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

J. O. Ajetomobi[1], I. A. Adedeji[2]

[1]*Department of Agricultural Economics, Ladoke Akintola University of Technology, Ogbomoso, Nigeria (ijibby77mail.com)*
[2]*Department of Agricultural Economics and Extension, Landmark University, Omu-Aran, Kwara State, Nigeria.*

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 results show that the magnitude of productivity progress vary across models applied and by segmentation of the data set. Nevertheless, the overall results indicate that technical change has had the greatest impact on productivity and producers have tendencies to catch-up with front runners. A closer look at the total factor productivity differences in ECOWAS and pre-ECOWAS sub-period shows larger total factor productivity in ECOWAS period (1979-2005) than in pre-ECOWAS period for cotton and millet for SFA model. In terms of policy reform's effects, productivity growth in ECOWAS and pre-ECOWAS sub-period differ across crops depending on model applied.

Key words: DEA, ECOWAS, Productivity growth, SFA.

INTRODUCTION

An important issue for empirical analysis in Agricultural production economics has been the ability of an economy or a firm to transform agricultural inputs into output(s). The central focus is usually a measure of output differences that is not explained by inputs chosen, otherwise termed Total Factor Productivity (TFP). Explicitly, such technical relationship between output and inputs is:

$$Y_{it} = A_{it}F(X_{it})$$

Where Y is the output (firm/industry/country) i at time t, X is the vector of inputs, A refers to how much output a given unit is able to produce from a certain amount of inputs, given the technological level and F(.) is the state of technology common to all i's. Therefore

$$TFP_{it} = A_{it} = \frac{Y_{it}}{F(X_{it})}$$

As simple as this idea can be, it has not been an easy task for researchers to handle the measurement. This paper examines two of measurement approaches that seem to dominate recent literatures. 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 (Espoti, 2011), (Wei and Hao, 2011), (Linh, 2009). Two advantages of the methods over simple productivity methods are their ability to (i) include multiple outputs and inputs in the estimation of productivity growth and (ii) decompose productivity growth to efficiency and technical changes. Each method is however, fraught with some inherent limitations. First, DEA assumes that datasets are free of noise and error. 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 (Coelli, et al., 2005).

The parametric approach, in contrast to DEA, specifies a particular functional form as well as assumptions about the error term, however, the distributional assumptions on the error term are too restrictive and can lead to specification error. Using only one of these methods to improve efficiency therefore, may cause incorrect measurement of increased output or reduced input. Before any correctional improvements are taken, the stability of the technical efficiency estimates from a parametric (or nonparametric) method has been 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 (Deliktas and Baleila, 2002) – (Huang and Wang, 2002). The Table shows that such empirical evidence of methods comparison in African agricultural sector analysis is scarce. In addition, the table shows that signs and magnitudes of TFP vary with methodology used. The objective of this study therefore is to compare the efficiency scores and productivity growth between the SFA and DEA methods for ECOWAS selected common staple crops, namely, rice, cotton and millet.

MATERIAL AND METHODS

In explaining productivity growth in this study, total factor productivity is defined using output distance function which defines the Malmquist index (Coelli, et al., 2005). The output orientation is selected because most agricultural activities in developing countries attempt to maximize output from a given set of inputs rather than the converse. Symbolically, assuming that for each time period t= 1, 2, …, T, production technology S_t models the transformation of inputs $x_t \in R_+^N$ into product $y_t \in R_+^M$ x_t and y_t denote a 1 × N input vector and a 1 × M output vector for period t respectively. (t=1, 2,…, T). The set of production possibilities is given by the closed set,

$$S_t = \{(x_t, y_t) : x_t \text{ can produce } y_t\} \tag{1}$$

where technology is assumed to have the standard properties such as convexity and strong disposability, as described by (Fare, et al., 1994). The output sets are defined in terms of S_t as:

$$P_t(x_t) = \{y_t : (x_t, y_t) \in S_t\} \tag{2}$$

Table 1. Empirical Literatures

Author	Year	Country	commodity	Period	Results
Deliktas	2002	Soviet Union	GDP	1991 - 2000	SFA = DEA
Lavado	2004	Phillipine	Electric companies	1990 - 2002	SFA < DEA
Lee	2005	Global	Forest products	2002	SFA > DEA
Moreno	2005	Spain	Retail industry	1996 - 2002	SFA > DEA
Lin and Tseng	2005	Global	Container ports	1999 - 2002	SFA > DEA
Li	2009	OECD countries	Mobile telecom	1995 - 2007	SFA < SFA
Hefferman, and 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 and Turgutlu	2007	Turkey	Life insurance	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 countries	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 and Wang	2002	China	Bank	1982-97	SFA > DEA

According to Shephard (1970), the output distance function in t for any productivity unit would be:

$$d_o^t(x_t, y_t) = \inf\{\theta : (\mathrm{y_t}/\theta) \in P_t(x_t)\} \qquad (3)$$

where subscript "o" stands for "output oriented". The distance function was the Farrell's reciprocal measurement (Farrell, 1957). This distance function represents the smallest factor, θ by which an output vector $\mathrm{y_t}$ is deflated so that it can be produced with a given input vector x_t under period t's technology. That is to say $d_o^t(x_t, y_t)$ provides a standardized average of distance of a unit in the period t to frontier t of production set when inputs are constant. It will take the value of less than 1 if the output vector y is an element of the feasible production set. It will take the value of 1 if y is located on the outer boundary of the feasible set and value of greater than 1 if y is located outside the feasible production set.

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 (Coelli and Rao, 2003). The productivity change using technology of period t as reference is as follows:

$$M_o^t(x_t, y_t, x_{t+1}, y_{t+1}) = \left[\frac{d_o^t(x_{t+1}, y_{t+1})}{d_o^t(x_t, y_t)}\right] \quad (4)$$

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

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

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

$$M_o(x_t, y_t, x_{t+1}, y_{t+1}) = \left[\frac{d_o^t(x_{t+1}, y_{t+1})}{d_o^t(x_t, y_t)} * \frac{d_o^{t+1}(x_{t+1}, y_{t+1})}{d_o^{t+1}(x_t, y_t)}\right]^{1/2} \quad (6)$$

An equivalent way of writing this productivity index is

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

Equation 6 can be decomposed into the following two components, namely efficiency change index, which measures the changes in technical efficiency 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 technical change which measures changes in the underlying production technology between two periods. Symbolically,

$$\text{Efficiency change} = \frac{d_o^{t+1}(x_{t+1}, y_{t+1})}{d_o^t(x_t, y_t)} \quad (7)$$

$$\text{Technical change} = \left[\frac{d_0^t(x_{t+1},, y_{t+1})}{d_o^{t+1}(x_{t+1}, y_{t+1})} X \frac{d_o^t(x_t, y_t)}{d_o^{t+1}(x_t, y_t)}\right]^{1/2} \quad (8)$$

In order to take cognizance of the return to scale properties of the technology, (Grifell-Tatje´ 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. Given constant return to scale, the envelopment of decision making units (DMU) is estimated through linear programming methods (Deliktas and Baleila, 2002). The distance measures required for the

Malmquist TFP index calculations can also be measured relative to a parametric technology using stochastic production function. The stochastic production function for panel data can be written as:

$$\ln(y_{it} = f(x_{it}, t, \alpha, v_{it} - u_{it}) \tag{9}$$

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. In this parametric case, μ_{it} s are the technical inefficiency effects defined by

$$\mu_{it} = \{Exp[-\eta(t-T)]\}\mu_{it} \tag{10}$$

i = 1, 2… N and t = 1, 2… T and η is a scalar parameter which accounts for time-varying effects. The technical efficiency (TE) measures are computed as

$$TE_{it} = E(\exp)(-u_{it}) / v_{it} - u_{it}) \tag{11}$$

This can be used to compute the efficiency change component by observing that $TE_{it} = d_o^t(x_{it}, y_{it})$ and $TE_{i,t+1} = d_o^{i,t+1}(x_{i,t+1}, y_{i,t+1})$. The efficiency change is

$$EC = TE_{it} / TE_{i,t+1} \tag{12}$$

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, et al., (1998), the technical change (*TC*) index is

$$TC_{it} = \left\{\left[1 + \frac{\delta f(x_{it}, t+1, \alpha)}{\delta t+1}\right] X \left[1 + \frac{\delta f(x_{it}, t, \alpha}{\delta t}\right]\right\}^{1/2} \tag{13}$$

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

$$TFP_{it} = EC_{it} * TC_{it} \tag{14}$$

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 1-14. 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:

$$\begin{aligned}\ln y_{it} &= \alpha_0 + \alpha_h \ln H_{it} + \alpha_s \ln S_{it} + \alpha_f \ln F_{it} + \alpha_l \ln L_{it} \\ &+ \ln K_{it} + \ln I_{it} + \alpha_t t + 0.5\alpha_{tt} t^2 + \alpha_{ht}(\ln H_{it})t \\ &+ \alpha_{st}(\ln S_{it})t + \alpha_{ft}(\ln F_{it})t + \alpha_{lt}(\ln L_{it})t \\ &+ \alpha_{kt}(\ln K_{it})t + \alpha_{it}(\ln I_{it})t + v_{it} - u_{it}\end{aligned} \tag{15}$$

For cotton, fertilizer and irrigation are eventually omitted from the model because they remain insignificant, and empirical evidence alludes to their less importance in cotton production in the study area. The time trend variable was still included in the regression runs to account for general long-term time trends, which may have been influenced by a number of other factors. Examples of such influences are technological change and innovations (e.g. improvements in agricultural inputs and/or practices, and/or changes in production patterns), and increased productivity due to pesticide effects. The specification, therefore, is:

$$\begin{aligned}\ln y_{it} &= \alpha_0 + \alpha_h \ln H_{it} + \alpha_s \ln S_{it} \\ &+ \alpha_l \ln L_{it} + \ln K_{it} + \alpha_t t + 0.5\alpha_{tt} t^2 \\ &+ \alpha_{ht}(\ln H_{it})t + \alpha_{st}(\ln S_{it})t \\ &+ \alpha_{lt}(\ln L_{it})t + \alpha_{kt}(\ln K_{it})t + v_{it} - u_{it}\end{aligned} \tag{16}$$

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

$$\begin{aligned}\ln y_{it} &= \alpha_0 + \alpha_h \ln H_{it} + \alpha_s \ln S_{it} + \alpha_f \ln F_{it} \\ &+ \alpha_l \ln L_{it} + \alpha_k \ln K_{it} + \alpha_t t + 0.5\alpha_{tt} t^2 \\ &+ \alpha_{ht}(\ln H_{it})t + \alpha_{st}(\ln S_{it})t + \alpha_{ft}(\ln F_{it})t \\ &+ \alpha_{lt}(\ln L_{it})t + \alpha_{kt}(\ln K_{it})t + v_{it} - u_{it}\end{aligned} \tag{17}$$

Where y_{it} is the output of crop i in the t^{th} 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, $\ln$ 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:

$$u_{it} = \beta_0 + \beta_1 \frac{K_{it}}{L_{it}} + \beta_{dj} \sum_{j=1}^{n} D_{tj} \tag{18}$$

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

$$u_{it} = \beta_0 + \beta_1 \frac{K_{it}}{L_{it}} + \beta_2 M_{it} + \beta_{dj} \sum_{j=1}^{n} D_{tj} \tag{19}$$

Where M indicates import of rice milled measured in tonnes. 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.

RESULTS AND DISCUSSION

The Frontier 4.1 software was used in the estimation of the SFA model while DEAP 2.1 was used for DEA. If the value of the Malmquist index or any of its components is less than one, it implies regress between two adjacent periods, whereas values greater than 1 imply progress or improvement. In order to obtain the magnitude of progress or regress, the values of Malmquist indices or any of its components can be subtracted from 1. The values of the indices capture productivity relative to the best performers. The Malmquist index showing the rice TFP indicates an average productivity progress of about 15.2% and 4.3% as measured by SFA and DEA, respectively. This implies that 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. Both methods show, on average, that technical change components in ECOWAS rice agriculture are larger than efficiency change. 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. The results further reveal that a major contributor to rice TFP growth in all the countries has been the technical change. All the countries have impressive technological progress, on the average. The TFP changes indicate more progress in ECOWAS than in pre-ECOWAS era for both SFA and DEA. 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) that 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. The results indicate technological progress of 9.5% and 4.5% for SFA and DEA methods, respectively. Despite average technological and productivity progress across the analysis period, some of the cotton producing countries has not performed well. For instance, the Malmquist indices are less than 1 for Benin, Burkina Faso and Cote d'Ivoire. 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 (Chakraborty and Mistra, 2002). The adoption of Bt cotton in West Africa as shown by (Elbehri, A. and Steve, 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.

Overall, Togo is the most impressive country for both SFA and DEA approaches. Incidentally, at the other end of the spectrum for both SFA and DEA, Benin has the lowest growth performance for most of the analysis period. The TFP growth in all the countries is more due to technical change than efficiency change. The impressive productivity growth in Togo is most likely a consequence of keen interest of the countries in export of cotton and development of indigenous industries using cotton as raw material. Another impetus to cotton productivity growth in Togo might be because of remarkable investment and support programmes in the country to promote growth of cotton. Such programmes include supply of credit programme, extension services, input supply and marketing through national companies. By and large, the growth rate recorded on the average for ECOWAS cotton sector can actually provide a basis for sustained growth in cotton in the region.

Contrary to the results for rice and cotton, the overall total factor productivity 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. Apart from these two ECOWAS millet producing countries, average productivity growth is less than 1% for other nations over the analysis period. 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. The empirical results give a clear evidence of the ECOWAS reforms enhancing millet productivity growth better than in pre-ECOWAS reform period. Similar to the case of rice, the main contributor to TFP growth has been technical change.

Table 2. Average Total Factor Productivity: 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

Table 3. Average Total Factor Productivity: 1961-2005

	Efficiency change		Technical change		Malmquist index	
Country	SFA	DEA	SFA	DEA	SFA	DEA
RICE						
Côte d'Ivoire	0.965	0.997	1.138	0.964	1.098	0.962
Ghana	0.986	1.000	1.067	0.963	1.052	0.963
Guinea	1.029	0.996	1.033	1.001	1.063	0.997
Mali	1.027	0.999	1.144	1.093	1.175	1.093
Nigeria	1.030	0.975	1.166	1.193	1.201	1.163
Senegal	1.056	1.000	1.135	1.241	1.198	1.214
Mean	1.016	0.995	1.114	1.076	1.131	1.065
COTTON						
Benin	0.965	1.030	1.012	0.878	0.977	0.904
Burkina Faso	1.008	0.994	1.005	1.041	1.013	1.035
Cote d'Ivoire	1.003	1.000	1.018	1.082	1.021	1.082
Mali	1.015	0.992	1.012	1.126	1.027	1.117
Nigeria	0.980	1.000	1.012	1.216	0.993	1.216
Togo	1.040	1.000	1.008	1.249	1.047	1.249
Mean	1.002	1.003	1.011	1.099	1.013	1.140
MILLET						
Burkina Faso	1.002	1.000	1.119	0.656	1.121	0.656
Mali	1.002	0.998	1.115	0.754	1.117	0.753
Niger	1.001	0.998	1.120	0.859	1.121	0.857
Nigeria	1.000	0.971	1.143	0.987	1.143	0.959
Togo	1.007	1.010	1.122	1.092	1.129	1.103
Mean	1.002	0.995	1.124	0.870	1.126	0.866

Table 4. Average Annual Total Factor Productivity: 1979-2005

	Efficiency change		Technical change		Malmquist index	
Country	SFA	DEA	SFA	DEA	SFA	DEA
RICE						
Côte d'Ivoire	0.970	0.997	0.989	0.907	0.960	0.905
Ghana	1.015	0.999	1.004	0.917	1.019	0.916
Guinea	1.009	0.997	1.002	0.952	1.011	0.949
Mali	1.023	0.999	1.003	1.123	1.026	1.122
Nigeria	1.009	1.006	0.960	1.179	0.969	1.186
Senegal	1.014	1.000	0.993	1.189	1.007	1.189
Mean	1.007	1.000	0.992	1.045	0.999	1.045
COTTON						
Benin	0.962	0.998	1.032	0.912	0.993	0.910
Burkina Faso	0.999	0.998	1.034	0.933	1.032	0.932
Cote d'Ivoire	1.010	1.007	1.038	0.950	1.048	0.957
Mali	1.000	1.000	1.032	1.036	1.032	1.036
Nigeria	0.977	1.001	1.054	1.050	1.030	1.051
Togo	1.041	1.000	1.038	1.095	1.081	1.094
Mean	0.998	1.001	1.038	0.996	1.036	0.997
MILLET						
Burkina Faso	1.002	1.000	1.127	0.793	1.129	0.793
Mali	1.001	0.987	1.121	0.864	1.123	0.852
Niger	1.002	1.001	1.131	0.991	1.133	0.992
Nigeria	1.000	0.983	1.144	1.089	1.144	1.071
Togo	1.000	1.000	1.121	1.207	1.121	1.254
Mean	1.001	0.994	1.129	0.989	1.130	0.992

CONCLUSIONS

This study applied non-parametric (DEA) and parametric (SFA) models to a sample of panel data of ECOWAS rice, cotton and millet production for the period 1961-2005. The productivity growth was estimated using the Malmquist index obtained through both SFA and DEA approaches. 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. A closer look at the total factor productivity differences in ECOWAS and pre-ECOWAS sub-period shows larger total factor productivity in ECOWAS period (1979-2005) than in pre-ECOWAS period for cotton and millet for SFA model. In contrast, a larger TFP is obtained in pre-ECOWAS period than in ECOWAS period for rice with SFA model. The same inference can be drawn from DEA estimate of total factor productivity for rice and millet. However, the conclusion from DEA estimate of cotton total factor productivity is different from SFA's. The total factor productivity in pre-ECOWAS is significantly larger than in the ECOWAS period. Nevertheless, in both periods, productivity growths in all the crops are sustained through technological progress.

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 terms of efficiency measurements, the differences between the methodologies are very sensitive on levels of segmentations. 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 used 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. 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.

2. 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.

3. Finally, studies are yet to 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. To this end, there is need for further research in understanding the observed differences since none of the methods seems to have absolute advantage over the other. Meanwhile, researchers can either continue the routine practice of cross checking by running the two models or use average of the two approaches to make recommendation when absolute advantage of any of them cannot be determined easily. Otherwise, they could rely on simulated data to determine the relative precision and policy value.

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Rast produktivnosti tipičnih poljoprivrednih kultura ECOWAS-a: priča o dvije suprotstavljene granične metode analize

SAŽETAK

Koristeći analizu stohastičkih granica (SFA) i analizu omeđenih podataka (DEA) ovaj rad istražuje rast produktivnosti kod 3 poljoprivredne kulture ECOWAS-a (Ekonomske zajednice zapadnoafričkih država): riže, pamuka i prosa. Rezultati pokazuju da magnituda produktivnosti varira ovisno o primijenim modelima i segmentaciji podataka. Unatoč tome, sveukupni rezultati upućuju na to tehnička promjena ima najveći utjecaj na produktivnost te da proizvođači nastoje dostići one na čelu razvoja. Detaljnija analiza razlika između ukupne faktorske produktivnosti u razdoblju ECOWAS-a u odnosu na onu u podrazdoblju prije osnivanja ECOWAS-a u SFA modelu pokazuje veći ukupni faktor produktivnosti za pamuk i proso u razdoblju ECOWAS-a (1979. – 2005.) od onog u podrazdoblju prije ECOWAS-a. Po pitanju učinka zakonskih reformi, rast produktivnosti u ECOWAS-u i podrazdoblju prije ECOWAS-a razlikuje se za pojedine poljoprivredne kulture ovisno o primijenjenom modelu analize.

Ključne riječi: DEA, ECOWAS, rast produktivnosti, SFA