Trends in Agricultural Production Efficiency and Its Implications for Food Security in Sub-Saharan African Countries.

Christian Nsiah
Baldwin Wallace University

Bichaka Fayissa
Middle Tennessee State University

Abstract

The main objective of this paper is to estimate trends in the agricultural sector production efficiency of a cross-section of African countries over time using panel data and data envelopment type analysis in order to assess the state of food security, or insecurity in the African continent. In particular, the study employs data for 49 African countries from 1995 to 2012 to estimate the year to year agricultural efficiency for cereal, crop, food, and non-food sectors against natural inputs for the agricultural sector. We analyze the determinants of annual efficiency scores and their growth rate, and subsequently investigate the impact of agriculture efficiency on food security. We find that the agriculture aid, capital infrastructure for the agriculture industry, sanitation, and good governance are the main drivers of agriculture efficiency and its growth. We find that a large portion Africa's agriculture sector growth for the period under consideration can be attributed to technical progress as opposed to efficiency changes. Substantively, we find that agricultural efficiency has a positive and significant effect impact on food security in Africa.

Key Words: *Technical and Allocative Efficiency, Agricultural production Efficiency Food Security, Africa, Data Envelopment Analysis (DEA), Food Security, and Africa*

JEL: D21, D24, L23 L25, 012

Keywords: Food Security, agricultural production efficiency, data envelopment analysis (DEA), African countries

African Finance & Economics Association Meeting/ASSA Annual Meeting

January 6-8, 2017

Chicago, Illinois

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1. Introduction

Africa has 54 nation states with an estimated population of 1.2 billion and the second largest and populous continent in the world in 2016. [1] In the absence of effective and focused measures to slow down the rate of population growth through education, family planning, delayed marriage, and abstinence, the population is expected to double in 27 years. According to the World Bank statistics, five of the fastest population growth countries in Africa between 2014 and 2015 are: Niger (4%), South Sudan (3.5%), Burundi (3.3%), Chad (3.3%), and Uganda (3.3%).[2] The young and the elderly make up more than 50 % of the dependent population who rely on the middle age group for their livelihood. With the young and relatively more educated population migrating to the cities in search of job opportunities and other amenities of life which typically have concentrated in and around the major cities in Africa, the rapid growth of armies of unemployed youths in the urban areas poses a ticking time bomb in the continent. In the backdrop of these scenarios, the fragmentation of land among the growing rural population and the intense pressure of transnational land transactions (known as land grabbing) expose farmers and urban dwellers to severe food insecurity and livelihood vulnerabilities, posing major concerns which African governments have to address sooner than later. A study of the changes in the agricultural production efficiency and their implications for domestic food security in the African continent is, therefore, timely and relevant.

The main objective of this paper is to estimate the trends in the agricultural sector production efficiency of a cross-section of African countries over time using panel data and data envelopment type analysis (*DEA*) known as the Malmquist Total Factor Productivity Index (*MPI*) model in order to assess the state of food security, or insecurity in the African continent. In particular, the study will explore the impacts the conventional sources of economic growth such as aid for agriculture, infrastructure investment, and governance on the annual agricultural production efficiency scores and its year-to-year rate of growth for a cross-section of 49 African countries from 1995-2012. The rest of the paper is organized as follows. The next section will highlight the existing literature pertaining to the recent trends in agricultural productivity during the study period. Section 3 will discuss the measures of efficiency and productivity of the African agricultural sector in an effort

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[1] (http://worldpopulationreview.com/continents/africa-population/).
[2] http://data.worldbank.org/indicator/SP.POP.GROW

to specify the empirical framework of the study. Section 4 discusses the main results of the study. The last section summarizes the findings and draws some policy implications of the state of food security in the African continent.

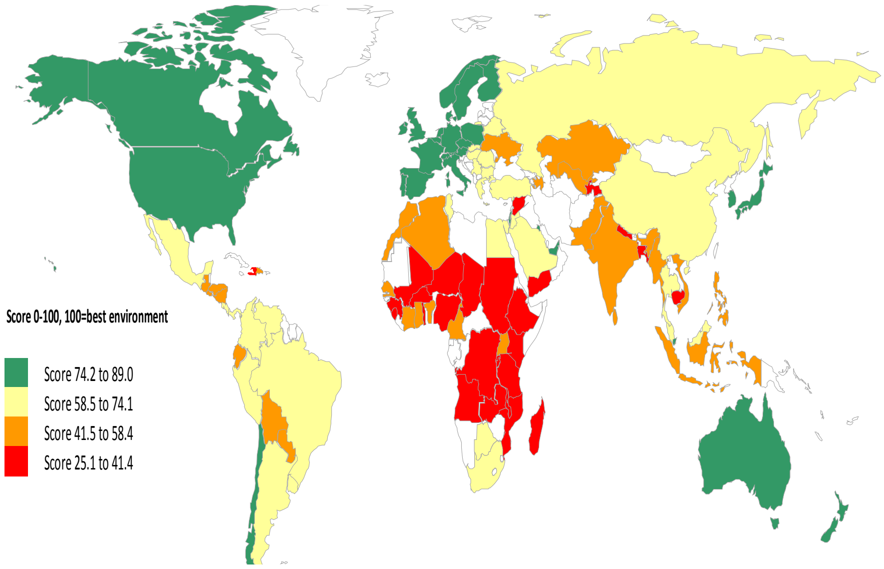
2. A Review of Selected Literature

The Green Revolution was adopted as the second wave of the growth and development strategy in less developed countries (LDCs) in Africa and throughout the developing world in the 1950s and the 1960s to increase agricultural production to meet rural and urban food supplies. The strategy was aimed at increasing agricultural productivity through a minimum package program of agricultural inputs such as improved seeds, fertilizer, and extension service workers who demonstrated to farmers on the correct applications of the inputs for realizing maximum yield of crops.

By all measures of productivity, the Green Revolution was a resounding success in terms of increasing agricultural productivity, but the strategy utterly failed in terms of providing complementary supporting services such as storage facilities, access to markets by investing in reliable transportation infrastructure so that farmers who took the risk of adopting the strategy can benefit from the marketing of their surplus production. Instead, they were exposed to a devastating risk due the spoilage of tons of their agricultural products and also by the backlash of being evicted by landlords who wanted to seize the opportunity to expand their mechanized commercial farming. Consequently, the potential benefits of the strategy in terms of improving the standard of living in the agricultural sector and its transformation from agrarian toward industrial economy, and more importantly, the potential for attaining food security in the African content and elsewhere became elusive as the aggressive pursuit of the strategy in developing countries waned over time.

While scientists have recently raised hopes that agricultural productivity can be increased to potentially cope with the problem of food insecurity of feeding the 9 billon people of the world's population, the same argument cannot be asserted in the case of the African continent which is the second most populous content of the world (Godfray et al., 2010). In fact, Figure 1 below shows that nearly two-thirds of African countries rank at the bottom of the Global Food Security Index (*GFSI*) owing to political instability, environmental degradation, climatic changes, the rapid rate of population growth, and the recent frenzy of the transnational land transactions phenomenon (otherwise, known as land grabbing) further squeezing, displacing, exposing famers to livelihood vulnerabilities.

Figure 1. Global food Security Index Score Map (2015)



Source: Economic Intelligence Unit

Estimating the total factor productivity (*TFP*) growth in agriculture for a panel of 39 sub-Saharan African countries from 1961 - 2007, Rezek et al. (2011) find that three estimation methods (stochastic frontier, generalized maximum entropy, and Bayesian efficiency) generate relative rankings that are consistent with the development outcome measures while the data envelopment (*DEA*) analysis approach performs poorly in this regard. Measuring and comparing the sources of total factor productivity (*TFP*) growth in African agriculture under contemporaneous and sequential technology frontiers over the period 1970–2004 and using a fixed-effects regression model and a polynomial distributed lag structure for agricultural R&D expenditures, Alene (2010) finds that African agricultural productivity grew at a rate of 1.8% per year. His findings further suggest that technical progress, rather than efficiency change, was the principal source of productivity growth. He also finds that agricultural R&D, weather, and trade reforms have significant effects on the productivity of African agriculture. In a recent study, Mugera (2013) uses data envelopment analysis and bootstrap data envelopment analysis to investigate whether technical efficiency in the agricultural sector of 33 African countries improved (catching up) for the 1966–2001 period and finds no evidence of efficiency catching-up (improving) in his full sample, although countries in the East African region exhibit evidence of efficiency catching-up.

Employing a two-stage procedure to investigate the impact of macroeconomic policy reforms on the agricultural productivity growth of 33 African countries from 1981 to 2001 and measuring agricultural productivity using a nonparametric Malmquist productivity index in the first stage and a generalized method of moments (GMM) model with a measure of structural adjustment program (SAP) intensity as a key instrument for macroeconomic policy reform in the second stage, Ojede et al. (2013) find a strong positive relation between the SAP intensity and agricultural productivity, suggesting that the macroeconomic policy reforms improved agricultural productivity growth in the sample countries. This study follows similar steps to assess the impact of various factor inputs on agricultural production efficiency during a given time period and their changes over time to draw inferences with respect to their implications for food security in the African continent in the next section.

3. Model

The goals of this study are threefold. First, we seek to measure the trends in African agricultural efficiency and the year-over-year efficiency growth rate for African countries over time. The second objective is to perform a statistical analysis to determine the dynamics of the major drivers of African agricultural efficiency and its growth over time. Thirdly, we seek to analyze and draw inferences with respect to the impact of agricultural production efficiency on food security in Africa. To accomplish the intended objectives, our analysis is done in two stages. We first will use the Malmquist Total Factor Productivity Index *(MPI*) statistical routine to figure out the annual efficiency scores for each country and their associated related growth rate and use the efficiency scores in the second stage of the analysis to articulate its identify their main determinants. Our analyses include data for 49 African countries for the period of 1995-2012. The choice of countries and periods included in the study is based on data availability.

3.1 Measuring the Efficiency and Productivity of the African Agriculture Sector

Our study seeks to estimate the efficiency scores and its growth rate for the Agriculture sector in a typical African country in the sample. For this study, we specifically focus on the efficiency of the natural inputs in the African agriculture production process. Hence, the input variables include agricultural land (percentage of land area), land under cereal production (hectares) arable land (hectors per person), average precipitation in depth (mm per year), rural population (as percent of total population), total economically active population in agriculture, and agricultural area (1,000 hectares). On the other hand, the output variables considered include cereal production (metric tons), cereal yield, crop production index, food production index, nonfood production index, and cereal production index. We eliminated livestock production from our analysis because it made our model unstable. All the data for this stage of our analysis are from the Food and Agriculture Organization of the United Nations (FAO) dataset.

It is common in the efficiency measurement literature to either use parametric and or nonparametric frontier estimation techniques to measure the efficiency of decision-making units (DMUs). Both types of analyses have their advantages and disadvantages (see, Jarzębowski, 2013). For our analysis, however, we employ a nonparametric efficiency scores estimation model called the Malmquist Production Index (*MPI*), popularized by Caves et al. (1982) and improved upon by Fare et al. (1994). One of the criticism of the model postulated by Caves et al. (1982) is that it does not provide a means of estimating inefficiency scores. Fare et al. (1994) solved the problem by including the measurement of efficiency to the productivity index provided by the Caves et al. (1982) paper. It is worth noting that the Malmquist total productivity index (*MPI*) estimator is dependent on Data Envelopment Analysis (DEA), which itself is a linear programming based model. The model, not only presents annual efficiency scores similar to what *DEA* models, but will present on a year to year basis for all the countries in our analysis. It also provides a measurement for the rate of productivity changes between periods for each decision making unit (*DMU*) which in this case refers to the 49 individual African countries included in this study.

Before defining the formula for the Malmquist Productivity Index (*MPI*), it is appropriate to define two groups of linear programming distance functions as given in equations 1 and 2.

$$\left\{\widehat{D}_i^t(x_i^t, y_i^t)\right\}^{-1} = \text{Max } \theta \tag{1}$$

s.t.

$$\theta y^{t}_{im \leq \sum_{j=1}^{L} \tau_j^t y_{mj}^t}; \ m = 1,\ldots,M; \ \sum_{j=1}^{L} \tau_j^t x_{jn}^t \ \leq x_{in}^t, \ n = 1,\ldots,N; \ \tau_i^t \geq 0, \ \ i=1,\ldots,L.$$

where x_i and y_i denote inputs and output for country *i*, respectively, and *t* denotes time period one.

$\tau_i^t = (\tau_1^t, \ldots, \tau_L^t)$ is a vector of weights that forms a convex combination of each country's efficiency observation relative to the reference country in the analysis. We can replace *t* with *t+1* to reflect the next period information. These calculations measure the distance of each country's efficiency score from the reference best practice country for each year. The inverse of Equation 1 presents DEA type efficiency scores for any period and country. It is worth noting at this junction that $\widehat{D}_i^t$=1 indicates the i^{th} country is technically efficient and as such will lie on the efficiency frontier, whereas $\widehat{D}_i^t$≤1 denotes at technically inefficient country. The distance between a country's efficiency score and the frontier value of one (1) represents the magnitude of the technical inefficiency of the country in question for that particular year.

$$\left\{\widehat{D}_i^t(x_i^{t+1}, y_i^{t+1})\right\}^{-1} = \text{Max } \theta \qquad (2)$$

s.t.

$$\theta y^{t+1}_{im \leq \sum_{j=1}^{L} \tau_j^t y_{mj}^t}; \ m = 1,\ldots,M; \ \sum_{j=1}^{L} \tau_j^t x_{jn}^t \ \leq x_{in}^{t+1}, \ n = 1,\ldots,N; \ \tau_i^t \geq 0, \ \ i=1,\ldots,L.$$

As one can notice, Equation 2 information above includes data for time t and time *t+1*. We can also switch the periods in Equation 2 and calculate a second mixed period distance function denoted by$\widehat{D}_i^{t+1}(x_i^t, y_i^t)$. This set of two equations measures the distance of the reference technology in period *t+1* relative to time t. Historically, the estimation of Equations 1 and 2 has been done with an assumption of either constant returns to scale (CRS) or variable return to scale (VRS) assumptions. For our purpose, we deploy the CRS to aid as with our estimation of the distance functions which we will use for our Malmquist Productivity Index. Further, Grifell-Taje and Lovell (1995b) indicate that the Malmquist Index typically underperforms in estimating productivity index when the model specification is not CRS. One can model equations 1 and 2 from the perspective of input minimization or output maximization. For our analysis, we employ input minimization orientation.

The Malmquist Total Factor Productivity Index *(MPI*) between period *t* and *t+1* is calculated as the geometric mean of the input-based Malmquist Production Indices for periods *t* and *t+1* is presented in Equation 3.

$$MPI(y^{t+1}, x^{t+1}, y^t, x^t) = \left[\frac{D^t(y^{t+1}, x^{t+1})}{D^t(y^t, x^t)} \ X \ \frac{D^{t+1}(y^{t+1}, x^{t+1})}{D^{t+1}(y^t, x^t)}\right]^{1/2} \qquad (3)$$

The *MPI* specifically measures the productivity changes along with time variations and this index can be decomposed into technical efficiency change also known as "catch up effect" (*EFFCH*) and technical change between the two periods, respectively (*TECHCH*). Equation 4 breaks down Equation 3 into two categories described above.

$$MPI(y^{t+1}, x^{t+1}, y^t, x^t) = \left[\frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)}\right]\left[\frac{D^t(y^{t+1}, x^{t+1})}{D^{t+1}(y^{t+1}, x^{t+1})} \ X \ \frac{D^t(y^t, x^t)}{D^{t+1}(y^t, x^t)}\right]^{1/2} \qquad (4)$$

where the first part of the equation measures the efficiency change and the second argument measures the pure technical change between periods. The pure technical change essentially measures the shift in the reference frontier, whereas the efficiency change measures "catch up" in technical efficiency, i.e. it measures how much closer, or further away an African country can get to African countries with the best practice in terms of Agriculture efficiency.

As indicated in Lee et al. (2011), the technical efficiency change can be further broken down into two parts including a scale efficiency change (*SECH*) and a pure efficiency change (*PECH*). These measures are represented by equations 5 and 6, respectively

$$SECH = \left[\frac{D_{vrs}^{t+1}(x^{t+1},y^{t+1})/D_{crs}^{t+1}(x^{t+1},y^{t+1})}{D_{vrs}^{t+1}(x^{t},y^{t})/D_{crs}^{t+1}(x^{t},y^{t})} X \frac{D_{vrs}^{t}(x^{t+1},y^{t+1})/D_{crs}^{t}(x^{t+1},y^{t+1})}{D_{vrs}^{t}(x^{t},y^{t})/D_{crs}^{t}(x^{t},y^{t})}\right]^{1/2} \quad (5)$$

$$PECH = \frac{D_{vrs}^{t+1}(x^{t+1},y^{t+1})}{D_{crs}^{t}(x^{t},y^{t})} \quad (6)$$

3.2 Analysis of the determinants of African Agriculture Efficiency & Their Impact on Food Security

The main goals of this paper are to estimate the static efficiency of the African agriculture sector and the growth rate of the agricultural efficiency over time, analyze the determinants of the efficiency and its growth, and subsequently explore the impact of agricultural efficiency on food security. This is to say that in stage 2 of this project, we will conduct two different analyses: (1) the determinants of static agriculture sector efficiency scores and the year on year growth and (2) the impact of agriculture efficiency on the food security of African countries. To estimate our coefficients in both analyses, we employ a model which considers the first difference transformation and considers in its dynamics the lagged levels as well as lagged differences. Specifically, it is noteworthy to mention that our second stage analysis will be conducted using STATA's Arellano-Bover/Blundell-Bond (XTDPSYS) estimator which uses the xtabond moment conditions and moment conditions in which lagged first differences of the dependent variable are instruments for the level equation (see, Arellano and Bover, 1995; and Blundell and Bond, 1998).

We employ the following GMM equation (7) to conduct our analysis of the determinants of the static annual efficiency scores for Africa's agriculture sector, its growth rate, and its impact on food security in Africa.

$$\Delta EFF_{ijt} = \gamma_t - \gamma_{t-1} + \alpha \Delta EFF_{ij,t-1} + \Delta x_{it}' \beta + n_i + \Delta \vartheta_{it} \;\; for\ i = 1, \ldots, N \;\; and\ t = 3, \ldots T. \quad (7)$$

where ΔEFF_{ijt} denotes the log difference of the jth efficiency measure for country *i* at time *t*, where the efficiency measure *j* can either be the annual efficiency scores (EFF), or the year- to-year productivity changes (M*PI*). Note also that n_i and γ_t denote the differences in the initial level of efficiency and the productivity changes that are common to all countries (also known as the period specific), respectively. x_{it} is a vector of other variables considered as determinants of agricultural efficiency and the year-to-year productivity changes. The explanatory variables employed include total agriculture aid (*AFFA*), agricultural research aid (*AGRAC*), fertilizer usage (*TFERT*), agricultural machinery availability index (*MACH*), land with irrigation (*IRRIG*), domestic food price volatility index (DFPVI), official exchange rate (*EXCH*), and openness to trade (*TRADE*). Other variables employed includes inflation rate (*INFLA*), real gross domestic product (*GDP*), governance index (*GOV*), access to communication technology proxied with telephone technology index (*TEL*), and access to sanitation facilities (*SAN*). Please note that the *MACH*, *GOV*, *TEL*, and *SAN* are all indices generated via factor analysis (see, appendix for more information about these indices).

3.3 Analysis of the Impact of Agriculture Efficiency on Food Security for Africa

To estimate the impact of the static annual agricultural efficiency scores on food security in Africa, we estimate a variation of Equation 7 above with proxies for food security ($DOFD_{ijt}$) as our dependent variables.

$$\Delta DOFD_{ijt} = \gamma_t - \gamma_{t-1} + \alpha \Delta DOFD_{ij,t-1} + \Delta x'_{it}\beta + n_i + \Delta\vartheta_{it} \;\; for\; i = 1, \dots, N \;\; and\; t = 3, \dots T. \tag{8}$$

It is important to note that there exist myriad definitions for food security. However, the most widely used definition is the one that came out of the 1996 World Food Summit which indicate that "food security is achieved when all people, at all times, have physical, social and economic access to sufficient, safe and nutritious food to meet their dietary needs and food preferences for an active and healthy life." (FAO, 2009). In the same spirit, one can follow FAO and define food insecurity as "A situation that exists when people lack secure access to sufficient amounts of safe and nutritious food for normal growth and development and an active and healthy life" (FAO, 2002). In its 2002 food insecurity report, FAO disaggregated food security into four parts including food availability, food accessibility, food utilization, and food system stability. Availability focuses on food production whereas accessibility focuses on the ability of people to obtain food through either production, purchase, or transfers. Food utilization focuses on the nutritional value of food, the interaction with physiological condition and food safety. Food system stability focuses on stability of supply and access as well as the ability to respond to food emergencies. In this spirit, we employ four food security proxies, one for each part of the food security descriptors including average dietary energy supply adequacy (*ADESA*) for availability, depth of food deficit (*DOFD*) for access, number of people undernourished (*NOPUN*) for utilization, and per capita food supply variability (*PCFSV*) for stability.

Our main explanatory variables in this case include the estimated annual static agriculture efficiency scores (*EFF*) and annual food aid (*AFFA*). Following the existing literature, we control for openness to trade (*TRADE*) and governance performance (*GOV*). We also include infrastructure development proxied by telephone lines (*TEL*), financial development proxied with Domestic credit provided by financial sector as a percent of GDP (*DCFS*), and macroeconomic performance measured with inflation (*INLA*). Purchasing power is proxied with the per capita GDP (*GDPPC*), dependency ratio (*ADR*), and global competitive positioning proxied with the exchange rate defined as the number of African currency units needed to a dollar (*ACUPD*). The results of thee analyses are presented in the next section.

4.0 The Estimation Results

4.1 Productivity and Efficiency of the African Agriculture Sector

The *DEA* type annual efficiency scores were calculated for each country. We find that 12 African countries in including Botswana, Carpe Verde, Congo Democratic Rep., Egypt, Gabon, Libya, Namibia, Niger, Sao Tome and Principe, Somalia, South Africa and Zambia were on the efficiency frontier each year of our analysis. On the other hand, 17 countries including nine from West Africa were never efficient in any of the period under consideration. These countries include Benin, Burkina Faso, Burundi, Cote d'Ivoire, Ethiopia, Ghana, Guinea, Guinea Bissau, Kenya, Madagascar, Malawi, Morocco, Mozambique, Senegal, Sierra Leone, Togo, and Uganda. The rest of the countries were a mixed bag of efficient and inefficient years.

Next, we turn our attention to the results of the MPI growth rate estimation. Here, we must recall that the MPI can be broken down into technological change (*TECHCH*) and efficiency change (*EFFCH*), which itself can be further broken up into scale efficiency change (*SECH*) and pure efficiency change (*PECH*). We find that for the period under consideration, Africa experienced a 3.9% average growth in total efficiency (MPI), 0.9% in catch up effect (*EFFCH*), 3.3% in technical change (*TECHCH*), 1.011% in pure efficiency change (PECH), and 0.5% in scale efficiency change. This result is similar to Alene (2010) finding that technical progress rather than efficiency change is the main source of African agriculture sector's productivity growth. The top 5 highest average total productivity gains include Cape Verde (18.2%), Botswana (13.6%), Malawi (11.1%), Morocco (7.9%), and Rwanda (7.2%). On the other hand, the worst growth countries include Sao Tome and Principe (-1.2%), Gambia (-0.9%), Lesotho (-0.9%), Swaziland (-0.3%), Mauritius (-0.2%). Angola scored the highest average growth (5.1%) in *EFFCH*, whereas Zimbabwe experienced the worst *EFFCH* growth (-2.1%). In terms of technical efficiency change, Cape Verde recorded the highest average growth rate of 18.2%, whereas Sao Tome and Principe experienced the worst technical efficiency change of -01.2%. In terms of the pure efficiency change, Malawi recorded the highest average growth rate of 7.0%, whereas Sudan lagged behind with a -0.6% growth. Lastly, we find that Angola experienced the highest average growth of 5.2% for the scale efficiency change, whereas Sudan and Tanzania lagged the group with an identical negative growth rate of -0.5%. The table presenting the summary of the average growth rates in the efficiency scores by country is located in the appendix.

We combine the *DEA* type results with the *MPI* results to differentiate each county's performance for the period under consideration. Presented in the 2x2 matrix below is the outcome of this analysis.

Table 2. Efficiency Performance Matrix

1995 Efficiency Position	1995 - 2012 Average MPI Growth Rate: High Growth	1995 - 2012 Average MPI Growth Rate: Low Growth
Efficient	Botswana, Cabo Verde, Chad, Gabon, South Africa, Sudan, Tanzania, Zambia	Central African Republic, Comoros, Congo D.R., Congo R., Egypt, Eritrea, Gambia, Lesotho, Libya, Mali, Namibia, Niger, Nigeria, Sao Tome and Principe, Somalia, Swaziland
Inefficient	Angola, Burkina Faso, Cameroon, Cote d'Ivoire, Ethiopia, Ghana, Guinea, Guinea-Bissau, Kenya, Liberia, Malawi, Morocco, Mozambique, Rwanda, Senegal, Sierra Leone	Algeria, Benin, Burundi, Zimbabwe, Madagascar, Mauritius, Togo, Tunisia, Uganda, Zimbabwe

Table 2 presents a 2x2 matrix of the efficiency performance of the countries considered in our analysis. The vertical axis measures whether the country in question was efficient in 1995, or not, whereas the horizontal axis measures whether a country experienced a more than average total growth in efficiency, or inefficiency over the 1995-2012 period. Thus, the countries in the upper left portion of the matrix are countries which were efficient in 1995 and recorded a growth rate that is higher than the average for African countries for the period (we label these countries the "*trend setters*"). The countries in the top right portion of the matrix are the ones that were efficient in 1995, but experienced below average efficiency growth for the period (we label these countries "*falling stars*"). The countries located at the bottom left of the matrix are the ones that were inefficient in 1995, but has recorded higher than average growth rates in efficiency (we label these countries "*shooting stars*"). Lastly, the countries at the bottom right of the matrix are the ones which were inefficient in 1995 and also recorded below average efficiency growth rates over the period of our study (these countries are labeled "*the strugglers*").

4.2 Determinants of African Agriculture Efficiency

We employed STATA's Arellano-Bover/Blundell-Bond dynamic GMM estimator for analyzing the determinants of agriculture efficiency and its growth as specified in Equation (7). We run the two estimation models for the annual static efficiency scores (see, columns 1 and 2 in Table 2 below) and two for the year-to-year agriculture efficiency growth rates (MPI), the results of which are presented in columns 3 and 4 of Table 2. The main difference between models: 1 and 2, 3 and 4, respectively is the fact that while Models 1 and 3 employ total agricultural aid (*AFFA*) disbursed to the countries as a proxy for foreign agriculture aid, Models 2 and 4 control for agriculture research aid (*AGRAC*).

<<Insert Table 2 here>>

Broadly, the results of the models reveal the expected relationship between the agriculture efficiency and growth rates and the explanatory variables. Because we estimated a double-logarithmic model, all the coefficients represent elasticities. We find that the lag of the annual efficiency scores (*EFF)* has a positive impact on the current performance in Models 1 and 2. This indicates a situation where the "catch up effect" is not present in the sense that countries that performed well in the previous year are more likely to perform better in the current period. Specifically, we find that a percentage difference in past efficiency scores lead to between 0.40and 0.44 percent difference in the most current efficiency scores. In the case of total agriculture aid, we find that while current total aid (*AFFA*) has a negative relationship with performance, its lag has a positive impact on efficiency scores. More specifically, we find that a 1% increase in current total agriculture aid disbursement leads to a -0.0113% decrease in current efficiency scores and a 0.0097% increase in the next period's scores. This may be the case because the current aid disbursement maybe in reaction to a crisis in the African countries (hence the negative sign), it helps to build capacity for the future, thus, increasing the efficiency scores for the next period. Other significant determinants of agriculture efficiency scores when controlling for total agriculture aid include: agriculture machinery index (MACH), governance performance (GOV), and access to improved sanitation facilities (SAN). Here, we find that a 1% increase in MACH, GOV, and SAN leads to a 0.027%, 0.42%, and 1.119% increase in agriculture efficiency scores, respectively.

For the case where we control for agriculture research aid (*AGRAC*), we find that it is the lag of *AGRAC* has a positive impact on agriculture production efficiency (see Model 2 of Table 1). Specifically, a 10% percent increase in agriculture research aid leads to a 0.09% increase in the next period's efficiency scores. Other variables that significantly affect efficiency scores when controlling for research aid include: trade, governance, availability of telephone service, and access to improved sanitation. We find that a 1% increase in GOV, TEL and SAN leads to a 0.25%, 0.49% and 1.08% increase in the annual agriculture efficiency performance, respectively. On the other hand, a 1% increase in trade leads to -0.01% decrease in the annual agriculture efficiency performance.

Combining Models 2 and 3 of Table 2, we can conclude that the variables that consistently and significantly impact African country's annual agricultural efficiency include: past efficiency attainments, agriculture aid, governance, and improved access to sanitation facilities. We also find that the variables with the largest impact on annual agriculture efficiency scores include access to improved sanitation facilities, past efficiency performance, and governance.

Models 3 and 4 of Table 2 report the analysis of the growth rate in total agriculture productivity (MPI). Here, we find that previous year's growth rate has a significantly negative impact on current year growth rates. This result is in line with the argument that the growth prospects of worst performers is better than good performers. Specifically, we find that a 1% increase in the previous year's productivity growth rates lead to between -0.19% and -0.46% decrease in current growth rate depending on the model in question (see, Models 3 and 4 of Table 2).

Model 3 presents the case where we employ total agriculture aid as the proxy for agriculture aid. Here, we find that the variables that significantly affect the total agriculture productivity growth include the lag of agriculture aid, irrigated land (*IRRIG*) and its lag, domestic food price volatility (*DFPVI*) and its lag, and Trade. Specifically, we find that a 1% increase in total agricultural aid leads to a 0.012% in agricultural productivity growth. We find that the current state of irrigation in a country positively affects current agriculture growth, whereas the lag of it has a negative impact on agricultural productivity growth. Specifically, we find that a 1% increase in the number of irrigated lands, leads to 0.373% and -0.367% growth in agriculture productivity growth in the current period and the next period, respectively. We find that a 1% increase in current food price volatility have a positive impact on current growth but a negative impact on the next period's productivity growth. We find that a 1% increase in DFPVI leads to 0.04% and -0.05% increase in the productivity growth in the current and next period, respectively. The negative effect may be due to the fact that farmers are risk averse and may choose to underutilize their capacity in the face of more current price volatility. The only other variable that significantly affects agricultural growth in Model 3 is trade for which we find that a 1% increase in it leads to a -0.09% decrease in agriculture productivity growth. For the case where we control for agricultural research aid, apart from its own lag, the only variable that significantly affects agricultural productivity growth is the lag of agricultural research aid and TEL. We find that a 1% increase in research aid in the current period and a 1 % increase in telephone service availability leads to 0.01% and 0.78% increase in the next period's agriculture productivity growth, respectively.

4.3 The Impact of Agriculture Efficiency on Food Security in Africa

As mentioned earlier, food security can be broken down into four parts including access, availability, stability, and utilization. In order to assess the impact of agricultural production efficiency on food security in our analysis, we proceed to ran four versions of Equation (6). Table (3) presents the results of these analyses. Specifically, model 1 deals with the issue of access which we proxy with the depth of the food deficit (*DOFD*) and model 2 presents our analysis of availability issue which is proxied by average dietary energy supply adequacy (*ADESA*). Proxied with per capita food supply variability (*PCFSV*), model (3) presents our stability while model (4) presents the utilization analysis proxied by number of people undernourished (*NOPUN*).

<<Insert Table 3 here>>

In the case of access, the variables that significantly increase the depth of food deficit include its own lag, the lag of domestic credit provided by the financial sector (*DCPFS*), exchange rate *(EXCH*), and food aid (*FAID*). More specifically, we find that a 1% increase in previous year's depth of food deficit leads to 1.02% increase in the current food deficit. This is to say that the countries that experience higher food shortage today are more likely to experience even greater food deficits in the future. A 1% increase in the lag of *DCPFS*, *EXCH*, *GDP*, and *FAID* leads to a 0.02%, 0.01%, 0.03% and 0.005% increase in the depth of food deficit, respectively. The variables that significantly help to reduce food deficit includes current values of *DCPFS*, the lag of agricultural efficiency performance (*EFF*), real gross domestic product (*GDP*), governance (*GOV*), telecommunication infrastructure (TEL), and accessibility of improved sanitation facilities (SAN). We find that a 1% increase in *DCPFS*, *EFF*, *GDP, GOV, TEL* and *SAN* leads to 0.02%, -0.07%, 0.12%, 0.28%, and 0.01% decrease in the depth of food deficit, respectively.

In terms of availability, we find that a 1% difference in prior year's average dietary energy supply adequacy leads to a 1.011% difference in current year's adequacy. Again, this indicates that the countries that have a history of adequacy are the ones that are most likely to have higher adequacy numbers. The variables that have a significant positive effect on the average dietary energy supply adequacy includes agricultural efficiency performance (*EFF*), domestic food price volatility index (*DFPVI*) and its lag, age dependency ratio (*ADR*), and telecommunication infrastructure (*TEL*). Specifically, we find that a 1% increase in *EFF*, *DFPVI*, the lag of *DFPVI, ADR*, and TEL leads to a 0.01%, 0.0018%, 0.002%, 0.04%, and 0.03% change in the average dietary supply adequacy, respectively. The results for the age dependency ratio and the food price volatility are somewhat confusing because one will expect these variables to have a negative impact on adequacy. The variables that have a significant negative impact on availability include the lags of the *EFF* and *ADR*, exchange rates (*EXCH*), income real gross domestic product (*GDP*), and food aid (*FAID*). Specifically, we find that a 1% increase in the lag of *EFF*, the lag of *ADR*, *EXCH*, *GDP*, and *FAID* leads to 0.01%, 0.44%, - 0.001%, 0.004%, and 0.0001% decrease in average dietary energy supply adequacy, respectively.

We employed per capita food supply variability (*PCFSV*) as our proxy for the stability dimension of food security. As in the two previous cases, we find that countries with high current per capita food supply variability are more likely to experience more food supply variability in the future. Specifically, we find that a percent difference in current food supply variability today will lead to 0.70% difference in food variability in the future. Here, the only variables that significantly affect the food supply variability include agricultural efficiency scores, the lag of domestic food price variability, and access to improved sanitation facilities. Specifically, we find that a 1% increase in current agricultural efficiency leads to a 0.31% increase in the next period's per capita food supply variability. This indicates that an increase in agricultural efficiency significantly increases future variability in food supply. On the other hand, we find that a 1% increase the previous period's domestic food price volatility leads to a 0.03% increase in current period's food supply volatility. Interestingly, we find that a 1%t increase in the availability of improved sanitation facilities is associated with a 1.172% decrease in food supply volatility.

Model 4 presents our analysis of the determinants the utilization dimension of food security, which we proxied with the number of undernourished people. Similar to the three previously discussed food security dimensions, we find that countries with previously high portion of their population undernourished are more likely to have more of their population undernourished in the current period. Specifically, we find that a 1% difference in the number of undernourished people in a country will lead to 0.99% difference in the current period of undernourishment. The only other variables that significantly impact the number of undernourished people in a country include domestic credit provided by financial sector (*DCPFS*), agricultural efficiency (*EFF*), exchange rate (*EXCH*), and food aid (*FAID*). We find that a 1% increase in *DCPFS* and *EFF* leads to 0.019% and 0.067% decrease in the number of malnourished people. On the other hand, we find that a 1% depreciation of the domestic currency and food aid leads to a 0.01% and 0.004% increase in the number of malnourished people. Thus, we can conclude the credit availability and improved agriculture performance lead to a significant reduction in the population of malnourished citizens of a country, while domestic currency depreciation and food aid exacerbate the malnourishment situation in a typical African country.

5. Summary and Conclusion

The objectives of this study are threefold. First, we seek to measure the trends in African agricultural efficiency and their changes over time. The second objective is to perform a statistical analysis to determine the dynamics of the major drivers of African agricultural efficiency over time. Thirdly, we seek to seek to draw inferences with respect to the impact of agricultural production efficiency on food security in Africa. To accomplish the intended objectives, our analysis is done in two stages. We will first use the Malmquist Total Factor Productivity Index *(MPI*) statistical routine to figure out the annual efficiency scores for each country and their related growth rate and use the efficiency scores in the second stage of the analysis to identify their main causal factors. Our analysis employs a panel data of 49 African countries over the 1995-2012. The choice of countries and the time period included in the study is based on data availability.

In terms of the agriculture efficiency scores, we find that 27 of the 49 African countries in this study were on the efficiency frontier in 1995, given the natural resources inputs. We also find that the African agriculture sector experienced average efficiency growth rates of 1.039%, 1.009%, and 1.033%, in total factor product productivity, technological change, and efficiency change, respectively for the period under consideration. This finding indicates that the growth rate of the Agriculture sector for the period under consideration was largely championed by technical progress as opposed to efficiency changes. Recalling our earlier argument that the efficiency change can be broken down into scale efficiency and pure efficiency change, we find that African countries experienced an average growth of 1.011% in pure efficiency change and 1.005% and in scale efficiency change for the period under consideration. We also find that only nine out of the 27 countries that were on the efficiency frontier in 1995 remained on the frontier throughout the period covered by this study. These nine countries which we refer to as "*trend setters*" include Botswana, Cape Verde, Chad, Gabon, South Africa, Sudan, Tanzania, and Zambia. On the other hand, 17 countries (nine from West Africa and the other eight from different African regions) were never efficient in any of the period under consideration. These countries include Benin, Burkina Faso, Burundi, Cote d'Ivoire, Ethiopia, Ghana, Guinea, Guinea Bissau, Kenya, Madagascar, Malawi, Morocco, Mozambique, Senegal, Sierra Leone, Togo, and Uganda. These are countries we labelled as "*the strugglers*" in terms of agricultural production efficiency.

With respect to the determinants of the annual agricultural production efficiency, we find that previous year efficiency performance positively impacts current year performance largely negating "catch up" effect similar to a recent study by Mugera (2013). The lags of general agricultural aid and agricultural research aid are found to be positively related with total agriculture efficiency, reflecting the importance of such aid in boosting the agricultural sector productivity in Africa. The other variables that consistently impact agricultural production efficiency include good governance and the availability of improved sanitation facilities. Good governance is important because it fosters the legal and institutional framework of land holding and other property rights which are critical for improving agriculture production efficiency. Good sanitation promotes health which increases labor productivity. We also analyzed the determinants of total factor productivity growth and found that countries that achieving high efficiency growth in the previous period less likely leads to high efficiency growth in the future, but agriculture aid consistently impacts agricultural efficiency growth.

Next, we explore the impact of agricultural sector efficiency on food security. Food security has four components including: food availability proxied by average dietary energy availability (*ADESA*), food accessibility proxied with the depth of food deficit (*DOFD*), food utilization proxied by the number of people undernourished, and food stability (*NOPUN*) proxied with per capita food supply variability (*PCFSV*). In the case of food availability, we find that countries with better current food availability history are more likely to experience better food availability in the future. We also find that food availability impacted by state of agricultural efficiency, governance, and telephone infrastructure. On the other hand, HIV infection rates, lag of age dependency, domestic currency depreciation, and food aid are negatively related to food availability. With respect to food accessibility, we find that countries with a current history of high food deficits are more likely to experience high deficits in the future as well. We find that the lag of agriculture efficiency, telephone infrastructure, the size of the economy, and financial sector improvement tend to improve the food deficit situation in a typical country, whereas the depreciation of the domestic currency relative to the dollar and food aid are found to worsen the food deficit situation. In the case of per capita food supply variability which we used as a proxy for food supply variability, we find that agricultural efficiency score and domestic food price variability are the two main causes of variability in food supply, whereas improvement in sanitation facilities actually help reduce the variability in food variability. For food utilization proxied with the number of undernourished people, we find that countries with a history of the prevalence of undernourishment are more likely to exhibit high numbers of undernourished population in the future. Other factors that contribute to worsening the undernourishment situation include the depreciation of the domestic currency and food aid. On the other hand, access to credit and agriculture efficiency tend to reduce the number of undernourished people in a country. From the above discussions, we can draw the conclusion that improved agriculture efficiency is a consistent determinant of food security as it helps to improve food availability, accessibility, and utilization. It is, therefore, critical for African governments, their stake holders, and development partners to promote the factors that positively impact agricultural production efficiency and its growth rate (agriculture aid, infrastructure, and good governance) to attain reliable food security in the face of ever rising population growth rate.

References

Alene, Arega D., 2010, “Productivity Growth and the Effects of R & D in African Agriculture,” *Agricultural Economics*, 41 (3-4):223-238.

Arellano, M. and S. Bond. (1998). Dynamic panel data estimation using DPD98 for GAUSS: a guide for users. Mimeo, Institute for Fiscal Studies, London.

Arellano, M. and O. Bover. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics*, 68: 29-52.

Binam, J.N., J. Tonye, N. Wandji, G. Nyambi, and M. Akoa,, 2004, "Factors Affecting the Technical Efficiency Among Smallholder Farmers in the Slush-Burn Agriculture," *Food Policy*, 29(5):531-545.

Caves, D.W., Christensen, L.R., and Diewert, W.E. (1982). The economic theory of index numbers and the measurement of input, output, and productivity, *Econometrica*, 50(60): 1393-1414.

Coelli, Tim J. and D.S. Prasada Rao, 2005, "Total factor productivity growth in agriculture: a Malmquist index analysis of 93 countries, 1980–2000," *The Journal of the International Association of Agricultural Economists*, 32(1), (January 2005): 115-134.

FAO (2009), Food Security and Agricultural Mitigation in Developing Countries: Options for Capturing Synergies, pages 1 – 84, http://www.fao.org/docrep/012/i1318e/i1318e00.pdf

Fare, R., Grosskopf, S., Norris M., and Zhang, Z. (1994). Productivity growth, technical progress, and efficiency change in industrialized countries. *American Economic Review*, 84(1): 66-83.

Godfray, H. Charles, John R> Beddington, Ian R. Crute, Lawrence Haddad, David Lawrence, Jame F. Muir, Jules Pretty, Sherman Robinson, Sandy M. Thomas, and Camila Toulmin, 2010, Food Security: The Challenge of Feeding 9 Billion People," *Science*, (5967, February 12, 2010):810-818.

Grifell-Tatjé, E., and Lovell, C.A.K. (1995). A note on Malmquist productivity index, *Economic Letters*, 47(2): 169-175

Jarzębowski, S (2013), "Parametric and Non-Parametric Efficiency Measurement – The Comparison of Results," *Quantitative Methods in Economics*, 14(1):170-179.

Lee, K.-R., Lee, C. W., Leem, B.-I. & Lee, C., (2011). Malmquist productivity index using DEA frontier in Stata. *The* Stata *Journal*, Issue 2, 1-9.Mugera, A. and A. Ojede, 2014, Technical Efficiency in African Agriculture: Is It Catching Up or Lagging Behind," *Journal of International Development*, 26(6):779-795.

Nkamleu, Guy Blaise, 2004, "Productivity Growth, Technical Progress and Efficiency Change in African Agriculture," *African Development Review*, 16(1):203-222.

Ojede Andrew, Amin Mugera, and Daigyo Seo, 2013, "Macroeconomic Policy Reformas and Productivity Growth in African Agriculture, *Contemporary Economic Policy* 31 (4):814-830.

Rezek, Jon P., Randy Campbell and Kevin E. Rogers, 2011, "Assessing Total Factor Productivity Growth in Sub-Saharan African Agriculture," *Journal of Agricultural Economics*, 62(2):357-374**.**

Table 1. Descriptive Statistics of Variables for Stage 2 Analysis

Variable	Description	Source	Mean	Stdev	MIN	MAX
Efficiency Analysis Variables						
AFFA	Agriculture, forestry, fishing aid disbursement (Millions $)	FAO	26.10	41.26	0.00	404.09
AGRAC	Agricultural research aid disbursement (constant million$)	FAO	1.77	4.16	0.00	56.69
TFERT	Total fertilizer use in thousands of tonnes (Phosphate + Potash + Nitrogen Ferilizers)	FAO	82.01	225.94	0.00	1840.40
MACH	Agricultural Machinery Index	FAO	55.28	5.53	52.37	100.00
IRRIG	Percentage of arable land equipped for irrigation (%) (3-year average)	FAO	11.25	22.89	0.10	100.00
Both Effiiency and Food Secutity Analysis Variables						
DFPVI	Domestic food price volatility (index)	FAO	13.34	11.12	1.60	89.80
EXCH	Official exchange rate (LCU per US$, period average)	WDI	605.23	1711.51	0.00	19068.42
TRADE	Trade (% of GDP)	WDI	78.35	48.59	14.77	531.74
INFLA	Inflation, consumer prices (annual %)	WDI	20.53	-173.50	9.80	4145.11
GOV	Governance Index	Multiple	79.52	7.95	58.16	100.00
SAN	Sanitation Develoment Index	WDI	78.48	7.85	63.96	100.00
TEL	Telephone Infrastructure Index	WDI	67.91	6.79	61.12	100.00
GDP	Gross Domestic Product (MILLIONS US$, 2005 prices)	WDI	1657.15	2519.71	50.04	15098.62
Food Security Analysis Variables						
ADESA	Average dietary energy supply adequacy (%) (3-year average)	FAO	109.38	15.23	77.00	152.00
DOFD	Depth of the food deficit (kilocalories per person per day)	FAO	181.43	122.10	4.00	666.00
PCFSV	Per capita food supply variability (kcal/capita/day)	FAO	37.75	21.49	3.00	162.00
NOPUN	Number of people undernourished (millions) (3-year average)	FAO	3.99	5.98	0.10	40.60
DCPFS	Domestic credit provided by financial sector (% of GDP)	WDI	31.35	40.94	0.00	247.00
FAID	Food and Nutrition Assistance, Agriculture and Rural Development aid disbursemnt (millions$)	FAO	61.99	127.88	0.00	1555.67
HIV	Adults (ages 15+) newly infected with HIV (in 1,000)	WDI	35.30	87.36	0.10	780.00
ADR	Age dependency ratio (% of working-age population)	WDI	84.55	15.49	41.10	112.00

Note: We use a panel data set which covers the period from 1995-2012. The data is comprised of 87 countries in two regions of the world (51 from Africa and 36 from the Americas).

Table 2. Estimates for Analysis of Determinants of Agricultural Efficiency

	Model 1 - EFF			Model 2 - EFF			Model 3 - MPI			Model 4- MPI		
Variables	***Coeff.***	***S. Error***		***Coeff.***	***S. Error***		***Coeff.***	***S. Error***		***Coeff.***	***S. Error***	
Lag	0.4044	(0.0462)	***	0.4429	(0.0844)	***	-0.4622	(0.0388)	***	-0.1940	(0.0897)	**
AFFA	-0.0113	(0.0039)	***				0.0019	(0.0057)				
AFF Lag	0.0097	(0.0035)	***				0.0156	(0.0051)	***			
AGRAC				-0.0027	(0.0054)					-0.0032	(0.0060)	
AGRAC Lag				0.0087	(0.0052)	*				0.0071	(0.0037)	*
TFERT	0.0014	(0.0074)		0.0104	(0.0072)		-0.0076	(0.0109)		0.0036	(0.0079)	
TFERT Lag	0.0049	(0.0071)		0.0002	(0.0072)		-0.0011	(0.0105)		0.0047	(0.0081)	
MACH	0.2685	(0.1356)	*	0.2963	(0.3503)		-0.0657	(0.2001)		0.4688	(0.4162)	
Mach Lag	-0.0589	(0.1354)		0.1185	(0.3590)		0.0866	(0.1971)		-0.3708	(0.3959)	
IRRIG	-0.1107	(0.1034)		-0.0139	(0.2453)		0.3725	(0.1470)	**	0.0523	(0.2650)	
IRRIG Lag	0.1314	(0.1014)		0.0044	(0.2459)		-0.3669	(0.1436)	**	-0.0549	(0.2658)	
DFPVI	0.0148	(0.0147)		-0.0274	(0.0287)		0.0385	(0.0212)	*	0.0006	(0.0311)	
DFPVI Lag	-0.0244	(0.0149)		-0.0313	(0.0246)		-0.0476	(0.0221)	**	-0.0375	(0.0268)	
EXCH	0.0056	(0.0072)		-0.0042	(0.0090)		0.0040	(0.0109)		-0.0032	(0.0100)	
TRADE	-0.0386	(0.0303)		-0.0888	(0.0426)	**	-0.0846	(0.0454)	*	-0.0568	(0.0487)	
INLFA	0.0017	(0.0012)		-0.0006	(0.0025)		-0.0021	(0.0019)		0.0028	(0.0027)	
PCI	0.0119	(0.0256)		-0.0263	(0.0389)		-0.0162	(0.0372)		-0.0658	(0.0427)	
GOV	0.4193	(0.1833)	**	0.2540	(0.1400)	*	-0.1534	(0.2717)		-0.4541	(0.3455)	
TEL	0.0821	(0.1352)		0.4899	(0.2706)	*	0.2719	(0.2031)		0.7827	(0.3115)	**
SAN	1.1189	(0.1632)	***	1.0747	(0.2144)	***	0.0465	(0.2514)		0.2071	(0.1807)	
Constant	-5.3329	(1.3940)	***	-6.5048	(2.2086)	***	6.5216	(2.1305)	***	3.6034	(2.2352)	

Note: ***, ***,* denotes significance at the 1%, 5% and the 10% levels, respectively. Standard errors are in parentheses.

Table 3. Estimates for Analysis of Determinants of Food Security

	Model 1 - DOFD			Model 2 - ADESA			Model 3 - PCFSV			Model 4 - NOPUN		
Variables	***Coeff.***	***S. Error***		***Coeff.***	***S. Error***		***Coeff.***	***S. Error***		***Coeff.***	***S. Error***	
Lag	1.0229	(0.0047)	***	1.0107	(0.0069)	***	0.6983	(0.0302)	***	0.9852	(0.0080)	***
HIV	0.0052	(0.0117)		-0.0050	(0.0030)	*	0.0310	(0.1220)		0.0414	(0.0258)	
HIV Lag	-0.0033	(0.0117)		0.0037	(0.0030)		-0.0523	(0.1225)		-0.0318	(0.0260)	
DCPFS	-0.0215	(0.0056)	***	0.0002	(0.0014)		0.0159	(0.0558)		-0.0193	(0.0108)	*
DCPFS Lag	0.0195	(0.0055)	***	-0.0007	(0.0014)		0.0126	(0.0538)		0.0012	(0.0105)	
EFF	0.0014	(0.0135)		0.0112	(0.0033)	***	0.3072	(0.1370)	**	-0.0666	(0.0246)	***
EFF Lag	-0.0708	(0.0140)	***	-0.0110	(0.0035)	***	-0.1178	(0.1385)		-0.0307	(0.0255)	
DFPVI	0.0022	(0.0042)		0.0018	(0.0010)	*	-0.0344	(0.0424)		-0.0007	(0.0084)	
DFPVI Lag	0.0035	(0.0042)		0.0025	(0.0010)	**	0.1040	(0.0426)	**	0.0010	(0.0082)	
ADR	0.1466	(0.2310)		0.4371	(0.0583)	***	-2.1849	(2.3237)		-0.0720	(0.4270)	
ADR Lag	-0.4194	(0.3350)		-0.4357	(0.0594)	***	1.9667	(2.3645)		-0.0527	(0.4381)	
EXCH	0.0074	(0.0018)	***	-0.0013	(0.0004)	***	-0.0153	(0.0185)		0.0129	(0.0037)	***
TRADE	-0.0093	(0.0081)		-0.0027	(0.0020)		-0.0967	(0.0798)		-0.0105	(0.0145)	
INLFA	0.0000	(0.0000)		0.0000	(0.0000)		0.0000	(0.0001)		0.0000	(0.0000)	
PCI	-0.0336	(0.0057)	***	-0.0044	(0.0014)	***	-0.0819	(0.0580)		0.0266	(0.0119)	**
GOV	-0.1145	(0.0521)		0.0188	(0.0131)		-0.1324	(0.5056)		-0.1449	(0.1025)	
TEL	-0.2779	(0.0362)	***	0.0246	(0.0090)	***	-0.0788	(0.3746)		-0.0400	(0.0744)	
SAN	-0.0132	(0.0426)		-0.0111	(0.0108)		-1.1718	(0.4113)	***	-0.0848	(0.0755)	
FAID	0.0048	(0.0009)	***	-0.0005	(0.0002)	**	-0.0001	(0.0091)		0.0036	(0.0017)	**
Constant	2.8476	(0.4035)	***	-0.1350	(0.1040)		8.1027	(4.2190)	*	1.9148	(0.8033)	

Note: ***, ***,* denotes significance at the 1%, 5% and the 10% levels, respectively. Standard errors are in parentheses.

Appendix

Table A1. Average Efficiency Score Growth

Country	Code	MPI	EFFCH	TECHCH	PECH	SECH
Cabo Verde	CPV	1.182	1.000	1.182	1.000	1.000
Botswana	BWA	1.136	1.000	1.136	1.000	1.000
Malawi	MWI	1.111	1.036	1.079	1.070	1.007
Morocco	MAR	1.079	1.045	1.028	1.012	1.026
Rwanda	RWA	1.072	1.046	1.031	1.028	1.031
Angola	AGO	1.065	1.051	1.024	1.023	1.052
Liberia	LBR	1.063	1.011	1.059	0.996	1.017
Kenya	KEN	1.062	1.030	1.038	1.054	1.003
Ghana	GHA	1.057	1.018	1.048	1.011	1.008
Zambia	ZMB	1.055	1.000	1.055	1.000	1.000
Gabon	GAB	1.054	1.000	1.054	1.000	1.000
Cameroon	CMR	1.053	1.027	1.027	1.036	0.999
Senegal	SEN	1.053	1.032	1.027	1.033	1.003
Ethiopia	ETH	1.048	1.028	1.025	1.040	0.998
Cote d'Ivoire	CIV	1.047	1.013	1.036	1.010	1.005
Burkina Faso	BFA	1.046	1.032	1.017	1.030	1.031
Guinea	GIN	1.044	1.003	1.046	0.997	1.007
Sudan	SDN	1.044	0.991	1.050	0.994	0.995
Tanzania	TZA	1.043	1.017	1.041	1.017	0.995
Mozambique	MOZ	1.043	1.027	1.020	1.037	1.013
South Africa	ZAF	1.043	1.000	1.043	1.000	1.000
Sierra Leone	SLE	1.041	1.023	1.026	1.039	1.018
Chad	TCD	1.041	1.000	1.041	1.000	1.000
Guinea-Bissau	GNB	1.040	1.020	1.025	1.043	1.005
Average for Africa		**1.039**	**1.009**	**1.033**	**1.011**	**1.005**
Tunisia	TUN	1.038	1.020	1.014	0.999	1.018
Eritrea	ERI	1.037	1.001	1.038	1.001	0.994
Algeria	DZA	1.034	1.006	1.026	1.000	1.006
Somalia	SOM	1.032	1.000	1.032	1.000	1.000
Mali	MLI	1.032	1.002	1.029	1.001	1.001
Uganda	UGA	1.031	0.989	1.047	1.010	1.005
Libya	LBY	1.028	1.000	1.028	1.000	1.000
Nigeria	NGA	1.028	1.001	1.026	1.000	1.001
Benin	BEN	1.025	1.004	1.025	1.009	1.005
Madagascar	MDG	1.024	1.002	1.029	1.004	1.001
Togo	TGO	1.022	1.019	1.012	1.050	1.000
Central African Republic	CAF	1.022	1.000	1.022	1.000	1.000
Burundi	BDI	1.018	0.995	1.028	1.001	1.006
Namibia	NAM	1.017	1.000	1.017	1.000	1.000
Niger	NER	1.012	1.000	1.012	1.000	1.000
Congo, Rep.	COG	1.011	1.000	1.011	1.000	1.000
Comoros	COM	1.011	1.000	1.012	1.000	1.000
Congo, Dem. Rep.	ZAR	1.010	1.000	1.010	1.000	1.000
Egypt, Arab Rep.	EGY	1.005	1.000	1.005	1.000	1.000
Zimbabwe	ZWE	1.004	0.979	1.026	0.996	1.005
Mauritius	MUS	0.998	1.000	0.998	1.000	1.000
Swaziland	SWZ	0.997	0.991	1.007	0.995	0.996
Lesotho	LSO	0.991	1.005	0.997	1.007	0.999
Gambia, The	GMB	0.991	0.998	0.997	0.999	1.006
Sao Tome and Principe	STP	0.988	1.000	0.988	1.000	1.000

Table A2. Factor Analysis Variables Used to Create GOV, MACH, TEL and SAN

Variable	Contributing Variables to Index of Governance (GOV)

VA	Voice and Accountability
PS	Political Stability and Absence of Violence/Terrorism
GE	Government Effectiveness
RQ	Regulatory Quality
RL	Rule of Law
CC	Control of Corruption
EF	Economic Freedom Index

Variable	**Contributing Variables to Index of Availability of Agriculture Machinery (MACH)**
TRACCIV	Agricultural tractors, total import value (1,000 US$)
AGMAIV	Agricultural machinery, total import value (1,000 US$)
SMACIV	Soil machinery, total import value (1,000 US$)
ATRACIU	Number of agricultural tractors in use
HTRIV	Harvester and threshers, import value (1,000 US$)
TRACIN	Number of agricultural tractors, total imports

Variable	**Contributing Variables to Index of Telephone Communication Infrastructure (TEL)**
TELL	Telephone lines (per 100 people)
MCSC	Mobile cellular subscriptions (per 100 people)

Variable	**Contributing Variables to Index of Improved Access to Water and Sanitation facilities (SAN)**
IMPSR	Improved sanitation facilities, rural (% of rural population with access)
IMPWR	Improved water source, rural (% of rural population with access)