Agricultural Productivity Growth in Africa: Is Efficiency Catching-up or Lagging Behind?

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Summary

Recent empirical studies on agricultural productivity growth in African countries have produced mixed results; some find that uptake of new technology (technical progress) is the main source of total factor productivity growth while others point to improved use of existing technology (efficiency catch-up). This study tests for efficiency catch-up in the agricultural productivity of 33 African countries from 1966 to 2001. We use recent advances in data envelopment analysis (DEA) to generate standard and bootstrap bias corrected technical efficiency scores. In general, we find no evidence of efficiency catching-up. The standard DEA overestimated the efficiency scores of some countries due to small sample bias.

Topic: Production Economics, International Development

Key words: Agriculture, Efficiency Catch-up, Bootstrap DEA, Africa

1. Introduction

Research in African agricultural productivity is starting to receive substantial attention in the literature (Alene 2010, Nin-Pratt and Yu 2008, Fulginiti et al. 2004, Nkamleu 2004). Agricultural productivity has long been viewed as a critical determinant of rural welfare and an engine for overall economic growth in most African countries. Two major strands of research dominate the literature on agricultural productivity growth; one strand seeks to measure agricultural productivity growth across countries over time while the other strand seeks to explain sources of productivity growth or stagnation, i.e., what factors affect productivity performance.

Productivity is defined as output per unit of input and productivity growth aims at capturing output growth not accounted for by growth in inputs (Fulginti et al., 2004). Studies that measure productivity growth decompose total factor productivity (TFP) into two components, efficiency change and technical change. Efficiency measures the ability of a country to fully exploit its available agricultural resources in producing total output, relative to other countries and available technology represented by the best-practice frontier. Therefore, efficiency change measures the rate at which a country moves towards (catches up) or away (lags behind) from the best-practice production frontier. Technical change represents a shift in the production frontier through time; it is a measure of the level of innovation in agricultural production. Studies that focus on factors that affect productivity growth have centered on political/institutional factors, investment in research and development, and trade reforms (Fulginti et al., 2004; Alene 2010). These studies indicate that institutional factors are important determinants of agricultural productivity growth as well as per capita GDP growth.

Empirical evidence indicate that African productivity growth made some progress in the 1960s, suffered a regression during the 1970s, but recovered in the mid-1980s to achieve a reasonable rate of productivity improvement through the end of the century (Block, 2010). However, the studies provide mixed results in regard to sources of productivity growth. Some point to technical change as the main source of productivity growth while others point to efficiency change. The studies are silent on whether production efficiency has improved over time or not.

For instance, Nkamleu (2004) examined the economic performance of 16 countries over the period 1970 to 2001. Productivity growth was found to have experienced a positive evolution and the good performance was due to progress in efficiency change rather than technical change. Institutional factors as well as agro-ecological factors were found to be important determinants of productivity growth. Fulginiti et al (2004) examined agricultural productivity growth of 41 Sub-Saharan African (SSA) countries from 1960 to 1999. A significant reduction in productivity was found during political conflicts and wars, and a significant increase in productivity was observed among countries with higher levels of political rights and civil liberties. Nin-Pratt and Yu (2008) examined the evolution of agricultural productivity for 30 SSA countries from 1963 to 2003. The study shows a remarkable recovery in the performance of agricultural productivity during the 1984-2003 periods. The recovery is a consequence of improved efficiency in production, including an overall reduction in fertilizer use. Alene (2010) measured and compared TFP growth in African agriculture over the period 1970 to 2004. Technical change, rather than efficiency change, was found to be the principal source of growth. Agricultural R&D, weather and trade reforms were found to have significant effects on productivity. Policy reforms as well as improved weather contributed to agricultural productivity recovery after the mid 1980s.

The mixed results regarding the main source of productivity growth are not surprising. Productivity growth measures are normally influenced by a number of factors, including the number of variables in the model, number of fixed and variable inputs, method used (i.e., data envelopment analysis or stochastic frontier analysis), functional form used, sample size, and type of data used (i.e. whether the data is cross-sectional or panel) (Thiam et al., 2001). In general, the studies recommend sustained agricultural productivity growth at a much higher rate than in the past as crucial for reducing hunger and poverty across the continent. Agricultural productivity growth can be achieved through improved production efficiencies, such as adoption of modern technologies and practices, and accelerating innovation, such as investment in research and development.

In estimating productivity growth, two competing approaches are used, data envelopment analysis (DEA) or stochastic production frontier. The DEA approach of measuring productivity growth has been preferred over the SFA approach mainly because it does not require any parametric assumption on the structure of production technology or the inefficiency term. Likewise, as long as inputs and outputs are measured in the same unit, the assumption about complete homogeneity of the economic agents is not needed. However, the standard DEA approach has been critiqued for lacking a solid statistical foundation; it assumes away measurement errors and is sensitive to outliers. The approach generates point estimates of efficiency scores that do not provide any measures of variability of the individual scores. To overcome those problems, Simar and Wilson (1998; 2000; 2008) have introduced bootstrapping into the standard DEA framework. Their method, based on statistically well-defined models, allows for consistent estimation of the production frontier, corresponding efficiency scores, as well as standard errors and confidence intervals. These advances have not been included in recent studies that have examined productivity growth in African agriculture.

In this paper, we apply recent advances in bootstrap DEA to investigate whether technical efficiencies in 33 African countries have been improving (catching up) or deteriorated (lagged behind) for the period 1966 to 2001. We also investigate whether there is convergence in efficiency scores within the entire sample. Our goal is to determine whether, in general, countries have been utilizing their resources more efficiently relative to their peers. Results of this study have policy implications of the past performance of African agriculture. Increased production efficiency in African agriculture is important because it releases manpower for other work and for increasing industrialization. Greater industrialization has the potential of creating healthier economies and gradual improvement of welfare of both rural and urban dwellers.

2. Empirical Model

In this article, we follow the approach by Henderson and Zelenyuk (2007) to define the underlying production technology but with two important distinctions. First, our technology function consists of four input and one output variables. Second, our study focuses on analyzing technical efficiency within the agricultural sector and not the entire economy. There are n countries ranging from i to n ($i = 1, 2\ldots n$) and the period-t input vector is $x_i^t = (k_i^t, l_i^t, f_i^t, a_i^t)$, where, k_i^t is physical capital used in the agricultural sector by country *i* in period *t*, l_i^t is the economically active population in agriculture (FAO definition of labor used in agriculture), f_i^t is the total amount of fertilizer used in agriculture, and a_i^t is size of arable land. Further, y_i^t is a single output for country *i* in period *t*.

The technology for converting inputs for each country *i* in each time period *t* can be characterized by the technology set:

(1) $$T_i^t \equiv \left\{\left(x_i^t, y_i^t\right) \mid \text{can produce } y_i^t\right\}.$$

The same technology can be characterized by the following input sets:

(2) $$C_i^t\left(y_i^t\right) \equiv \left(x_i^t \mid x_i^t \text{ can produce } y_i^t\right), x_i^t \in \Re_+^n.$$

We assume that the technology follows standard regularity assumptions under which the Shephard (1970) input-oriented distance function can be represented as:

(3) $$TE_i^t \equiv TE_i^t\left(x_i^t, y_i^t \mid C_i^t\left(y_i^t\right)\right) = \text{supremum}\left\{\theta > 0 \mid x_i^t/\theta \in C_i^t\left(y_i^t\right)\right\} \forall y_i^t \in \Re_+^1.$$

A country is considered to be technically efficient when $TE_i^t = 1$ and technically inefficient when $0 < TE_i^t < 1$. The true technology and input sets are unknown and therefore the individual value of technical efficiency must be estimated using either the nonparametric (data envelopment analysis) or parametric (stochastic frontier analysis) techniques. Given the production technology in equation (3), we use linear programming to estimate the input distance function. The Farrell input-based efficiency index for country *i* at time *t* is defined as:

(4) $$e\left(x_i^t, y_i^t\right) = \min\left\{\theta \mid \left\langle x_i^t / \theta, y_i^t\right\rangle \in T^t\right\}.$$

In the above equation y is output, x is the input matrix, θ is the technical efficiency measure to be calculated, and T is the available technology. The subscript i refers to an individual country and the superscript t represents the individual time. The efficiency index value for each country is found using the following linear program:

$$\underset{\theta, z^1,\ldots,z^j}{\text{Minimize}}\, \theta_i$$

$$\text{(5)} \qquad \text{subject to} \begin{Bmatrix} Y_i \le \sum_k z_k Y_k^t \\ \theta K_i \ge \sum_k z_k K_k^t \\ \theta L_i \ge \sum_k z_k L_k^t \\ z_k \ge 0 \forall k. \end{Bmatrix},$$

where θ_i is the efficiency measure to be calculated for country i at time t, and z_k is the intensity variable for country i. The above model assumes constant returns to scale (CRS). Constant returns to scale suggest that all firms operate at an optimal scale. However, imperfect competition and financial constraints may cause countries to operate below optimal scale. Adding $\sum_{k=1}^{k} z_k = 1$ to the constraints in the above model imposes variable returns to scale (VRS) while adding the equation $\sum_{k=1}^{k} z_k < 1$ imposes decreasing returns to scale (DRS).

The smooth homogenous bootstrap DEA approach introduced by Simar and Wilson (1998; 2000; 2008) is used to allow for consistent estimation of the production frontier, corresponding efficiency scores, bias, bias corrected efficiency scores, as well as standard errors and confidence intervals. Bootstrapping investigates the reliability of a data set by creating a pseudo-replicate data set. Bootstrapping allows the assessment of whether the distribution has been influenced by stochastic effects and can be used to build confidence intervals for point estimates that cannot be derived analytically. Random samples are obtained by sampling with replacement from the standard data set, which provides an estimator of the parameter of interest. With DEA bootstrapping, the data generation process (DGP) is repeatedly simulated by resampling the sample data and applying the standard estimator to each simulated sample. It is expected that the bootstrap distribution will mimic the standard unknown sampling distribution of the estimators of interest (using a nonparametric estimate of their densities). Hence, a bootstrap procedure can simulate the DGP by using Monte Carlo approximation and may provide a reasonable estimator of the true unknown DGP. The bootstrap estimates are biased by construction and the empirical bootstrap distribution is used to estimate the bias. An estimate of the bias is defined as the difference between the empirical mean of the bootstrap distribution and the standard efficiency point estimates. The bias-corrected estimator is obtained by subtracting the bias from the standard efficiency estimates. Details of the DEA bootstrapping process are well documented in Simar and Wilson (1998; 2000; 2008). Bootstrapping enables the investigation of the sensitivity of efficiency scores to sampling variations and this may result in a change in the ranking of bias-corrected efficiencies scores from the standard efficiency scores.

Since all countries are not equally endowed with natural resources and do not operate at similar stages of economic development, we also want to compute technical efficiency scores that take into consideration the relative economic weights of an individual county versus the others. This is because the efficiency scores per se are standardized to be between zero and one and thus ignore the relative effort or economic importance of the country that earned this score (Simar and Zelenyuk, 2007). Computing the weighted efficiency scores is a two stage process. First, the DEA model is run to estimate technical efficiency scores. Second, the economic weight is computed as the share of output for each country over all countries $S_i^t = \frac{y_i^t}{\bar{y}_i^t}$ (all with respect to the same period and technology). The weighted efficiency score, $\overline{TE}_i^t$, is the product of the share and unweighted efficiency score.

(6) $$\overline{TE}_i^t = TE_i^t\left(x_i^t, y_i^t\right) \times S_i^t, S_i^t = \frac{y_i^t}{\bar{y}_i^t}, \bar{y}_i^t = \sum_{i=1}^{n_i} y_i^t$$

3. Data Sources

Panel data on agricultural production and inputs (land, labor, fertilizer, and machinery) for 33 African countries for the period 1966-2001[1] were accessed from the World Development Indicators of the World Bank and the Food and Agricultural Organization Statistics (FAOSTAT) of the United Nations. Agricultural output is measured as the volume of agricultural production in millions of 1999-2001 international dollars. For inputs, capital stock used in the agricultural industry is defined as the farm machinery or the number of tractors employed in agriculture in any given year. Labor is measured as the total number of economically active population in agriculture (FAOs definition of labor used in agricultural industry). Fertilizer is defined as tons of plant nutrients consisting of nitrogen, potash, and phosphorous used in agriculture. Agricultural land is defined as the size of a county's arable land. These data have been used in previous studies of agricultural productivity in SSA countries (Alene 2010, Fulginiti et al. 2004).

4. Empirical Results

This section presents the results of our efficiency estimates based on the standard DEA and bias correction DEA techniques.

4.1 Comparing the standard and bias corrected technical efficiency scores

Table 1 lists the annual average efficiency scores for the 33 countries from 1966 to 2001. The standard and bias corrected efficiency scores are in the second and third columns, the fourth and fifth columns present the bias and standard error, while the last two columns are the 95 percent confidence interval for the bias corrected scores. Using 2000 bootstrap samples, the DEA smooth bootstrap procedure, as described in Simar and Wilson (2008, 455-463), was used to generate the bias corrected efficiency scores, bias, standard error, and confidence intervals.

The results indicate that technical inefficiencies do exist in African agriculture. The overall average efficiency score is 0.745 and 0.526 for the standard and bias corrected scores and the mean 95 percent confidence band ranges from 0.537 to 0.734[2]. The standard efficiency scores indicate that efficiency reached its peak in 1979 (0.797) while the bias corrected scores indicate 1967 (0.688). In general, the technical efficiency scores generated using the standard DEA estimators are greater than the bias corrected scores. The results of this study also demonstrate the usefulness of estimating confidence intervals of DEA efficiency scores. The intervals indicate that the point estimates overstate the efficiency scores, implying that the standard scores overstate what the true values should be. The bias corrected efficiency scores show a decline in the mean efficiency scores from the 1960s, 1970s, 1980s and 1990s (0.585, 0.578, 0.558, and 0.548). However, the standard scores indicate that efficiency was lowest in the 1970s and caught up in the 1980s. We find that all the bias is positive, which implies that the standard DEA efficiency scores are biased upwards.

Can the bias be disregarded? This question is addressed by analyzing the ratios of the estimated bias to the standard error of the bootstrapped estimates. When the ratio is less than 0.25, the bias is insignificant and not usually a problem (Efron and Tibshirani 1993). Since the ratios far exceed 0.25, the bias is significant and we conclude that the bias corrected efficiency scores are different from the standard efficiency scores and provide a better indication of technical efficiencies in the agricultural sectors of the 33 countries.

< Table 1 >

The average efficiency scores for each country over the sample period are reported in Table 2. Estimates based on the standard DEA estimator imply that on average countries such as Burundi, Gambia, Mozambique, Sudan, and Zambia dominated in defining the best-practice production frontier. However, the bias corrected efficiency scores indicate that those countries were relatively inefficient. For instance, the average efficiency score of Sudan fell from 1 to 0.473 and that of Zambia from 1 to 0.437. These results may imply measurement errors in the standard DEA scores computation and the bootstrap DEA is used to correct this bias.

< Table 2 >

In Tables 3 and 4, we report the results of efficiency scores for each country for 1966 and 2001. The two tables show whether there is any evidence of efficiency catching up or lagging behind. The standard DEA estimator in both tables indicates that Burkina Faso, Gambia, Mozambique, South Africa, Sudan, and Zambia were technically efficient in the two

periods. This means that those countries have exploited their resources relatively better than other countries in the sample with similar levels of inputs. Therefore, further agricultural productivity growth in those countries can only come from changes in technology or in physical and human capital accumulation. A somewhat puzzling result is that some countries, such as Sierra Leone, that have been at war the entire last three decades seem to have always exploited their available resources more efficiently than the other countries that have enjoyed relative peace (e.g., Tanzania and Kenya). This implies that those war torn countries have the capacity to obtain higher productivity levels than the relatively peaceful countries if they would be able to increase all inputs by the same proportion, while maintaining their same efficiency levels under a constant returns to scale technology.
The standard DEA estimator also indicates that Central Africa Republic, Angola, Benin, Congo Republic, and Madagascar have increased their scores from being inefficient in 1966 to full efficiency by 2001.

< Table 3 and 4 >

However, the bias corrected efficiency scores in the third columns of Tables 3 and 4 indicate otherwise. Countries that defined the frontier under the standard efficiency scores no longer do so. For instance, Burkina Faso now has efficiency scores of 0.493 and 0.634 for 1966 and 2001. Some countries are now more technically efficient, though not fully efficient, while others have regressed. We also find the degree of retrogression to be more prevalent among conflict prone countries, such as Angola, than those that are least marred by conflict or have had no conflict at all. For instance, the bias corrected technique estimates the average technical efficiency score of Angola to have fallen from 0.534 in 1966 to 0.303 in

2001. However, the standard DEA estimator indicates Angola to have attained a full efficiency score of 1 in 2001.

The above results are summarized in Figure 1; we draw a scatter plot comparing the results of the standard efficiency scores with those generated through bias correction approach. Most countries fall along the 45 degrees line indicating a strong correlation between the estimated two scores. Countries such as Burkina Faso, Cameroon, Gambia, Ghana, Guinea, Mozambique, Niger South Africa, Sudan, Uganda, and Zambia were fully efficient in 1966 according to the standard DEA estimator, showing a clustering of efficiency scores at a value of 1. However, a horizontal reading of the bias corrected technical efficiency scores indicates that those countries never attained full efficiency scale in 1966 and in 2001.

< Figure 1 >

In Table 5, we present a summary of the qualitative comparison of the standard efficiency score and the bias correction efficiency scores for each country for 1966 and 2001 to determine whether there was catching up or lagging behind. Lagging behind here indicates countries whose 1966 efficiency scores are greater than 2001 scores. Catching-up indicates cases where efficiency scores are higher in 2001 than in 1966. A country that has maintained an efficiency score of 1 in the two periods is labeled as efficient. While there are many instances when the change in efficiency under the standard DEA estimator and the bias corrected scores move in the same direction (21 out of 33 cases), there are cases where the results of the two approaches drift in opposite directions (12 out of 33 cases). In general, results under the standard efficiency scores indicate that 15 countries lagged behind, 11 countries caught up and 7 countries defined the production frontier. In contrast, the bias corrected scores indicate that 23 countries lagged behind and 10 countries caught up.

< Table 5 >

The argument we make in this article is that the technical efficiency scores of African agriculture estimated through the bias correction DEA techniques are more plausible and robust than those estimated with the standard DEA estimator. This poses the question of whether any finite sample DEA estimates of technical efficiency in the previous studies show realistic technical inefficiencies of the evaluated countries. Bootstrapping in DEA, one of the recent advances in non-parametric econometrics, enables one to account for the small sample biases involved in estimating technical efficiency scores.

Both estimators seem to indicate stagnation in technical efficiency in African agriculture. Figure 2 plots the relationship between the coefficient of variation of the standard and bias corrected efficiency scores from 1966 to 2001. An increase in this measure of spread indicates widening dispersion in overall efficiency within the sample where some countries are drifting further away from the best-practice frontiers while others are catching up.

< Figure 2 >

4.2 Weighted versus non-weighted efficiency scores

One of the assumptions of the DEA is that it compares all countries in the sample to only one best-practice frontier. As noted in Henderson and Zelenyuk (2007), there is a common misperception sometimes in the literature that would portray relatively wealthy countries to be more efficient than their poorer counterparts. To compare efficiency scores across countries, we generated a weighted efficiency scores based on the country's agricultural output sizes. After accounting for the different country weights, we show in Table 6 that the weighted efficiency scores generated by the standard DEA and those generated through bias corrections are both lower when compared to the non-weighted efficiency scores. Although the computed scores are statistically different, the difference is not so large to change the implications of our results regarding efficiency in 1966 and 2001 periods, in that, African countries have on average lagged behind the best practice frontiers.

< Table 6 >

4.3 Efficiency Distributions

We used the non-parametric kernel density distribution to evaluate the distributions of efficiency scores generated with bootstrap DEA in 1966 and 2001. Simar and Zelenyuk (2006) notes that one has to take care of at least three things when using kernel density estimation: the random variable whose density is to be estimated must have a bounded support, only the consistent estimate of the efficiency scores should be used and there is no violation of the continuity assumption needed to ensure consistency of the density estimation. We use the Silverman reflection method to correct for the bounded support, bootstrap DEA to compute the consistent efficiency scores, a Gaussian kernel density to estimate the bias corrected efficiency scores, and Silverman's (1986) rule of thumb for bandwidth selection.

We are particularly interested in whether there is uni-modal or bi-modal distribution in efficiency scores. Such an analysis provides insights whether there is any evidence of "club convergence" among sub-groups within the sample. Figure 3 presents the distribution of efficiency scores for the bootstrap DEA scores for 1966 and 2001. The Figure indicates that the distributions of efficiency scores have shifted to the left suggesting that, on average, African countries moved away from their best-practice frontiers or have become more technically inefficient. We use the diptest[3] by Hartigan and Hartigan (1985) to test the null hypothesis of unimodality in the distributions of the bias corrected efficiency scores for 1966 and 2001. In both bases, unimodality is rejected suggesting that the distributions have more than one mode. This suggests the presence of "club convergence" where the productive efficiency of the 33 countries may be converging to different points (some countries are improving their efficiency while others are not).

< Figure 3 >

5. Conclusion

This paper applied recent advances in DEA to examine technical efficiency in the agricultural sectors of 33 African countries from 1966 to 2001. Bias corrected efficiency scores were estimated using bootstrap DEA technique and the results are compared with efficiency scores generated from standard DEA. The goal of the paper was to investigate whether overall efficiency scores have been improving over time (catching-up) or declined (lagged behind). We find that due to small sample biases, efficiency scores are misjudged when employing standard DEA techniques. For instance, while estimates based on standard DEA would show that conflict prone countries, such as, Angola, Sudan, and Sierra Leone have become fully efficient by 2001, the bias corrected efficiency estimates in this paper show just the opposite. Both standard and bias corrected efficiency scores indicate that technical inefficiencies have persisted in African agriculture and the general trend is that most countries are slipping further from the best practice frontiers. The biased corrected efficiency scores suggest evidence of "club convergence" among sub-populations within the sample.

The immediate policy question arising from the reported results is how African countries can catch up in the agricultural production front. In many African countries, agricultural practices, such as, the use of fertilizers, plant breeding and mechanization are available to improve production efficiency. Those practices need to be tailor made for each region or country situation. Those technologies should not be put on the shelf but be adapted and new technologies developed to help the African agriculture. Uptake of available technologies at the farm level requires effective extension, input supply, and credit systems that enable farmers to access needed inputs such as improved seeds or breeds of animals, planting materials, fertilizers, and veterinary medicines. The availability of improved technologies should go hand in hand with farmers' access to key inputs and market prices that make adoption of the improved technology profitable. Education and training of farmers are a prerequisite for effective uptake of available technologies. Finally, there is need for both public and private extension programs that facilitate sustained increases in productivity, especially in high-potential areas where rapid intensification of agriculture is expected.

A useful extension of this paper is the analysis of the factors that influence uptake of available technology (i.e., efficiency change). This will provide relevant information for policy makers on where to focus available resources in improving agricultural production efficiency in African agriculture

Notes

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1. The analysis was restricted to 33 countries because data quality was poor for the other African countries and for some years.

2. The 95% confidence intervals for the bias-corrected efficiency estimates include the bootstrapped efficiency scores for all the sample years. This implies that, in the long run, in 95 out of 100 cases, intervals like these will contain the true technical efficiency estimates.

3. This statistic is the maximum difference between the empirical distribution function and the unimodal distribution function that minimizes that maximum difference. The dip statistic measures departure of a sample from unimodality

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Table 1. Standard and Bias-Corrected Efficiency Estimates, 1966-2001

Year	Efficiency	Bias Corrected Efficiency	Bias	Standard Error	Lower Confidence Bound	Upper Confidence Bound
1966	0.774	0.592	0.182	0.029	0.575	0.765
1967	0.796	0.642	0.154	0.025	0.607	0.788
1968	0.762	0.599	0.163	0.029	0.576	0.753
1969	0.747	0.570	0.178	0.031	0.556	0.737
1970	0.715	0.524	0.191	0.048	0.523	0.705
1971	0.737	0.556	0.181	0.041	0.547	0.727
1972	0.725	0.541	0.183	0.042	0.534	0.715
1973	0.727	0.548	0.179	0.034	0.533	0.717
1974	0.709	0.510	0.199	0.051	0.516	0.698
1975	0.688	0.479	0.208	0.041	0.494	0.674
1976	0.706	0.525	0.181	0.040	0.520	0.696
1977	0.734	0.527	0.207	0.050	0.534	0.721
1978	0.753	0.549	0.204	0.057	0.547	0.743
1979	0.797	0.600	0.197	0.056	0.585	0.788
1980	0.786	0.591	0.194	0.042	0.576	0.776
1981	0.771	0.598	0.173	0.050	0.574	0.763
1982	0.763	0.569	0.194	0.056	0.559	0.754
1983	0.760	0.569	0.191	0.052	0.556	0.751
1984	0.757	0.517	0.239	0.056	0.537	0.744
1985	0.754	0.533	0.221	0.056	0.537	0.744
1986	0.755	0.526	0.230	0.063	0.536	0.745
1987	0.740	0.501	0.239	0.062	0.524	0.728
1988	0.743	0.514	0.229	0.055	0.530	0.731
1989	0.756	0.544	0.212	0.056	0.545	0.745
1990	0.731	0.478	0.253	0.061	0.513	0.717
1991	0.755	0.495	0.260	0.079	0.531	0.742
1992	0.740	0.442	0.298	0.086	0.508	0.725
1993	0.762	0.505	0.257	0.057	0.537	0.747
1994	0.751	0.507	0.243	0.066	0.534	0.737
1995	0.732	0.490	0.241	0.077	0.518	0.719
1996	0.725	0.454	0.271	0.073	0.505	0.709
1997	0.727	0.423	0.305	0.091	0.494	0.711
1998	0.738	0.462	0.275	0.069	0.511	0.722
1999	0.739	0.471	0.269	0.060	0.512	0.725
2000	0.720	0.446	0.274	0.069	0.496	0.706
2001	0.755	0.532	0.223	0.064	0.537	0.743
Mean	0.745	0.526	0.219	0.055	0.537	0.734
Mean 60s	0.756	0.585				
Mean 70s	0.736	0.578				
Mean 80s	0.753	0.558				
Mean 90s	0.739	0.548				

Table 2. Standard and Bias-Corrected DEA Estimates (Averages for 33 Countries, 1966-2001)

Country	Efficiency	Bias Corrected Efficiency	Bias	Standard Error	Lower Confidence Bound	Upper Confidence Bound
ANG	0.400	0.316	0.084	0.025	0.306	0.394
BEN	0.924	0.650	0.274	0.031	0.669	0.909
BOT	0.779	0.666	0.113	0.005	0.621	0.769
BRU	0.591	0.453	0.138	0.013	0.426	0.582
BUR	1.000	0.488	0.512	0.207	0.630	0.984
CAM	0.989	0.773	0.217	0.015	0.747	0.974
CFA	0.938	0.491	0.447	0.236	0.609	0.923
CHA	0.768	0.588	0.179	0.023	0.564	0.755
CON	0.827	0.561	0.265	0.069	0.579	0.813
COT	0.512	0.397	0.115	0.026	0.386	0.504
GAM	1.000	0.653	0.347	0.045	0.708	0.983
GHA	0.757	0.602	0.155	0.011	0.566	0.745
GUI	0.898	0.708	0.190	0.017	0.681	0.884
KEN	0.940	0.693	0.247	0.037	0.680	0.927
LSO	0.535	0.429	0.106	0.005	0.408	0.528
MLI	0.451	0.374	0.077	0.003	0.352	0.446
MSA	0.904	0.729	0.175	0.012	0.693	0.890
MTS	0.516	0.435	0.081	0.002	0.408	0.508
MWI	0.599	0.493	0.105	0.004	0.466	0.590
MZA	1.000	0.457	0.543	0.204	0.626	0.983
NGA	0.349	0.281	0.068	0.002	0.263	0.344
NIG	0.885	0.531	0.355	0.134	0.572	0.873
RSA	0.871	0.641	0.231	0.027	0.636	0.858
SEN	0.674	0.558	0.115	0.004	0.531	0.664
SRA	0.892	0.665	0.228	0.036	0.652	0.879
SUD	1.000	0.473	0.527	0.210	0.619	0.983
SZA	0.700	0.569	0.131	0.008	0.536	0.690
TOG	0.982	0.719	0.263	0.027	0.715	0.966
TZA	0.447	0.365	0.082	0.003	0.345	0.440
UGA	0.810	0.642	0.168	0.013	0.608	0.798
ZAM	1.000	0.437	0.563	0.355	0.616	0.983
ZAR	0.230	0.186	0.044	0.001	0.174	0.227
ZBA	0.426	0.330	0.096	0.004	0.317	0.419
Mean	0.745	0.526	0.219	0.055	0.537	0.734

Table 3. Standard and Bias-Corrected DEA Estimates (1966)

Country	Efficiency	Bias Corrected Efficiency	Bias	Standard Error	Lower Confidence Bound	Upper Confidence Bound
ANG	0.597	0.534	0.063	0.001	0.501	0.590
BEN	0.723	0.586	0.137	0.007	0.551	0.714
BOT	0.608	0.510	0.098	0.004	0.474	0.603
BRU	0.852	0.656	0.195	0.027	0.596	0.843
BUR	1.000	0.493	0.507	0.274	0.590	0.986
CAM	1.000	0.812	0.188	0.013	0.762	0.989
CFA	0.697	0.585	0.112	0.005	0.542	0.689
CHA	0.985	0.773	0.212	0.021	0.721	0.974
CON	0.739	0.580	0.158	0.010	0.550	0.729
COT	0.460	0.395	0.065	0.002	0.370	0.453
GAM	1.000	0.675	0.325	0.044	0.709	0.987
GHA	1.000	0.734	0.266	0.025	0.734	0.989
GUI	1.000	0.662	0.338	0.052	0.696	0.985
KEN	0.870	0.761	0.109	0.005	0.705	0.863
LSO	0.459	0.391	0.068	0.002	0.365	0.452
MLI	0.679	0.615	0.063	0.001	0.578	0.671
MSA	0.833	0.690	0.143	0.006	0.655	0.820
MTS	0.440	0.376	0.065	0.001	0.349	0.435
MWI	0.694	0.581	0.112	0.004	0.547	0.687
MZA	1.000	0.552	0.448	0.152	0.639	0.986
NGA	0.427	0.356	0.071	0.002	0.332	0.421
NIG	1.000	0.611	0.389	0.106	0.647	0.989
RSA	1.000	0.723	0.277	0.025	0.734	0.989
SEN	0.827	0.699	0.128	0.005	0.663	0.818
SRA	0.927	0.751	0.176	0.014	0.701	0.917
SUD	1.000	0.642	0.358	0.073	0.665	0.984
SZA	0.615	0.498	0.117	0.008	0.459	0.608
TOG	0.852	0.711	0.141	0.007	0.664	0.842
TZA	0.513	0.444	0.069	0.002	0.414	0.507
UGA	1.000	0.690	0.310	0.047	0.690	0.985
ZAM	1.000	0.827	0.173	0.008	0.792	0.986
ZAR	0.275	0.233	0.042	0.001	0.211	0.272
ZBA	0.486	0.403	0.083	0.002	0.378	0.479
Mean	0.774	0.592	0.182	0.029	0.575	0.765

Table 4. Standard and Bias-Corrected DEA Estimates (2001)

Country	Efficiency	Bias Corrected Efficiency	Bias	Standard Error	Lower Confidence Bound	Upper Confidence Bound
ANG	1.000	0.303	0.697	0.813	0.556	0.984
BEN	1.000	0.677	0.323	0.039	0.702	0.985
BOT	0.600	0.475	0.125	0.007	0.449	0.593
BRU	0.813	0.634	0.179	0.012	0.605	0.797
BUR	1.000	0.718	0.282	0.028	0.719	0.986
CAM	0.866	0.679	0.187	0.016	0.641	0.853
CFA	1.000	0.453	0.547	0.323	0.601	0.981
CHA	0.734	0.561	0.173	0.012	0.539	0.723
CON	1.000	0.671	0.329	0.045	0.693	0.982
COT	0.436	0.355	0.081	0.002	0.340	0.429
GAM	1.000	0.638	0.362	0.047	0.700	0.984
GHA	0.651	0.538	0.113	0.005	0.499	0.643
GUI	0.995	0.853	0.142	0.005	0.807	0.978
KEN	0.778	0.610	0.167	0.017	0.562	0.767
LSO	0.584	0.463	0.120	0.006	0.440	0.573
MLI	0.285	0.232	0.052	0.001	0.215	0.281
MSA	1.000	0.819	0.181	0.013	0.761	0.983
MTS	0.753	0.652	0.101	0.003	0.616	0.743
MWI	0.531	0.446	0.084	0.002	0.425	0.522
MZA	1.000	0.464	0.536	0.246	0.611	0.986
NGA	0.294	0.231	0.063	0.001	0.221	0.289
NIG	0.695	0.506	0.189	0.040	0.464	0.687
RSA	1.000	0.730	0.270	0.031	0.710	0.983
SEN	0.537	0.445	0.093	0.003	0.423	0.529
SRA	1.000	0.577	0.423	0.096	0.654	0.986
SUD	1.000	0.539	0.461	0.175	0.617	0.985
SZA	0.651	0.528	0.123	0.009	0.478	0.643
TOG	0.910	0.769	0.142	0.008	0.707	0.898
TZA	0.546	0.414	0.132	0.011	0.387	0.538
UGA	0.692	0.545	0.147	0.009	0.514	0.683
ZAM	1.000	0.592	0.408	0.087	0.667	0.985
ZAR	0.189	0.150	0.039	0.001	0.137	0.187
ZBA	0.361	0.277	0.084	0.004	0.262	0.356
Total	0.755	0.532	0.223	0.064	0.537	0.743

Table 5. **A Summary of Results on Efficiency Change between 1966 and 2001**

Country Code	Country Name	Standard DEA efficiency scores	Bias corrected efficiency scores
ANG	Angola	Caught up	Lagging behind
BEN	Benin	Caught up	Catching up
BOT	Botswana	Lagging behind	Lagging behind
BUR	Burkina Faso	Efficient	catching up
BRU	Burundi	Caught up	Lagging behind
CAM	Cameroon	Lagging behind	Lagging behind
CFA	Central African Republic	Caught up	Lagging behind
CHA	Chad	Lagging behind	Lagging behind
ZAR	Congo, Democratic Rep.	Lagging behind	Lagging behind
CON	Congo, Republic	Catching up	Catching up
COT	Cote d'Ivoire	Lagging behind	Lagging behind
GAM	Gambia, The	Efficient	Lagging behind
GHA	Ghana	Lagging behind	Lagging behind
GUI	Guinea	Lagging behind	Catching up
KEN	Kenya	Lagging behind	Lagging behind
LSO	Lesotho	Catching up	Catching up
MSA	Madagascar	Caught up	Catching up
MWI	Malawi	Lagging behind	Lagging behind
MLI	Mali	Lagging behind	Lagging behind
MTS	Mauritius	Catching up	Catching up
MZA	Mozambique	Efficient	Lagging behind
NIG	Niger	Lagging behind	Lagging behind
NGA	Nigeria	Lagging behind	Lagging behind
SEN	Senegal	Lagging behind	Lagging behind
SRA	Sierra Leone	Efficient	lagging behind
RSA	South Africa	Efficient	Catching up
SUD	Sudan	Efficient	Lagging behind
SZA	Swaziland	Catching up	Catching up
TZA	Tanzania	Catching up	Lagging behind
TOG	Togo	Catching up	Catching up
UGA	Uganda	Lagging behind	Lagging behind
ZAM	Zambia	Efficient	Lagging behind
ZBA	Zimbabwe	Lagging behind	Lagging behind

Table 6. Weighted and Non-weighted Efficiency Scores, 1966-2001

	Weighted Efficiency Scores		Non-weighted Efficiency Scores	
Year	Standard Efficiency	Bias Corrected Efficiency	Standard Efficiency	Bias Corrected Efficiency
1966	0.734	0.557	0.774	0.592
1967	0.755	0.604	0.796	0.642
1968	0.732	0.581	0.762	0.599
1969	0.703	0.537	0.747	0.570
1970	0.671	0.477	0.715	0.524
1971	0.695	0.518	0.737	0.556
1972	0.669	0.504	0.725	0.541
1973	0.695	0.534	0.727	0.548
1974	0.641	0.468	0.709	0.510
1975	0.618	0.437	0.688	0.479
1976	0.634	0.482	0.706	0.525
1977	0.665	0.473	0.734	0.527
1978	0.677	0.497	0.753	0.549
1979	0.713	0.555	0.797	0.600
1980	0.711	0.544	0.786	0.591
1981	0.692	0.542	0.771	0.598
1982	0.673	0.519	0.763	0.569
1983	0.670	0.511	0.760	0.569
1984	0.661	0.465	0.757	0.517
1985	0.658	0.480	0.754	0.533
1986	0.652	0.472	0.755	0.526
1987	0.644	0.456	0.740	0.501
1988	0.652	0.470	0.743	0.514
1989	0.665	0.491	0.756	0.544
1990	0.636	0.437	0.731	0.478
1991	0.640	0.447	0.755	0.495
1992	0.611	0.388	0.740	0.442
1993	0.636	0.430	0.762	0.505
1994	0.628	0.430	0.751	0.507
1995	0.624	0.428	0.732	0.490
1996	0.634	0.401	0.725	0.454
1997	0.639	0.381	0.727	0.423
1998	0.636	0.405	0.738	0.462
1999	0.635	0.417	0.739	0.471
2000	0.610	0.388	0.720	0.446
2001	0.630	0.455	0.755	0.532
Mean	0.662	0.477	0.745	0.526

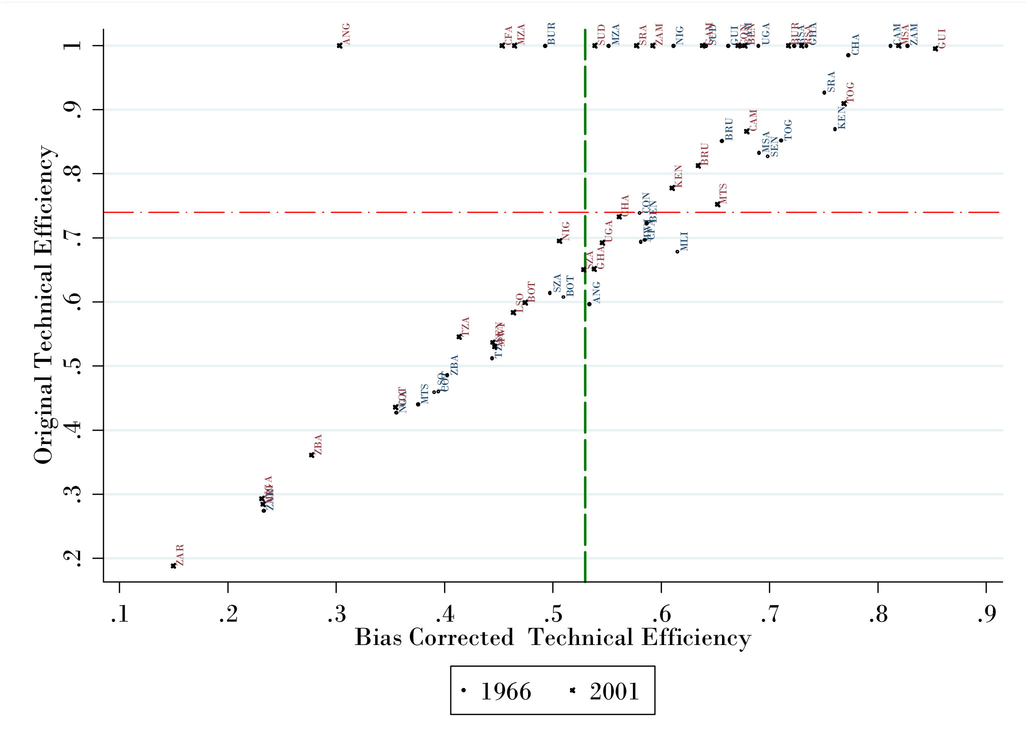

Figure 1: Scatter plot of standard and bias-corrected technical efficiencies, 1966 and 2001

Figure 2. Coefficient of variation

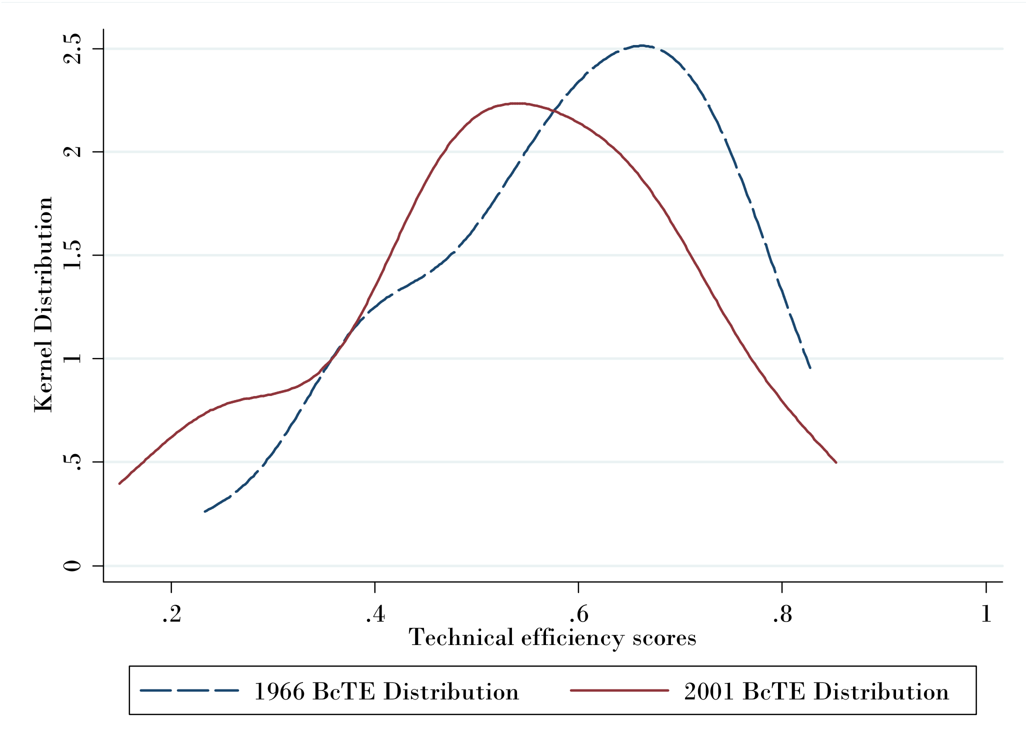

Figure 3: Kernel distribution of bias corrected efficiency scores, 1966 and 2001