	0.94
lnx1. lnx2	-0.80	1.2E-03	-1.07	-0.52	1.15	8.2E-03	-0.54	3.15	-0.06	4.3E-03	-0.86	0.88
ln**x1. lnx3**	-0.05	1.2E-04	-0.08	-0.02	-0.13	3.5E-03	-0.86	0.60	0.42	8.5E-04	0.25	0.62
lnx1. lnx4	0.13	2.7E-04	0.07	0.20	0.32	7.4E-03	-1.07	2.22	-0.43	3.1E-03	-0.99	0.13
lnx11. X5	0.77	7.6E-04	0.60	0.94	-1.41	7.9E-03	-3.31	0.31	0.49	2.1E-03	-0.07	0.86
lnx2x lnx2	3.72	3.5E-03	2.87	4.48	-0.76	3.5E-03	-1.66	-0.10	-0.21	5.1E-03	-0.96	0.78
lnx2. lmx3	-0.14	4.2E-04	-0.23	-0.04	0.30	1.2E-03	0.02	0.61	0.16	9.4E-04	-0.05	0.36
lnx2. lnx4	-0.25	6.4E-04	-0.40	-0.11	0.10	2.9E-03	-0.60	0.64	-0.08	3.0E-03	-0.57	0.57
lnx2. lnx5	0.17	1.4E-03	-0.13	0.48	0.59	2.9E-03	0.05	1.18	0.23	2.1E-03	-0.21	0.61
lnx3 x lnx3	0.04	1.1E-04	0.02	0.06	-0.04	6.9E-04	-0.22	0.11	0.02	6.1E-04	-0.11	0.17
lnx2. lnx4	-0.02	9.4E-05	-0.05	0.00	0.05	8.7E-04	-0.14	0.23	-0.20	7.8E-04	-0.37	-0.07
lnx3. lnx5	0.07	3.3E-04	0.00	0.15	-0.25	1.0E-03	-0.47	-0.02	0.05	1.2E-03	-0.21	0.29
lnx4 x lnx4	0.26	1.7E-04	0.22	0.30	-0.16	2.8E-03	-0.76	0.42	0.65	2.3E-03	0.19	1.02
lnx4. lnx5	-0.19	4.5E-04	-0.29	-0.08	-0.03	3.1E-03	-0.69	0.70	-0.02	1.4E-03	-0.27	0.27
lnx5 x lnx5	-0.93	1.6E-03	-1.25	-0.56	-0.32	3.6E-03	-1.07	0.39	-0.61	1.6E-03	-0.96	-0.27
t	0.03	3.2E-05	0.02	0.04	-0.01	3.8E-05	-0.02	0.00	0.01	8.5E-05	-0.01	0.03
$\mathbf{t^2}$	0.00	8.7E-07	0.00	0.00	0.00	1.0E-06	0.00	0.00	0.00	2.2E-06	0.00	0.00
Sigma2	4.E-03	6.3E-06	1.7E-03	8.8E-03	1.E-03	4.5E-07	5.3E-04	2.5E-03	2.E-03	5.5E-07	5.6E-04	3.5E-03
Gamma	0.79	4.5E-05	0.52	0.93	0.67	1.8E-04	0.38	0.90	0.75	3.8E-05	0.47	0.93

Note: X1= Land; X2=Labour; X3=machinery; X4=fertilizer; X5=livestock; MCE=MCMC error

Table 1b Parameter estimates of the stochastic frontier model: Exponential inefficiency distribution

	Northern region				Central region			
	Coef.	MCE	2.5%	97.5%	Coef.	MCE	2.5%	97.5%
Constant	0.42	1.9E-03	-0.03	0.83	-0.01	2.8E-03	-0.72	0.63
lnx1	0.20	2.5E-03	-0.31	0.87	-0.70	3.1E-03	-1.40	-0.15
lnx2	1.09	5.3E-03	-0.09	2.23	0.13	8.3E-03	-1.32	1.67
lnx3	0.09	1.0E-03	-0.20	0.26	0.24	5.7E-04	0.07	0.35
lnx4	-0.04	1.8E-03	-0.48	0.28	-0.11	7.2E-04	-0.31	0.08
lnx5	0.66	1.4E-03	0.30	0.95	0.78	1.6E-03	0.41	1.14
lnx1xlnx1	0.11	2.0E-03	-0.32	0.67	-0.47	1.3E-03	-0.79	-0.25
lnx1. lnx2	0.57	3.0E-03	-0.20	1.26	-0.50	2.1E-03	-0.89	-0.06
ln**x1. lnx3**	0.10	9.4E-04	-0.12	0.30	-0.04	3.3E-04	-0.10	0.05
lnx1. lnx4	0.00	9.1E-04	-0.21	0.22	-0.10	8.8E-04	-0.24	0.07
lnx11. X5	-0.34	1.3E-03	-0.59	-0.02	0.46	9.0E-04	0.30	0.67
lnx2x lnx2	0.38	4.9E-03	-0.51	1.28	-2.24	1.2E-02	-4.42	0.15
lnx2. lmx3	0.00	7.9E-04	-0.22	0.15	-0.28	1.2E-03	-0.55	-0.03
lnx2. lnx4	0.12	2.2E-03	-0.24	0.58	-0.15	1.3E-03	-0.42	0.13
lnx2. lnx5	0.03	2.8E-03	-0.60	0.54	1.58	2.1E-03	0.99	1.95
lnx3 x lnx3	0.01	4.6E-05	0.00	0.02	0.01	4.7E-05	0.00	0.02
lnx2. lnx4	0.03	2.1E-04	-0.03	0.06	0.08	1.3E-04	0.05	0.11
lnx3. lnx5	-0.02	6.7E-04	-0.20	0.13	0.04	4.9E-04	-0.08	0.14
lnx4 x lnx4	-0.22	7.3E-04	-0.39	-0.06	-0.03	3.0E-04	-0.10	0.03
lnx4. lnx5	0.22	1.5E-03	-0.06	0.53	0.02	5.2E-04	-0.09	0.15
lnx5 x lnx5	-0.69	2.7E-03	-1.32	-0.05	-0.80	2.1E-03	-1.31	-0.49
t	0.01	4.9E-05	0.00	0.02	0.02	4.5E-05	0.00	0.02
$\mathbf{t^2}$	0.00	1.8E-06	0.00	0.00	0.00	1.5E-06	0.00	0.00
Sigma2	1.E-03	8.5E-07	2.9E-04	3.3E-03	1.E-03	3.1E-07	4.2E-04	1.9E-03
Gamma	0.79	1.4E-04	0.47	0.96	0.70	3.4E-05	0.43	0.89

Note: X1= Land; X2=Labour; X3=machinery; X4=fertilizer; X5=livestock; MCE=MCMC error

The metafrontier parameter estimates are slightly different from the group frontier parameters (Table 2). Generally, the metafrontier output is driven highly by labour input compared to non-labour inputs, implying that a percentage change in labour input will increase the industrial output by about 73 percent.

Table 2 Metafrontier parameter estimates

	Mean	MCMC error	2.5%	97.5%
Constant	0.76	4.8E-04	0.66	0.88
lnx1	0.56	3.4E-04	0.48	0.64
lnx2	0.73	3.2E-04	0.66	0.80
lnx3	0.14	2.1E-04	0.09	0.18
lnx4	0.37	2.5E-04	0.31	0.42
lnx5	-0.45	4.2E-04	-0.54	-0.35
lnx1xlnx1	0.30	3.4E-04	0.23	0.39
lnx1. lnx2	0.44	4.8E-04	0.34	0.55
ln**x1. lnx3**	-0.07	1.6E-04	-0.11	-0.04
lnx1. lnx4	0.29	1.9E-04	0.25	0.34
lnx11. X5	-0.61	4.2E-04	-0.70	-0.51
lnx2x lnx2	0.16	5.5E-04	0.04	0.29
lnx2. lmx3	-0.11	2.1E-04	-0.16	-0.07
lnx2. lnx4	0.29	1.5E-04	0.25	0.32
lnx2. lnx5	-0.59	6.4E-04	-0.74	-0.45
lnx3 x lnx3	0.04	9.2E-05	0.03	0.07
lnx2. lnx4	-0.04	9.5E-05	-0.06	-0.02
lnx3. lnx5	0.16	2.7E-04	0.10	0.22
lnx4 x lnx4	0.17	1.5E-04	0.13	0.20
lnx4. lnx5	-0.44	2.6E-04	-0.50	-0.38
lnx5 x lnx5	1.03	7.3E-04	0.86	1.19
t	0.03	3.9E-05	0.02	0.04
$\mathbf{t^2}$	0.00	1.1E-06	0.00	0.00
Sigma2	0.88	7.6E-05	0.01	0.02
Gamma	0.01	5.5E-06	0.81	0.94

3.2 Technological changes

Technological change gives an indication of the change in productivity due to adoption of new production practices. Consistent with O'Donnell et al. (2008) suggestion of accounting for technological change in the metafrontier estimation, a time trend was introduced into the model to account for that change. The first order coefficient of the time trend variable estimates are estimates of the annual rate of technological change (Alem et al. 2010) and the squared time trend (second order) coefficient indicates the speed in which technical change operates. In all regions, with exception of Region 5, there has been an outward shift of the production frontier, suggesting that there was an increase in productivity resulting from the use of improved agricultural technologies.

3.3 Various performance indicators

The average regional technical efficiency (TE), metatechnology ratio (MTR) and the metatechnical efficiency (MTE) are presented in Tables 3-4. The results from the regional frontiers (Table 3) show that throughout the study period, (1971-2004), many of the regions in Africa were producing close to the regional frontiers. On average, Western region was producing about 88% of the regional frontier output while Eastern region was producing at 95%. Southern region, Northern region and Central regions were producing between 94%, 93% and 96% of the regional outputs, respectively.
Table 3 Performance indicators (averages for 19 Countries, 1971-2004).

Table 3 Performance indicators (averages for 19 Countries, 1971-2004)

	Technical efficiency			Metatechnology			Metatechnical efficiency		
Country	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
Western Africa									
Benin	0.90	0.75	0.98	0.62	0.32	0.87	0.56	0.30	0.83
Burkina Faso	0.92	0.80	0.97	0.73	0.50	0.92	0.67	0.48	0.86
Cote Devoir	0.90	0.72	0.97	0.89	0.64	0.96	0.80	0.60	0.92
Ghana	0.86	0.66	0.98	0.87	0.71	0.92	0.74	0.60	0.86
Mali	0.87	0.70	0.97	0.73	0.60	0.84	0.64	0.51	0.74
Niger	0.89	0.69	0.97	0.89	0.74	0.95	0.79	0.64	0.88
Nigeria	0.91	0.78	0.97	0.87	0.61	0.96	0.79	0.50	0.91
Senegal	0.83	0.52	0.97	0.85	0.75	0.93	0.70	0.41	0.90
Average	0.88	0.52	0.98	0.80	0.32	0.96	0.71	0.30	0.92
Eastern Africa									
Kenya	0.96	0.90	0.98	0.74	0.62	0.87	0.71	0.59	0.84
Ethiopia	0.96	0.92	0.98	0.65	0.28	0.88	0.62	0.27	0.84
Madagascar	0.96	0.89	0.98	0.80	0.51	0.93	0.77	0.50	0.89
Zambia	0.92	0.52	0.99	0.77	0.17	0.96	0.71	0.16	0.95
Average	0.95	0.77	0.99	0.60	0.17	0.93	0.58	0.16	0.89
Southern Africa									
South Africa	0.94	0.82	0.98	0.85	0.64	0.92	0.80	0.58	0.89
Botswana	0.95	0.91	0.98	0.76	0.36	0.95	0.73	0.35	0.90
Malawi	0.92	0.69	0.98	0.81	0.66	0.91	0.75	0.60	0.88
Average	0.94	0.69	0.98	0.81	0.36	0.95	0.76	0.35	0.90
Northern region									
Egypt	0.96	0.92	0.97	0.96	0.47	0.93	0.78	0.45	90
Mauritania	0.95	0.93	0.98	0.76	0.61	0.92	0.73	0.57	0.89
Morocco	0.89	0.70	0.99	0.73	0.55	0.85	0.65	0.50	0.83
Average	0.93	0.70	0.99	0.77	0.47	0.93	0.72	0.45	0.90
Central region									
Cameroun	0.96	0.86	0.99	0.90	0.73	0.96	0.86	0.70	0.95
Burundi	0.96	0.87	0.98	0.77	0.19	0.93	0.73	0.18	0.92
Chad	0.95	0.82	0.99	0.84	0.36	0.90	0.80	0.34	0.88
Average	0.96	0.82	0.99	0.84	0.19	0.96	0.80	0.18	0.95
All Africa	0.92	0.64	0.99	0.77	0.17	0.96	0.71	0.16	0.95

The estimated MTR values show that on average, Western region is producing 80% of the potential output given the technology available in the agricultural sector, whiles Eastern region, Southern region, Northern region and Central region are producing at 60% and 81%, 77% and 84%, respectively of the potential output in the agricultural sector. This finding confirms the study outcome of Nkamleu (2006) that although many countries are producing close to the regional frontiers, they are far below the overall industrial production frontier. Interestingly, the difference between the regional technical efficiency scores and the metafrontier performance indicators is quite huge. Specifically, the average efficiency values for Eastern region relative to the metafrontier is 60% while the mean for the regional efficiency value is 95%.

The agricultural sector in Central Africa achieved the highest mean technical efficiency relative to the metafrontier at 84% followed by Western Africa at 80%. Although Eastern region achieved one of the highest mean technical efficiency relative to the regional frontiers, the region tend to be further away from the potential output defined by the metafrontier function. The five African countries have productivity potential ratio ranging from 17% and 96% with an average of 77%. Eastern region has the lowest productivity potential ratio suggesting that even if all countries from Eastern region achieved best practice with respect to the technology observed in the regions, they are still lagging behind the Africa industrial technology gap ratio of 77%. The estimates from the metafrontier show that Central Africa is closer to the agricultural production frontier for Africa and for that matter is more productive (84%) compared with remaining regions.

We also observe from the findings that Central region is more technically efficient (80%), followed by Southern region (76%), Northern region (72%) with the least being the Eastern region (58%). However, we find that there is substantial inefficiency in agricultural sector in Africa. Specifically, the average MTE of 71% for all regions is very low, suggesting that the level of inefficiency is resulting from low technology gap ratio in African agriculture. Comparing the results of the study with previous studies, it is observed that generally, the values obtained from the study are higher than as obtained in Nkamleu (2006) and O'Donnell et al. (2008).

Specifically, it is observed that the average regional technical efficiency of 92% is higher compared with 74% obtained in Nkamleu (2006) study and 50% of O'Donnell et al's (2008) study. The results generally give an indication that the technical efficiency of the various regions in Africa have improved over the years. Also, the overall technical efficiency has improved, but the value of 71% is still relatively low compared to other values as reported in O'Donnell et al's study. The reason for the variations in the performance indicators as measured in this study compared with others could the attributed to the study period, the methodology employed and the countries examined.

Now we classify the performance indicators based on the structural adjustment period to examine whether the structural adjustment programmes implemented across the African continent had any effect on productivity. On that basis, we have three classifications: pre-structural adjustment period (1971-1980), structural adjustment period (1981-1990) and post-structural adjustment period (1991-2004). Results are reported in Table 4. Generally, we observe from the table that there were slight variations in the performance indicators during the structural and post structural adjustment period (Table 4). Specifically, there was a slight increase in the MTR values for the Western region during the structural adjustment and post structural adjustment periods. For the Eastern region, the improvement in the performance indicators during and post structural adjustment periods are not significantly different from the values recorded pre-structural adjustment period. For the Southern, Northern and Central regions, the regional frontier values were stable over the period but the MTR values increased during the structural adjustment period and declined slightly post structural adjustment period but the MTR and MTE values are greater compared to the pre structural adjustment period.

Table 4 Performance indicators for pre-structural adjustment period (1971-1980)

	Pre adjustment 1971-1980			During adjustment 1981-1990			Post adjustment 1991-2004		
Country	TE	MTR	MTE	TE	MTR	MTE	TE	MTR	MTE
Western Africa									
Benin	0.86	0.50	0.43	0.88	0.50	0.44	0.93	0.78	0.73
Burkina Faso	0.92	0.62	0.58	0.90	0.75	0.68	0.92	0.79	0.73
Cote Devoir	0.83	0.82	0.67	0.90	0.90	0.81	0.95	0.93	0.88
Ghana	0.88	0.80	0.70	0.75	0.89	0.67	0.92	0.90	0.83
Mali	0.94	0.67	0.62	0.88	0.77	0.68	0.82	0.75	0.62
Niger	0.87	0.92	0.80	0.92	0.84	0.78	0.89	0.89	0.79
Nigeria	0.91	0.80	0.72	0.89	0.86	0.76	0.93	0.93	0.87
Senegal	0.80	0.92	0.73	0.87	0.88	0.77	0.82	0.78	0.64
Average	0.88	0.75	0.66	0.87	0.80	0.69	0.90	0.84	0.76
Eastern Africa									
Kenya	0.96	0.75	0.72	0.96	0.78	0.75	0.96	0.70	0.68
Ethiopia	0.97	0.39	0.38	0.96	0.64	0.62	0.96	0.84	0.80
Madagascar	0.96	0.88	0.85	0.96	0.89	0.85	0.97	0.69	0.67
Zambia	0.92	0.26	0.24	0.91	0.21	0.19	0.93	0.20	0.19
Average	0.95	0.57	0.55	0.95	0.63	0.60	0.95	0.61	0.59
Southern Africa									
South Africa	0.94	0.77	0.72	0.94	0.89	0.83	0.93	0.88	0.82
Botswana	0.95	0.88	0.84	0.96	0.89	0.85	0.95	0.59	0.56
Malawi	0.93	0.78	0.72	0.93	0.83	0.77	0.91	0.83	0.76
Average	0.94	0.81	0.76	0.94	0.87	0.82	0.93	0.78	0.72
Northern region									
Egypt	0.96	0.91	0.87	0.95	0.87	0.83	0.96	0.70	0.67
Mauritania	0.95	0.76	0.72	0.96	0.85	0.81	0.95	0.70	0.67
Morocco	0.92	0.99	0.62	0.89	0.72	0.64	0.88	0.77	0.68
Average	0.94	0.78	0.74	0.93	0.81	0.76	0.93	0.73	0.68
Central region									
Cameroun	0.96	0.95	0.91	0.95	0.72	0.88	0.96	0.85	0.81
Burundi	0.96	0.50	0.48	0.96	0.88	0.88	0.96	0.85	0.81
Chad	0.95	0.80	0.77	0.95	0.93	0.81	0.95	0.86	0.82
Average	0.96	0.75	0.72	0.95	0.90	0.86	0.96	0.85	0.82

3.4 Drivers of technical efficiency

In examining drivers of technical efficiency, two approaches are commonly adopted in the production economics literature. The first is the two stage approach where the drivers are regressed on the technical efficiency scores obtained from the first stage estimation. The second approach relates to estimating the technical efficiency drivers as part of the production frontier estimation in a single stage. Although the single stage estimation is recommended in the literature, this study adopts the two stage estimation technique because of missing data for some countries in the sample. Specifically, the bootstrap truncated regression method was adopted to regress expenditure on R & D, literacy and trade on the regional technical efficiency scores. Research and development is of particular interest because it is important in boosting agricultural productivity (Alston 1995; Alene 2010). Literacy which is used as a proxy for education accounts for labour quality differences. It is often assumed that more educated farmers have better access to information in the production process and therefore are more productive. Trade also serves as a standard measure of openness of an economy giving an indication of a possibility of new technology adoption. The estimated results are reported in Table 5.

Table 5 Drivers of technical efficiency

	Technical efficiency	
	Mean	SE
Constant	0.804**	0.587
Expenditure on agricultural R & D	0.001**	0.001
Literacy	0.002**	0.001
Trade	0.004**	0.016

The sign of the estimated coefficients gives the relationship between technical efficiency and expenditure on R & D, literacy and trade. A positive estimated coefficient gives an indication of efficiency improvement while a negative sign is an indication of efficiency reducing effect. On that basis, it is observed that the estimated coefficient on expenditure on R & D is positive, giving an indication of efficiency increasing effect. That is, higher investment in agricultural research and development improves regional technical efficiency. The coefficients on literacy and trade are also positive and significant confirming the general hypothesis that education (literacy) and trade openness are important drivers of technical efficiency. The findings are consistent with that of Alene (2010) study on productivity growth and the effects of expenditure on R & D on African agriculture.

4. Conclusion

Productivity improvement in African agriculture is perceived as an important driver for poverty reduction. However, the agricultural sector in many African countries is characterised by low levels of productivity. Over the years, a number of strategies have been adopted including development and introduction of new technologies to boost productivity in African agriculture. Besides the introduction of new technologies to improve productivity, managerial capabilities of farmers could also serve as a measure of increasing productivity. The challenge for many policy makers has been about whether to pursue technology introduction or improvement in managerial capacities. In instances where farmers are efficient, then the policy should be directed towards introducing new technologies. However, if farmers are inefficient, then their managerial capacities have to be improved. The purpose of this paper therefore was to identify the sources of inefficiency in African agriculture by decomposing efficiency into technical efficiency and technology gap using a stochastic metafrontier model.

Altogether, 19 African countries were selected and classified into five regions based on standard geographical classification: Western region, Eastern region, Southern region, Northern region and Central region. Using a panel dataset for the period 1971-2004, the results show that many countries are producing close to the regional frontier and therefore are technically efficient. However, many of the countries are producing far below the regional meta technology, particularly, Zambia in Eastern Africa. Generally, considering the entire industry frontier, we observed substantial levels of inefficiency (about 29%) in African agriculture. Since the overall efficiency was computed using the regional frontier values and the metatechnology, the level of inefficiency is arising from the technology gaps and not technical efficiency. The results show that African countries are lagging behind technology wise. It is therefore important to close the technology gap by developing and introduction useful technologies that are country specific across the continent.

Considering the drivers of efficiency, the results revealed that expenditure on research and development, education and trade among nations have efficiency increasing effects. Therefore, it is important to invest in research and development as well as improving trade among African countries to ensure generation of improved technologies and technology transfer among countries. Such a measure would decrease the technology gaps and improve overall efficiency in African agriculture.

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