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Productivity Growth of ECOWAS Common Crops: A Tale of Two Competing Frontier Methods of Analysis

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Abstract

This study examines productivity growth of 3 ECOWAS crops, namely, rice, cotton and millet, using both Stochastic Frontier Analysis (SFA) and Data Envelopment analysis (DEA). The data cover a 45 year period (1961-2005). Calculations are based on data collected from FAOSTAT database, International Rice research Institute (IRRI) world rice statistics, and international cotton advisory committee database. The results for both SFA and DEA show that (1) there are inefficiencies but productivity progress among ECOWAS member nations producing rice, cotton and millet. (2) Though, magnitudes of the inefficiencies and productivity progress vary across models applied and by segmentation of the data set, there is little or no conflict in the overall results. (3) Technical change has had the greatest impact on productivity, indicating that producers have a tendency to catch-up with the front runners.

Keywords: *Stochastic Frontier Analysis, Data Envelopment Analysis, Crops, ECOWAS*.JEL codes: C13, C24, O33, O47,

Introduction

This paper examines two types of methodologies for measuring agricultural productivity growth and its components, namely, efficiency change and technological progress. The methods are Data Envelopment Approach (DEA), a non-parametric approach and Stochastic Frontier Approach, a parametric approach. Generally, the parametric stochastic frontier analysis (SFA) method or the equivalent nonparametric data envelopment analysis (DEA) method has been used to measure technical efficiency scores and productivity growth by several researchers. Each method is fraught with some inherent limitations. Coelli (2005) highlights three major drawbacks of DEA method. First, DEA assumes that datasets are free of noise and error. It is based on the assumption of an exact relationship between inputs and outputs. Second, DEA does not permit hypothesis testing of the significance of the variables in the model. Third, analysis based on the assumption of constant return to scale implies that the underlying technology is the same across all countries and regions. With respects to the directional Malmquist Index, Nin et al. (2003) points out further 2 limitations. First, there might be cases where the distance function takes on the value of -1, in which case, the Malquist Index is not well defined. Second, it is possible to encounter a reallocation factor bias in the measure, where there is movement of unallocated inputs from one activity to the other rather than technical growth.

The parametric approach, in contrast to DEA, specifies a particular functional form as well as assumptions about the error term. The primary advantage of the parametric approach is that it allows a firm to be off the frontier because of random noise or inefficiency while the main criticism is that the distributional assumptions on the error term are too restrictive and can lead to specification error since economic theory rarely justifies a particular functional form. Using only one of these methods to improve efficiency may cause incorrect measurement of output or input since each of these approaches has some inherent limitations. Before any correctional improvements are taken, the stability of the technical efficiency estimates from a parametric (or nonparametric) method should be evaluated by comparing them against those found using the nonparametric (or parametric) method. A brief summary of such type of studies in recent time is shown in Table 1. The Table shows that such empirical evidence of methods comparison is scarce in African agricultural sector analysis. In addition, the table shows that signs and magnitudes of the Total Factor Productivity (TFP) vary depending on the methodology used. The objective of this study therefore is to compare the productivity growth between the SFA and DEA methods for ECOWAS selected common staple crops, namely, rice, cotton and millet.

The paper proceeds thus: section 2 presents the methodology, section 3 discusses the main results and section 4 concludes.

Materials and Methods

According to Coelli (2003), the Malmquist TFP index measures the TFP change between two data points (e.g., those of a particular country in two adjacent time periods) by calculating the ratio of the distances of each data point relative to a common technology The productivity change using technology of period t as reference is as follows:

$$M_o^t(x_t, y_t, x_{t+1}, y_{t+1}) = \left[\frac{d_o^t(x_{t+1}, y_{t+1})}{d_o^t(x_t, y_t)}\right] \quad (1)$$

Similarly, we can measure Malmquist productivity index with period t+1 as references as follows:

$$M_o^{t+1}(x_t, y_t, x_{t+1}, y_{t+1}) = \left[\frac{d_o^{t+1}(x_{t+1}, y_{t+1})}{d_o^{t+1}(x_t, y_t)}\right] \quad (2)$$

In order to avoid choosing arbitrary period as reference, Fare et al (1994) specifies the Malmquist productivity index as the geometric mean of the above two indices under CRS

$$M_o(x_t, y_t, x_{t+1}, y_{t+1}) = \left[\frac{d_o^t(x_{t+1}, y_{t+1})}{d_o^t(x_t, y_t)} * \frac{d_o^{t+1}(x_{t+1}, y_{t+1})}{d_o^{t+1}(x_t, y_t)}\right]^{1/2} \quad (3)$$

Equation 3 can be decomposed into the following two components, namely efficiency change index, which measures the output-oriented shift in technology between two periods. When it is greater or less than one, there exist some improvements or deterioration in the relative efficiency of this unit. The second component is the geometric average of the efficiency component and technical change between period t+1 and t. The first component in TECHCH measures the position of unit t+1 with respect to the technologies in both periods. The second component also estimates this for unit t. If the TECHCH is greater (or less) than one, then technological progress (or regress) exists.

$$EFFCH = \frac{d_o^{t+1}(x_{t+1}, y_{t+1})}{d_o^t(x_t, y_t)} \quad (4)$$

and

$$TECHCH = \left[\frac{d_0^t(x_{t+1},, y_{t+1})}{d_o^{t+1}(x_{t+1}, y_{t+1})} \, X \, \frac{d_o^t(x_t, y_t)}{d_o^{t+1}(x_t, y_t)} \right]^{1/2} \quad (5)$$

TFP = EFFCH X TECHCH (6)

In order to take cognizance of the return to scale properties of the technology, Grifell and Lovell (1995) use a one input, one output example to illustrate that Malmquist index may not correctly measure TFP changes when Variable Return to Scale (VRS) is assumed for the technology. Therefore, Constant Return to Scale is imposed upon the technology used to estimate the distance functions for the calculation of the Malmquist index for this study.

The envelopment of decision making units (DMU) were estimated through LP methods to identify the best practice for each DMU.

The stochastic production function for panel data can be written as:

$$\ln(y_{it} = f(x_{it}, t, \alpha, v_{it} - u_{it}) \quad (7)$$

i = 1,2, …………..N and t = 1,2,………………….T (Battese and Coelli, 1992)

Where y_{it} , is the production of the ith firm in year t, α is the vector of parameters to be estimated. The v_{it} are the error component and are assumed to follow a normal distribution $N(0, \sigma_{it}^2)$, u_{it} are non negative random variables associated with technical inefficiency in production, which are assumed to arise from a normal distribution with mean μ and variance σ_{μ}^2, which is truncated at zero. $f(.)$ is a suitable functional form (e.g. translog), t is a time trend representing the technical change.

The technical effects measures are computed as

$$TE_{it} = E(\exp)(-u_{it}) / v_{it} - u_{it}) \quad (8)$$

This can be used to compute the efficiency change component by observing that

$TE_{it} = d_o^t(x_{it}, y_{it})$ and $\boldsymbol{E}_{i,t+1} = d_o^{i,t+1}(x_{i,t+1}, y_{i,t+1})$. The efficiency

change (EC) is $EC = TE_{it} / TE_{i,t+1}$ (9)

An index of technological change between the two adjacent periods t and $t+1$ for the ith region can be directly calculated from the estimated parameters of the stochastic production frontier. This is done by simply evaluating the partial derivatives of the production function with respect to time at x_{it} and $x_{i,t+1}$. If technical change is non-neutral, the technical change may vary for the different input vectors. Following Coelli, Rao and Batesse (1998), the technical change (TC) index is

$$TC_{it} = \left\{ \left[1 + \frac{\delta f(x_{it}, t+1, \alpha)}{\delta t + 1} \right] X \left[1 + \frac{\delta f(x_{it}, t, \alpha}{\delta t} \right] \right\}^{1/2} \qquad (10)$$

The TFP index can be obtained by simply multiplying the technical change and the technological change, i.e.:

$$TFP_{it} = EC_{it} * TC_{it} \qquad (11)$$

In estimating both DEA and SFA models, this study utilized data on output and inputs of rice, cotton and millet from major producers of the crops to construct their indices of TFP using the two methods described by equations 1-11. In estimating the SFA model for each crop, several functional forms were fitted, beginning with Cobb-Douglas technology. The underlying stochastic production frontier function upon which the results and discussion of this study are based is approximated by the generalized Cobb-Douglas form (Fan, 1991). The function may also be viewed as a translog specification without cross terms, i.e. a strongly separable-inputs translog production frontier function. For rice, the specification is:

$$\begin{aligned} \ln y_{it} &= \alpha_0 + \alpha_h \ln H_{it} + \alpha_s \ln S_{it} + \alpha_f \ln F_{it} + \alpha_l \ln L_{it} + \ln K_{it} + \ln I_{it} + \alpha_t t + \alpha_{tt} t^2 \\ &+ \alpha_{ht}(\ln H_{it})t + \alpha_{st}(\ln S_{it})t + \alpha_{ft}(\ln F_{it})t + \alpha_{lt}(\ln L_{it})t + \alpha_{kt}(\ln K_{it})t + \alpha_{It}(\ln I_{it})t + v_{it} - u_{it} \end{aligned} \qquad (12)$$

For cotton, the specification is:

$$\ln y_{it} = \alpha_0 + \alpha_h \ln H_{it} + \alpha_s \ln S_{it} + \alpha_l \ln L_{it} + \ln K_{it} + \alpha_t t + \alpha_{tt} t^2 + \alpha_{ht} (\ln H_{it}) t + \alpha_{st} (\ln S_{it}) t + \alpha_{lt} (\ln L_{it}) t + \alpha_{kt} (\ln K_{it}) t + v_{it} - u_{it} \tag{13}$$

For millet, the specification is also without irrigation, but fertilizer is an essential input for millet production, i.e.:

$$\ln y_{it} = \alpha_0 + \alpha_h \ln H_{it} + \alpha_s \ln S_{it} + \alpha_f \ln F_{it} + \alpha_l \ln L_{it} + \alpha_k \ln K_{it} + \alpha_t t + \alpha_{tt} t^2 + \alpha_{ht} (\ln H_{it}) t + \alpha_{st} (\ln S_{it}) t + \alpha_{ft} (\ln F_{it}) t + \alpha_{lt} (\ln L_{it}) t + \alpha_{kt} (\ln K_{it}) t + v_{it} - u_{it} \tag{14}$$

The symbols are defined as follows: y_{it} is the output of crop i in the tth year; H_{it} is the hectares of land cultivated to each crop; S_{it} is the quantity of seed planted in '000 tonnes; F_{it} is the quantity of fertilizer used in '000 tonnes;L_{it} is the amount of labour used in man-days;K_{it} is the amount of capital used; I_{it} is the proportion of each crop land area under irrigation;

In is the natural log; $\alpha_i s$ are unknown parameters to be estimated; $V_{it}S$ are $iidN(0, \sigma_{v^2})$ random errors and are assumed to be independently distributed of the $U_{it}S$ which are non-negative random variables associated with TE inefficiency.

The distribution of the $U_{it}S$ are obtained by truncation at zero. The mean is defined as:

$$u_{it} = \beta_0 + \beta_1 \frac{K_{it}}{L_{it}} + \beta_{dj} \sum_{j=1}^{n} D_{tj} \tag{15}$$

for cotton and millet.

where, $\frac{K_{it}}{L_{it}}$ is capital-labour ratio for crop i in the tth year; D_j is the dummy variable, which takes the value of 1 for the jth state producing the selected crops. βs are unknown parameters to be estimated.

For rice, rice import in tonnes is included to account for its influence on the inefficiency 0f rice producers in the region. The specification, therefore, is:

$$u_{it} = \beta_0 + \beta_1 \frac{K_{it}}{L_{it}} + \beta_2 M_{it} + \beta_{dj} \sum_{j=1}^{n} D_{tj} \tag{16}$$

where M indicates import of rice milled measured in tonnes.

In order to account for factors influencing the technical efficiency using DEA, the modification of the model by Ray (1991) and McCarty and Yaisawarng (1993) was used. In the modification, a two-stage approach is used to include the inefficiency factors. In the first stage, only the discretionary inputs are used in the DEA model. In the second stage, the efficiency index (E) obtained from the first stage is regressed upon the exogenous factors to disentangle inefficiency from production. The appropriate methodology for the regression is the Tobit model, since efficiency index (E), which is the dependent variable, lies between 0 and 1. The residual variance derived from the Tobit model captures the inefficiency unexplained by the production factors. This procedure has previously been documented and applied, among others, by Ruggiero and Vitaliano (1999). The regressor variables used in the Tobit model are the same as those that were used to explain technical efficiency in the SFA case for each crop.

Data for inputs and outputs are collected principally from FAOSTAT 2007. This is supplemented with International Rice Research Institute's (IRRI) world rice statistics, and International Cotton Advisory Committee's (ICAC) cotton statistics. The data covered a period of 45 years from 1961 to 2005. Rice data are from six countries producing more than 80% of rice paddy in ECOWAS. They are Côte d'Ivoire, Ghana, Guinea, Mali, Nigeria and Senegal. Similarly, cotton data come from Benin, Burkina Faso, Côte d'Ivoire, Mali, Nigeria and Togo, while millet data are obtained from Burkina Faso, Mali, Niger, Nigeria and Senegal. The selected countries accounted for more than 90% production of cotton and millet in ECOWAS. The Malmquist indices are calculated separately for each crop because of differences in the producing countries. The data set for each crop contains six inputs, namely: land area, seed, fertilizer, labour, tractor, irrigation and country dummies.

Results and Discussion

Malmquist productivity indices and their efficiency change and technical change components were computed for each country in the sample. The summary descriptions of annual changes over the entire period, pre-ECOWAS and ECOWAS era are shown in Tables 9, 10 and 11. The two methods agree that over the entire analysis period, there has been a productivity improvement in the ECOWAS rice production sector. The mean technical change components for the two approaches indicate technological progress of about 9.5% and 4.5%, respectively. The technical change and efficiency change components for the SFA approach are, however, higher in magnitude than those of the DEA approach. A breakdown of the results by different rice producing countries indicates productivity growth in all the major rice producing countries, on the average, irrespective of the method of analysis used. The means across the nations, however, indicate that the highest growth is recorded by Guinea for SFA model, but Senegal for the DEA model. Two things could be responsible for this phenomenon. First, is the impressive performance of West Africa Rice Development Association (WARDA) and International Institute for Tropical Agriculture (IITA), which led to adoption of over 20 improved varieties of rice in West Africa, including NERICA. The second is the ECOWAS liberalization schemes, which tend to boost farmers' income through increase in prices of agricultural export commodities. Quite similar conclusion was reached by Kwon and Lee (2004) when considering the TFP of Korean rice using both DEA and SFA methods. The finding is, however, contrary to Odeck (2007) who discovered that the DEA's efficiency scores and TFPs tend to be higher than SFA in Norwegian grain farming.

The Malmquist indices for cotton producing countries in ECOWAS indicate an average productivity progress of about 0.7% and 6.3% as measured by SFA and DEA, respectively. In similarity with the results for rice, the two methods agree that over the entire analysis period, there has been productivity improvement in the ECOWAS cotton production sector. However, in contrast to the results for rice, the Malmquist indices computed with DEA method are greater than SFA's. A breakdown of the results by reform era shows significant improvement of reform period over that of the pre-reform era. This might be due to the success of the cotton support system in the major cotton producing nations in the region. Another factor could be the increased adoption of Bt cotton variety (a product of biotechnology) introduced to the region in early 2000s, which greatly limits the incidence of pests and disease, and hence reduced application of pesticides. The results corroborate the findings of Charkraborty, Mistra and Johnson (2002). The adoption of Bt cotton in West Africa as shown by Elbehri and MacDonald (2003) appear to be creating an improvement in its productivity, as the productivity growth from 1979 is a tremendous improvement compared to the situation in the pre-ECOWAS.

Contrary to the results for rice and cotton, the overall total factor productivity for millet decreases at an annual rate of 0.2% for the DEA model but increases by almost the same proportion (0.2%) in case of the SFA model. However, in both models, the total factor productivity change in millet is driven mainly by technical change, such as the case of cotton and rice. Another interesting feature of the millet results is that a higher technical change is observed with SFA approach when compared with DEA as is the case with rice. In spite of differences in total factor productivity components, the country by country comparison for both SFA and DEA models indicates that Senegal and Nigeria performed better overall than other producing countries. The breakdown by reform era indicates that there was an upsurge in productivity growth in pre-ECOWAS period across all the major rice producing countries in the region. Coincidentally, Senegal has the most impressive result, with total factor productivity growth rate of about 0.7% and 7.5% for SFA and DEA models, respectively.

Conclusions and Policy Recommendations

The productivity measures are decomposed into two sources of growth, namely efficiency change and technical change. The results for both SFA and DEA methods show evidence of phenomenal growth in total factor productivity for rice and cotton. Millet, however, has mixed results. The total factor productivity decreases at an annual rate of 0.2% for the DEA model but increases by almost the same proportion (0.2%) for the SFA model. The following inferences can be drawn from the comparative analysis of DEA and SFA efficiency and productivity models examined. First, the DEA results tend to fluctuate more widely than SFA. This might be a direct consequence of the assumption on the stochastic component, something which may be intensified for agricultural data. Second, examining the components relating to the shift in the frontier (TC) and efficiency change (EC), technical change turned out to be a more important source of growth in both SFA and DEA models. A promising finding thereupon is that the two approaches applied are, on average, in conformity to each other although the magnitudes are different. In this respect, they somehow conform to previous findings in the literature, e.g. Wadud and White (2000). In terms of productivity measurement, even though both approaches track total productivity similarly, they do not map each well at the decomposition level. The deviations between DEA and SFA could have been anticipated because the SFA incorporates stochastic factor while DEA does not. A limitation of the study is that the data tend to fluctuate considerably. This means that the productivity measures are based on low productivity year. Also, a six country panel data is relatively short to draw convincing results on variation in productivity among the producing country. It is unlikely that the differences in productivity among the countries can be sustained; rather it is confined to the specific data period and countries. Despite the caution in interpreting the results, the following policy recommendations are suggested from the findings:

1. A major cause of inefficiency for countries producing the selected crops is capital-labour ratio. It is advisable for the region to invest more in labour-saving technologies to enhance the efficiency of the member nations producing cotton. More farmers are, however, required in the region to ensure the producing countries' efficiency in rice and millet production.

2. Given differences in the contribution of efficiency change and technological progress to the TFP of the selected crops, ECOWAS agricultural policy (ECOWAP) should marry policy with specific crop need within the framework of their programmes for member nations.

3. The differences between the techniques applied here suggests that policy makers as well as researchers should not be indifferent as to the choice of technique for assessing efficiency and productivity, at least with respect to the magnitudes of potential for efficiency improvements and productivity growth.

4. Finally, studies are yet to fully detect why and how the different approaches are so different with respect to the decomposed productivity measures. Hence, necessary caution should be observed in interpretation of either SFA or DEA until such time that the field of efficiency and productivity measurement understand how and why these approaches portray efficiency and productivity the way they do. A common practice is that average results from the methods are taken in situation where interpretation becomes difficult because of too wide margin between the methodologies.

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Table 1: Empirical Literatures

Author	Year	Country	commodity	Period	Results
Deliktas E.	2002	Soviet Union	GDP	1991 - 2000	SFA = DEA
Lavado, R.	2004	Philippine	Electric companies	1990 - 2002	SFA < DEA
Lee J. Y.	2005	Global	Forest products	2002	SFA > DEA
Moreno J. J.	2005	Spain	Retail industry	1996 - 2002	SFA > DEA
Lin, L. C. and L. A. Tseng	2005	Global	Container ports	1999 - 2002	SFA > DEA
Li, Y.	2009	OECD coun-tries	Mobile telecom	1995 - 2007	SFA < SFA
Hefferman, S. and X. Fu	2009	India and China	Banks	2000 - 2007	SFA < DEA
Zhao et. al	2009	India	Bank	1992 - 2004	SFA < DEA
Ghorbani et al	2010	Iran	cattle	2007-2008	SFA < DEA
Kasman, A. and E. Turgutlu	2007	Turkey	Life insur-ance	1999-2005	SFA < DEA
Florentino et.al.,	2006	Germany	Bank	1993-2004	SFA > DEA
Constantino et.al	2009	Brazil	grain crops	2001-2006	SFA > DEA
Sipilainen et.al	2008	Nordic coun-tries	Milk	2003	SFA < DEA
Headey et. al	2010	Global	agriculture	1970-2001	SFA > DEA
Jain et.al	2010	India	Electricity	2002-2007	SFA < DEA
Ajibefun	2008	Nigeria	Food crop	2005	SFA > DEA
Huang, T. H and M. H. Wang	2002	China	Bank	1982-97	SFA > DEA

Table 9: Average annual changes for the selected producing countries by SFA and DEA: 1961-2005

	Efficiency change		Technical change		Malmquist index	
Country	SFA	DEA	SFA	DEA	SFA	DEA
			RICE			
Côte d'Ivoire	1.025	0.998	1.097	0.846	1.125	0.844
Ghana	1.019	0.998	1.095	0.892	1.116	0.891
Guinea	1.179	0.996	1.087	0.941	1.281	0.938
Mali	1.026	0.999	1.107	1.162	1.136	1.161
Nigeria	1.038	0.997	1.084	1.199	1.125	1.195
Senegal	1.027	1.000	1.097	1.230	1.127	1.230
Mean	1.052	0.998	1.095	1.045	1.152	1.043
			COTTON			
Benin	0.979	1.011	1.009	0.887	0.988	0.896
Burkina Faso	1.001	0.999	1.009	0.938	1.010	0.937
Côte d'Ivoire	1.000	1.000	1.011	0.965	1.011	0.965
Mali	0.996	1.000	1.011	1.118	1.010	1.118
Nigeria	0.998	1.000	1.001	1.207	1.000	1.207
Togo	1.008	1.000	1.015	1.225	1.023	1.254
Mean	0.997	1.002	1.095	1.057	1.007	1.063
			MILLET			
Burkina Faso	1.002	1.000	1.124	0.909	1.002	0.909
Mali	1.002	0.993	1.119	0.959	1.002	0.952
Niger	1.002	1.002	1.126	0.968	1.001	0.970
Nigeria	1.000	0.990	1.144	1.026	1.000	1.015
Senegal	1.002	1.004	1.122	1.071	1.007	1.075
Mean	1.002	0.998	1.127	0.987	1.002	0.984