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The Paradigm of African Agricultural Efficiency, 1967-2012: What Does Meta-Analysis Reveal?

Kolawole Ogundari

Dept. of Agricultural and Resource Economics,
Kyushu University, Fukuoka, Japan.

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Kolawole OGUNDARI[1]
Dept. of Agricultural and Resource Economics,
Kyushu University, Fukuoka, Japan.

The most valuable of all capital is investment in human beings
–Alfred Marshal, 1920

Abstract

The present study investigates the development (i.e., rise or decline) in African agricultural efficiency level and what drives the efficiency over the years. A total of 379 frontier studies resulting in 534 farm level efficiency estimates were considered using meta-regression analysis (MRA) for the empirical analysis. The results show that mean efficiency estimates from the selected case studies decrease significantly as year of survey in the primary study increases. Apparently, this implies that over the years, negative efficiency change characterized the growth of African agriculture and food production. The effect of other study attributes considered in the MRA show that studies published in Journals, with parametric and primal technology specification produced significantly higher efficiency estimates, while those published in top ranking journals and with Cobb-Douglass and Translog functional forms produced significantly lower efficiency estimates. Other results show that education, followed by experience; extension and credit are the major drivers of agricultural efficiency levels in Africa over the years. Given these findings; we suggest policies that encourage investment in human capital development associated with education and extension should be prioritized to enhance the growth of agriculture and food production in the region.

Keywords: Agriculture, efficiency, meta-analysis, growth, fractional regression, Africa
JEL Classification: C13, Q12, Q18

1.0 Introduction

Agriculture remains the main trust of many countries in Africa, as the principal source of food and livelihood, making it a critical component of programs that seek to reduce poverty and attain food security in the continent. But in recent years, food insecurity has become a serious concern in Africa, especially in sub-Saharan Africa (SSA), which is reminiscent of the same issue in Asia for decades earlier (Otsuka, 2013). And, improvement in the efficiency levels of agriculture and food production has always been identified as a major component of total factor productivity (TFP) growth that needs to be explored to effectively address food insecurity problem in the developing economies (Brümmer, 2006).

Although, no country has successfully reduced poverty and food insecurity through agriculture alone as institutional and industrial development are often needed, but almost none has achieved it without first increasing its level of agricultural productivity and efficiency (POSTnote, 2006). In other words, the study of agricultural efficiency is important to all economies, developed and developing. And, this underscores why analysis of efficiency in agriculture and food production and the role of efficiency in increasing agriculture and food production, has received particular attention by researchers and policy makers alike as an

[1] Email: ogundarikolawole@daad-alumni.de
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important input for better informed policy decisions around the globe (Thiam *et al.,* 2001; Ogundari *et al.*, 2012).

According to Gallup *et al.,* (1997), increase in efficiency and productivity of agricultural enterprises is likely to enhance smallholder (or subsistence) farmers opportunities to produce more, which in turn could lead to increase in their food security and income levels. This is because improvement in agricultural efficiency level provides opportunities for farmers to produce more at same level of resources. In addition, productivity and efficiency affect agriculture and food production directly by increasing the available supply of food and indirectly by increasing household income. For example, study by Gallup *et al.*, (1997) has shown that 1% rise in per capita agricultural output (or TFP growth) could led to a 1.6% rise in income of the poorest. Likewise, Martin (2013) argues that the poverty impact of increase in agricultural productivity growth is much larger than for industry or services sector. In other word, agricultural productivity growth is much more beneficial for poverty reduction than other sectors of the economy.

The popularity of frontier efficiency studies in the last three decades has received attention among researchers and policy analysts and this is evidenced by the proliferation of the methodology and its application across the globe (Thiam et al., 2001). Nevertheless, recent empirical findings by Thiam et al., (2001), Bravo-Ureta et al., (2007) and Ogundari and Brümmer (2011) have shown that mean efficiency estimates of agricultural production reported in the primary study differ across many study attributes (or dimensions) such as methodology, data type, model specification, location etc. Given this, it will be necessary to understand also what literatures reveal about the trends (or development) in African agricultural efficiency level and what drives the efficiency level over the years as an important input in agricultural policy decisions in the region.

A search in the literature shows that two recent cross-country analyses of agricultural productivity growth in Africa based on FAOSTAT data by Alene (2010) and Yu and Nin-Pratty (2011) found evidence that change in efficiency contributed negatively to the growth of the sector over the years. This implies that decline in efficiency is the main cause of poor TFP growth in African agriculture and food production, while both studies also identify technical progress (technological change) as main driver of agricultural TFP growth in the region. In this regard, the present study is designed to complement the existing body of literature on productivity growth of African agriculture that uses aggregate or national level data to estimate agricultural TFP growth and its components.

Therefore, given the substantial number of efficiency studies that have been used to raise policy debates on the performance of African agriculture and food production over the years, the crucial question is, could similar findings obtained from existing cross-country studies on agricultural productivity be distilled from synthesized literature on efficiency of African agriculture over the years? As reveal by Ogundari *et al.*, (2012), lessons/policy implications drawn from previous studies on agriculture and food production and empirical studies, could be very useful as guides to agricultural policymakers in designing effective food security program. In view of this, the present study addresses the following research questions:

- *RQ1.* How did the relationship between mean efficiency estimates and year of survey from the selected case studies develop (i.e., rise or decline) over the years?
- *RQ2.* Are there differences in reported mean efficiency estimates to a set of study-specific attributes such as methodology used, model specification, publication outlet, data type, location etc.?
- *RQ3.* What factors (policy variables) have driven agricultural efficiency level as identified from the selected case studies over the years?

The present study builds on the earlier works by Thiam et al., (2001), Bravo-Ureta et al., (2007), and Ogundari and Brümmer (2011) that utilized meta-analysis to investigate how mean efficiency scores from the primary study on agriculture and food production differ across study attributes such as methodology used, data type, model specification etc. While Thiam *et al.*, (2001) focused on farm level efficiency estimates from the developing agriculture with 2 studies from Africa, Bravo-Ureta et al., (2007) examined efficiency estimates from both the developing and developed agriculture with 14 studies from Africa, and Ogundari and Brümmer (2011) focused exclusively on efficiency estimates from Nigeria with 124 studies involved.

Given this, the present study contributes to existing literature in the following ways: (1) unlike previous studies that includes few number of observations from Africa, the present study focuses exclusively on efficiency estimates from Africa with broader geographical coverage that would produce a better understanding of the link between efficiency estimates in African agriculture and attributes of studies reporting these estimates in the region; (2) unlike previous studies that uses Tobit, OLS and truncated regressions, believed to yield biased result as argued by McDonald (2009) and Ramaiho et al., (2011), the current study makes a significant contribution in terms of methodology employed by using fractional regression model for the meta-regression analysis (MRA); (3) unlike previous studies with exception of Ogundari and Brümmer (2011), we extended our discussion to include drivers of agricultural efficiency level over the years in Africa.

The paper is structured as follows. Section two provides overviews of frontier efficiency and meta-analysis. The next section provides detailed description of the meta-dataset used for the analysis. In section four, meta-regression model specification is provided. Section five presents the results and discussion, while conclusions are provided in section six.

2.0 **An overview of frontier efficiency and meta-analysis**

2.1. *An overview of frontier efficiency*

Efficiency is refers to how well a system or unit of production performs in the use of resources to produce outputs, given available technology relative to a standard (frontier) production (Fried, 2008). Given this, efficiency of decision-making units (DMU) can be represented by technical efficiency, especially when primal technology specification is considered to model the performance of the production unit. Alternatively, it could be allocative efficiency, economic (cost) efficiency, or profit efficiency when dual technology specification is considered, depending on the underlying behavioral assumption that are made to describe the performance of the production unit. But as noted by Thiam et al., (2001), the primal approach or direct estimation of the production function has been the more common route used for frontier estimation in the economic literature.

In a related development, the body of literature on measurement of agriculture and food production efficiency examined how farmers have been using resources efficiently by applying best technology and managerial practices (known as technical efficiency), while others have examined how much costs can be reduced if the combination of inputs is optimal according to prices (known as allocative efficiency) and or if farms are operating at the optimal size that guarantee production at the minimum cost (known as economic or cost efficiency).[2] Profit efficiency is the highest possible profit achieve by DMU relative to the frontier profit, given the optimum combination of output price and factor prices.

Economic theory offers numerous procedures for evaluating efficiency of a decision-making unit (Hoff, 2007). Nevertheless, the methodologies employ in estimating efficiency level of agriculture and food production has evolved over the years. This however, ranges from when simple indexing method and mathematical programming (or non-parametric method-Data Envelopment Analysis-DEA) was used, use of simple and sophisticated econometrics (or parametric method such a stochastic frontier analysis-SFA), introduction of

[2] Economic efficiency can also be defined as the product of technical and allocative efficiencies.

theoretically consistent functional forms, introduction of dynamic and spatial econometrics and systems of equations, use of multi-output technology estimation to introduction of meta-frontier technology among others (for detail discussion see, Kumbhakar and Lovell, 2000 and Coelli *et al.*, 2005). [3]

Another major extension in efficiency measurement is recent advances in panel data methodologies, which led to the incorporation of efficiency into TFP growth decomposition process similar to the Solow Growth model. As noted by Thiam et al., (2001), a major feature of panel data is the ability to decompose TFP growth into technical change (or technological change) and efficiency change (movement of frontier) and until lately into scale efficiency change (change in variety of inputs available), allocative efficiency change in inputs and output and mix- efficiency change (Kumbhakar and Lovell 2000; O'Donnell 2010). This decomposition makes it possible to study the source of TFP growth from different points of view (Nishimizu and Page, 1982) and this is very important for policymaking and designing of programs. In addition, estimation of farm level efficiency can be consistently achieved or yield more accurate estimate using panel data, thus avoids some of the limitations present in cross-sectional studies (Thiam et al., 2001).

Generally, frontier efficiency model does not only serve as a benchmark, which efficiency levels of DMU are estimated, but it is also used to identify the determinants of efficiency levels for policy references (Kumbhakar and Lovell, 2000). In this case, the approach used to incorporate the determinants of efficiency into frontier model has evolved over the years from when a two-stage approach was used to the use of a single stage approach that enables joint estimation of efficiency and its determinants (Kumbhakar and Lovell, 2000; Coelli., et al 2005).

A search in the literature however, shows that a number of studies have provided historical review of agricultural efficiency literature over the years. Some of these studies include Battese (1992), Bravo-Ureta and Pinheiro (1993), Ogundari *et al.*, (2012) and Darkn *et al.*, (2013). The conclusions from these studies underscore the efforts that have been devoted to measuring efficiency in agriculture using different frontier methods and models. In addition, these reviews reveal that efficiency estimates differ across many dimensions associated with study attributes such as methodology used, data type: cross-sectional vs. panel data, functional forms, products, sample size, geographical location and many more. These observations motivated the application of meta-analysis to investigate whether agricultural efficiency estimates from the primary studies differ across these dimensions as noted by Thiam et al., (2001), Bravo-Ureta et al., (2007) and Ogundari and Brümmer (2011).

2.2. *An overview of meta-analysis*

Meta-analysis (MA) allows researchers to combine results of several homogenous studies into a unified analysis that provides an overall estimate of interest for further discussion (Sterne, 2009). It provides the same methodological rigor to a qualitative review. A general model of carrying out MA is the use of regression techniques. Meta-regression analysis (MRA) as it is called is defined as a quantitative method used to evaluate the effect of methodological and other study-specific characteristics on published empirical estimates of some indicators (Alston *et al.* 2000). With reference to the present study, mean efficiency estimates (which could be technical, allocative, economic (cost), or profit efficiency) from the primary study is treated as dependent variable, while study attributes such as year of data collection (or year of survey) in the primary study, model specification, methodology, data type etc. are taken as explanatory variables.

[3] A major assumption underlying frontier models is that all firms have access to the same production technologies. Unfortunately, in practice some firms have access to different technologies. However, the use of meta-frontier model relaxes this assumption to allow firms of different technologies to be compared.

Although, MA is quite popular in medical, education, pharmaceutical, and marketing researches as noted by Thiam et al., (2001), a review of the literature however, shows that MA has also been extended to a wide range of results in economic research other than agricultural efficiency and productivity mentioned above in recent time. This includes effect of immigration on wages (Longhi *et al.*, 2005), income and calorie intake (Ogundari and Abdulai, 2013), income inequality and economic growth (de Dominicis et al., 2008), effect of aid on economic growth (Mekasha and Tarp, 2013), energy consumption and economic growth (Chen et al., 2012), effect of currency unions on trade (Havranek, 2010), price and income elasticity of demand for meat (Gallet 2010a,b), price and income elasticity of demand for alcohol (Gallet, 2007), income elasticity of demand for cigarette (Gallet and List 2003), exchange rate volatility and trade (Josheski and Lazarov, 2012), debt and economic growth (Moore and Thomas, 2010), Willingness to pay for reduction in pesticide risk exposure (Florax et al., 2005) and many more.

3.0 The Meta-Dataset

Meta-analysis requires a thorough search of literature that provides a complete description of study specific characteristics or attributes of interest needed for the MRA. To this end, a variety of sources were used to compile the primary studies in the present study, which include personal communication with the authors, economic database such as web of science, Google scholar, AgEcons and ASCI Index and a host of other online database using relevant keywords. In addition, we consulted PhD dissertation and Masters Thesis from website of various Universities. The criteria used in selecting studies for the current analysis was that the study reported mean efficiency estimates, data year or year of survey and sample size. Based on this, we selected 379 frontier studies for the current analysis. Because some of the retrieved studies reported more than one efficiency estimate, a total 534 farm level efficiency estimates was used for the MRA. The selected studies cut across the entire region in the continent with 27 countries fully represented in the meta-data. In addition, we find that the selected studies covered a range of products starting from grain related crops such as maize, rice etc., tubers such as cassava, yam, cocoyam, potatoes, cash crops (cocoa, coffee etc.) to non-crop products such as egg production, poultry, livestock in general, fish etc.

Therefore, using previous studies by Thiele et al., (2001), Bravo-Ureta et al., (2007), and Ogundari and Brümmer, (2011) and research questions outlined in section 1 as guides, we extracted and coded study specific attributes of interest for the meta-analysis, which is presented in Table 1. The summary statistics of the selected case studies, which contains detailed information regarding the authors, year of publication, the publication outlet for the primary study, and the mean efficiency estimate reported can be requested from the author. Because of space, this could not be included in the present paper.

4.0 The Meta-Regression Model and Empirical model

4.1 *The Meta-Regression Model*

To provide answer to the first and second research questions in the study, we use meta-regression analysis (MRA). Below is the specification of the meta-regression model used in the present study

$$EFF\_EST_{ir} = \psi_0 + \beta DATAYEAR_{ir} + \sum_{k=1}^{K} \alpha_k X_{kir} + \varepsilon_{ir} \quad ; \quad \varepsilon_{ir} \sim \mathrm{N}\left(0, \sigma_\varepsilon\right) \tag{1}$$

where EFF_EST_{ir} represents mean efficiency estimate from the i-th primary study, conducted in r-th region in Africa and ψ_0 is intercept; $DATAYEAR_{ir}$ is the average years of survey used in the primary study, which starts from 1967, 1981, 1989, ….2012. This is carefully constructed and included in equation 1 to investigate trends or development in efficiency level of African agriculture and food production over the years. According to Ogundari *et al.* (2012), it is possible to interpret the relationship between efficiency estimates reported (i.e., EFF_EST_{ir}) and the year of survey (i.e., $DATAYEAR_{ir}$) in primary studies as an implicit indicator of efficiency change over time in absence of reliable panel data. X_{kir} is a vector of other study attributes also considered in MRA model as control variables, which include $D\_PANELDATA$ representing articles that used panel data (articles published with cross section data served as reference); DF representing the degree of freedom in each study; D_OUTPUT representing studies with non-aggregated output (studies with an aggregated output served as reference); $D\_JOURNAL$ representing articles published in Journals (articles published in conference, working papers, and thesis/dissertation were taken as reference); $D\_IMPACTFACTOR$ representing articles published in top ranking journals with impact factor; $D\_COBBDOUGLAS$ representing articles that employed Cobb Douglass functional form (articles with other functional form and with no functional form served as reference); $D\_TRANSLOG$ representing articles that employed Translog functional form (articles with other functional form and with no functional form served as reference); $D\_PARAMETRIC$ representing articles that employed parametric method (articles with non-parametric method served as reference); D_PRIMAL representing articles that employed primal technology (articles with dual technology served as reference); D_GRAIN representing studies that focused on grain related products such as maize, rice etc. (non-grains articles served as reference); $D\_FOODCROP$ and $D\_CASHCROP$ represent studies with a focus on food crops and cash crops, respectively (non-crop studies such as livestock, poultry, fish etc. served as reference); D_EAST , $D\_CENTRAL$, $D\_SOUTHERN$, and D_NORTH represent articles published on countries in East Africa, Central Africa, Southern Africa, and North Africa, respectively (articles published in countries in West Africa served as reference). ψ_0, β, and α_k are parameters to be estimated and the sign of β and α_k will generally indicate the direction in which a given variable influence changes in EFF_EST_{ir}. While a positive sign would indicate the variable having a positive impact on the EFF_EST_{ir}, a negative sign would suggest otherwise.[4] ε_{ir} is the error term of the regression and is assumed to be normally distributed with mean 0 and variance σ_{ε}.

Estimating any economic relationship from data requires assumptions about the data generating process-DGP (Kumbhakar et al., 2013). In view of this, McDonald (2009) and Ramaiho et al., (2010), argue that the DGP for EFF_EST_{ir} is a fractional/proportional data bounded between zero and 1 and not censored data by construction. Consequently, the authors argue that the use of linear models such as ordinary least square (OLS) and Tobit models may not provide an accurate picture of the effects of explanatory variables on the dependent variable of equation 1. For example, if the explanatory variables in equation 1 are used to explain the dependent variable, the relationship must be bounded –otherwise, predicted EFF_EST_{ir} may be greater than one. In recognition of this, McDonald (2009) and Ramaiho et al., (2010) proposed the use of Papke and Wooldridge's (1996) fractional regression model for the second stage analysis of the determinants of efficiency scores in the literature. Unlike OLS and Tobit models, fractional regression model deals with dependent variable defined on the unit interval, irrespective of whether boundary value of 0 or 1 is observed or not (Ramaiho et al., 2010).

Intuitively, MRA of equation 1 is synonymous to investigating determinants of efficiency in second stage of DEA efficiency analyses by using regression to relate efficiency estimates to a number of factors seen to influence efficiency levels. These factors include managerial characteristics such as age, educational attainment, and experience of the

[4] With regards to the parameter of interest β - a positive sign would be taken as evidence of positive efficiency change in African agriculture over the years, while a negative sign would suggest opposite.

producers or DMU, and access to credit among others. Guided by this, the present study uses fractional regression model to estimate the parameters of equation 1. As earlier mentioned, this is a departure from previous studies on meta-analysis of frontier studies on agriculture and food production that employed OLS and Tobit regression models such as Thiam et al., (2001) and Bravo-Ureta et al., (2007) and Truncated regression model by Ogundari and Brümmer (2011). The fractional regression model is subsequently discussed below.

4.2. *Empirical Model*

Papke and Wooldridge (1996) highlight the drawbacks of linear models for fractional data that are analogues to the drawbacks of the linear probability model for binary data. Likewise, Kieschnick and McCullough (2003) argue that since fractional data are only observed over a closed interval implies that the conditional expectation function will not be normally distributed because they are not defined over $\Re$, which is a domain over which the normal distribution is defined. The authors therefore suggest that the use of linear models such as average response function (OLS), censored regression (Tobit), or transformed logistic normal model (e.g., the log-odds ratio of dependent variable) are inefficient as their error distributions will be heteroskedastic, because their conditional variance will approach zero as their conditional mean approaches either of their boundary points. [5]

The fractional response model is estimated using Quasi-Maximum Likelihood Estimation (QMLE) method and is a non-linear model. QMLE is asymptotically efficient and consistent compared to either OLS or Tobit or Truncated or transformed logistic normal often used by researcher to handle DGP of this nature.

QMLE is one in which the variance of the observed data are known (up to a scale parameter) functions of the means (Cox 1996). Papke and Wooldridge (1996) specify a quasi-likelihood regression model for continuously measured proportions with a finite number of boundary observations (i.e., 0s and 1s). It is robust to obtain an estimate of fractional response models without *ad hoc* transformation of boundary values of the dataset. The authors use the following Bernoulli Log-likelihood specification.

$$L_i(\beta \ or \ \alpha) \equiv y_i \ell n\big(G(Z_i)\big) + (1-y_i)\ell n\big(1-G(Z_i)\big) \tag{2}$$

where, $0 \le y_i \le 1$ denotes the dependent variable equivalent to EFF_EST in the present study, while Z_i refers to the explanatory variables of observation *i* equivalent to $DATAYEAR$ and X_k in the present study.

Accordingly, the specification above is well defined for $0 < G(Z_i) < 1$. The QMLE of $\beta \ or \ \alpha$ of equation 1 is obtain by simply maximizing equation 2 [that is., $\max_{\beta \ or \ \alpha} \sum_{l=1}^{N} L_i(\beta \ or \ \alpha)$].

Papke and Wooldridge concluded that Bernoulli QMLE $\beta \ or \ \alpha$ is consistent and $\sqrt{N}$ - asymptotically normal regardless of the distribution of y_i conditional on Z_i, while no special data adjustments are needed for the extreme values of zero and one for y_i. The conditional expectation of y_i given the explanatory variables according to the authors are estimated directly. y_i could be a continuous variable, a discrete variable, or have both continuous variable and discrete characteristics.

Asymptotically efficient, unbiased and consistent estimator is achieve in QMLE by simply transforming the $G(Z_i)$ to produce models similar to either logit or probit in the binary choice situation (McDonald, 2009). Cox (1996) and Papke and Wooldridge (1996) proposed different specification for $G(Z_i)$ such as logistic or probit distribution. However,

[5] The problem in using OLS on fractional dependent variable is that it is not asymptotically efficient estimator but rather unbiased and consistent estimator.

Papke and Wooldridge use logistic function for $G(Z_i)$ within the framework of generalized linear models (GLM) [that is., $G(Z_i)=\frac{\exp(Z_i)}{1+\exp(Z_i)}$] which was extensively discussed in their paper and implemented in STATA software used for the empirical analysis in this paper.[6] QMLE is estimated by weighted non-linear square allowing for heteroskedasticity and testing procedures, which are asymptotically efficient within a class of estimators (Oberhofor and Pfaffermayer, 2009).[7]

Therefore, the meta-QMLE regression employed for the empirical analysis is implicitly specified below.

$$\mathrm{E}\left(EFF\_EST_{ir}\,|Z_i\right)=G\left(\psi_0+\beta DATAYEAR_{ir}+\sum_{k=1}^{K}\alpha_k X_{kir}+\varepsilon_{ir}\right) \text{t= 1967, … 2012} \qquad (3)$$

where, EFF_EST_{ir} , $DATAYEAR_{ir}$, and X_{kir} are as defined earlier and $Z_i=\left[DATAYEAR_i, X_{ki}\right]'$; $G(.)$ is the logistic function.

5.0 Results and Discussion

As a preliminary step before discussing the results of the findings, we follow the work of Stanley and Rosenberger's (2009) Root-n meta-regression analysis (MRA) approach to investigate the presence of publication selection bias using the relationship $EFF\_EST_{ir}=\delta_i+\delta_0\left(\frac{1}{\sqrt{n_i}}\right)+\tau_i$ with $\frac{1}{\sqrt{n_i}}$ as measure of precision with which EFF_EST has been estimated.[8] The result of this auxiliary regression indicates the presence of publication bias represented by the significance of the estimated parameter δ_0 at 1% level of significance, while there is presence of genuine empirical effect that goes beyond publication bias represented by the significance of the estimated parameter δ_i at 1% level of significance. However, we do not investigate further the sources of potential publication bias, as this is not the focus of the present paper. Subsequent discussions address research questions in the study.

5.1. *RQ1: What is nexus between mean efficiency estimates and year of survey?*[9]

Before we provide answer to the first research question, we take a closer look at the distribution of the reported mean efficiency estimates from the primary study presented in Figure 1 of the appendix. The Figure shows that the mean efficiency scores from the selected primary study have a right-skewed distribution with most observations ranging from 0.52 - 0.99 with an average of about 0.69 (see Table 1). This result is not surprising because, a large number of studies place efficiency score of agriculture and food production in the developing countries in the range of 0.60-0.85 (for details see, Bravo-Ureta and Pinheiro, 1993; Thiam *et al.,* 2001; Ogundari *et al.,* 2012). But for the institution responsible for agriculture and food policy design in the Africa, it is very important to note that 0.69 average efficiency levels suggests that there is ample room for improvement of agriculture and food production in the region. Specifically, the results imply that there is need to focus attention on investment that pushes African agriculture towards the existing frontier.

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[6] In STATA QMLE could be estimated using generalized linear model (glm) command with family (binomial), link (logit), and robust standard error option.

[7] QMLE accommodates naturally, non-constant variances and skewness (Oberhofor and Pfaffermayer 2009).

[8] The *Root-n* MRA approach was estimated using weight least square with "n" as the weight, while n is number of observation per efficiency estimate. For brevity, we did not present the result in the paper. The results can be made available upon request from the author.

[9] As earlier mentioned, efficiency estimates in our case comprises of technical, allocative, economic (cost) and profit efficiency.

Nevertheless, a search in the literature shows that the mean efficiency estimate obtained in the present study is lower than 0.737 and 0.72 reported by Bravo-Ureta et al., (2007) and Ogundari and Brümmer (2011) from 14 and 124 published studies in Africa and Nigeria, respectively.

The results of the MRA based on equation 3, which also shed light on the first research question is presented in Table 2. We estimate 5 different models to provide robustness check to the result of the coefficient of $DATAYEAR_{ir}$, which happen to be the variable of interest designed to provide answer to the first research question using MRA in the study. In this regard, other variables included in MRA are considered as control variables, since studies have shown that efficiency estimates often differ across many dimensions other than year of primary survey, such as methodology used, data, functional forms, products, sample size, and geographical location among others (Thiam et al., 2001; Bravo-Ureta et al., 2007; Ogundari and Brümmer 2011). The first and second models focus on the primary studies from Africa but without and with the regional effects, respectively. The third model focuses on the selected case studies from sub Saharan Africa (SSA), while fourth and fifth models focus on the selected case studies published from 1984-2003 and 2004-2013, respectively.

Thus, our finding shows that the mean efficiency estimate EFF_EST_{ir} reported in the case studies consistently decrease significantly as survey year $DATAYEAR_{ir}$ in the primary study increases across all the models. Apparently, the coefficient of the $DATAYEAR_{ir}$ in all the estimated models implies that efficiency change contribute negatively to the TFP growth of African agriculture over the years.[10] Interestingly, the result lends support to the findings of two recent cross-country analysis of TFP growth of African Agriculture and food production based on FAOSTAT data from 1961-2008 by Alene (2010) and Yu and Nin-Pratty (2011). The authors found evidence that change in efficiency contributes negatively to agricultural productivity growth over the years in the region.

Given these findings, the contribution of efficiency to the growth (or development) of African agriculture and food production is apparently negative from both the meta-analysis results in the present study and the cross-country studies highlighted above.[11] The implication of this is that if food insecurity problem in Africa is to be address, then policy challenge is to be able to identify the drivers of African agriculture and food production efficiency necessary to improve its growth (or development) in the region. These drivers will be discussed in subsequent section.

5.2. *RQ2: Are there differences in mean efficiency estimates across other study attributes?*

To provide answer to the second research question, we focus our discussion on models 1- 3, while models 4 and 5 provide a robustness checks for the result of the coefficient of $DATAYEAR$ in the study as earlier discussed.[12] However, the results of models 1-3 show that studies published in journal (D_JOURNAL), with parametric method (D_PARAMETRIC), with primal technology representation (D_PRIMAL), with single output or un-aggregated output (D_OUTPUT) yield significantly higher mean efficiency estimates than studies not published in journals, with non-parametric, dual technology representation, and aggregated output, respectively across these models. A search in the literature shows that the result of D_PRIMAL conforms to the findings of Thiam et al., (2001), while Bravo-Ureta et al., (2007) found no significant effect. Other results show that studies published with panel data

[10] As noted by Ogundari and Brümmer (2011), in the absence of reliable panel data, it is possible to interpret the relationship between efficiency scores reported in the primary studies and the survey year or year of data in the case studies as an implicit indicator of efficiency change over time.

[11] TFP growth is driven by four distinct components namely efficiency change, technical change (or technology change), scale efficiency and allocative efficiency change in puts and outputs (Kumbhakar and Lovell 2000).

[12] The result of the preliminary test is not provided in the study for brevity. The result could be requested from the author.

(D_PANELDATA) have insignificantly higher efficiency estimates with exception of model 3 that has insignificantly lower efficiency estimates than studies with cross-sectional data.[13] And, looking through the literature, we notice that Thiam et al., (2001) and Bravo-Ureta et al., (2007) found evidence that studies with cross sectional data report significantly lower efficiency estimate compared to studies with panel data in their respective studies.

Furthermore, we find that studies with large degree of freedom (DF) shows significantly lower mean efficiency estimates with exception of model 3, which is significantly not different from zero than those with lower degree of freedom. Also, the study shows that studies with Cobb-Douglass (D_COBBDOUGLAS) and Translog (D_TRANSLOG) functional forms report significantly lower efficiency estimate, than those that uses other functional form and with no functional forms across model 1 and 2. But for model 3, studies with Cobb-Douglass and Translog functional forms report significantly lower and higher mean efficiency estimate, than those that uses other functional form and with no functional forms in the study. In support of this finding Thiam et al., (2001) found that Cobb-Douglass functional form yield significant lower efficiency estimates in their study. Also, we find that studies published in top ranking journals (D_IMPACTFACTOR) in model 1 have significantly lower efficiency estimates, compared to studies in lower ranking. In models 2 and 3, studies published in top ranking journals (D_IMPACTFACTOR) have insignificantly lower efficiency estimates. A search in the literature shows that Ogundari and Abdulai (2013) found evidence that studies published in top ranking journal report higher calorie-income elasticity in their study.

Studies with a focus on grain (D_GRAIN), food crops (D_FOODCROP), and cash crop (D_CASHCROP) yield insignificantly lower efficiency estimate compared to studies with, non-grain crops and non-food crops, respectively across the models 1-3. By contrast, studies with a focus on cash crop were found to have higher efficiency estimates by Ogundari and Brümmer (2011). But similar to the finding of the present study, Bravo-Ureta et al., (2007) found consistently lower efficiency scores for studies with a focus on grain.

While, no regional effects was considered in model 1, models 2 and 3 reveal that studies from East Africa (D_EAST), Central Africa (D_CENTRAL), Southern Africa (D_SOUTHERN), and North Africa (D_NORTH) yield lower efficiency estimates compared to studies from West Africa taken as reference region in the study. However, only the coefficient of studies from East Africa (D_EAST) is significantly different from zero. The implication of this finding is that regional differences (with exception of studies from eastern region) seems not to play a significant influence in the systematic heterogeneity that exist in the reported efficiency estimates conditional on study-specific attributes in the paper. Interestingly, Bravo-Ureta et al., (2007) found significant differences in reported efficiency estimates across the region and income groups considered in their study.[14]

5.3. *RQ3: What drives African agriculture and food production efficiency over the years?*

In an attempt to provide an answer to the third research question, we specially constructed a database to identify variables that are associated with the decision-making units (i.e., farmers) from the primary study, but had positive or negative significant effects on African agriculture and food production efficiency over the years. The idea is to be able to synthesis important socio-demographic variables of the decision-making units (DMU) that are key to improving/increasing agricultural efficiency levels and to also serve as guide to agricultural policy design and implementation in the continent in the future. This is important because literature identified socio-demographic variables of the DMU such as age, years of experience, educational level, etc. as the underlying causes of deviation from the frontier (Kumbhakar and Lovell, 2000; Coelli et al., 2005). This explains why Bravo-Ureta et al.,

[13] The result is consistent across all the models.

[14] Bravo-Ureta et al., (2007) employed efficiency studies from both the developed and developing agriculture, which probably explain the significant of the regional dummies in the study.

(2007) stress the importance of efficiency as a relative measure of managerial ability for a given technology, which could be related to a set of control variables associated with the decision-making unit (or farmers)

To this end, our database shows that out of the 534 farm level mean efficiency estimates from the 379 selected frontier studies, only 383 estimates sought to explain the sources of variation in the efficiency level from the primary study. Thus, the database shows that variable postulated to affect the efficiency level of the respondents in the primary study varies from region to region and this includes age, years of experience, educational level, health, occupation (farming as a major occupation), and gender (male) of the farmers in the primary study. Others include credit, extension activity, crop diversification, distant of the farm to market, membership of cooperative society, farm size, land tenure, age of the farm, crop rotation, and among others. Hence, Figure 2 shows the distribution of the socio-demographic variables of the respondents (farmers) from the primary study identified as the key drivers of African Agricultural efficiency over the years. Because of few significant observations recorded in many of the identified variables, the figure contains variables with highest percentage of occurrence for both the positive and negative significant effect on the efficiency estimates reported in the primary studies. Since, our interest is to identify the drivers of efficiency level of African agriculture and food production as retrieved from the primary studies, subsequent discussions are based on the variables with positive and statistical effect in Figure 2.

In this case, the result shows that 41% of the 383 estimates identified education as a major driver of efficiency level of African agriculture over the years. This was followed by year of farming experience (27%); age of the farmer (22%), contact with extension agents (20%), credit (16%), household size (14%), gender-male (13%) and membership of cooperative society and farm size both are 9%. Other analysis shows that 17%, 12%, and 11% of the 383 estimates recognized joint significance influence of education and experience, education and extension, and education and age on the efficiency level of African agriculture and food production over the years.

Given this, the ranking of education is a further confirmation of Philips's (1994) argument that "there is a general consensus that education has a positive effect on agricultural productivity and efficiency". Also, the ranking of experience after education lends support to Huffman (2001) suggestion that in some agricultural environments, experience and education are likely to be the most important form of human capital for enhancing the efficiency level of a producing unit in either a static or dynamic environment. Likewise, the ranking of age as third most important driver of agriculture and food production efficiency in Africa can be attributed to the fact that age is considered in many studies as a proxy for farming experience in the economic literature. According to Ogundari et al., (2012), one possible reason why a number of studies identified age as a key determinant could be as a result of the perceived correlation between experience and age of the primary respondents in the selected studies. The authors stated further that age is considered in many studies as proxy for farming experience. The implication of this is that the result of age could be taken as outcome of experience.

Furthermore, identification of extension service (a proxy for agricultural education) as also third most important factor driving agricultural productivity alongside age, underscores continue relevance of extension as inevitable vehicle for disseminating breakthrough technologies and innovation to farmers that should be intensify vigorously in Africa.

Thus, we believe the findings have a number of policy implications, in particular policy relevance of education in increasing agricultural production and productivity in Africa. Also, the results attest to the crucial role of other human capital indicators such as farming experience and extension, which are mainly related to training in new agricultural technologies to increase agricultural productivity in the region. While Pudasain (1983) argue that education contributes to agricultural production and productivity much higher in modernize environment, which underscores the role of investment in technology, Otsuka (2013) suggests that what is needed in SSA is an effective extension system to disseminate the potentially productive technology in the region. The author argues further that the vision of the appropriate technologies and their dissemination strategies is still missing or at best weak in SSA. While we acknowledge that this finding has been established in the literature on the efficiency of developing agriculture (see; Weir and Knight, 2000; Asadullah and Rahman, 2005; Ogundari and Brümmer, 2001; Ogundari *et al.*, 2012), the present review should be seen as a confirmation of the need to effectively foster agricultural policies that embrace human capital development in the region and sub Saharan Africa (SSA) in particular.

Given the evidence from this study that gains in African agricultural efficiency are associated closely with farmers' education over the years, the crucial question is, what exact role does education play to increase agricultural productivity in Africa? Pudasaini (1983) and Reimers and Klasen (2011) highlighted a number of roles, which education play in increasing agricultural production. *First*, education helps farmers become better managers of limited resource by enhancing their decision-making skills. *Second*, education enhances farmers access to information on low-cost and sustainable alternatives, that could potentially help them pay and receive better prices for inputs used and outputs sold, thus making education a remedy to prevailing information asymmetries in the market. *Third*, education helps farmers adapt new technologies faster to have a first mover advantage. *Fourth*, education helps farmers to prefer riskier production technologies since they are able to evaluate adequately the implied opportunities.

6.0 **Conclusions**

The paper attempts to shed light on how efficiency estimates of African agriculture and food production develop (increase or decrease) and what drives the efficiency levels over the years. We employed meta-regression analysis (MRA) on a total of 379 studies resulting in 534 farm level efficiency estimates for the analysis, given that some studies reported more than one estimate. The studies cut across all the regions in the continent with 27 countries represented.

The overall mean farm level efficiency of about 0.69 was obtained from all the selected studies, which indicates that there is still scope to improve efficiency level of African agriculture. The results of MRA show that efficiency estimates of African agriculture from the primary studies decrease significantly as year of survey in increases. Apparently, this implies that over the years, negative efficiency change characterized development of African agriculture and food production. Also, the results of other study attributes considered in MRA other than the survey years show that studies published in journal, with parametric method and primal technology significantly report higher efficiency estimates, while studies published in top ranking journals and with Cobb-Douglas and Translog functional forms significantly yield lower efficiency estimates. This suggests that systematic differences (or heterogeneity) that exist in the reported efficiency estimates from the selected case studies were explained by many of the study-specific attributes considered in the analysis, which is akin to previous findings. The variation in reported efficiency estimates is not well explained across the region.

Other results identify key drivers of efficiency level of African agriculture and food production over the years to be education, years of experience, extension, credit, farm size and membership of cooperative society. These findings have policy implications for strengthening food security through increase in efficiency of African agriculture and food production. Additionally, it is very useful for researchers and academicians to be able to identify study- specific attributes, essential for modeling farm level efficiency and to evaluate the sensitivity of their results to the choice of model specification and method in the region and elsewhere around the world.

Given these findings, the potential role of agriculture in reducing poverty and enhancing food security will not materialize without concerted and purposeful policy action that is align with identified drivers of efficiency of African agriculture obtained in the study. This is an indication that there is need for programmes and policies that will boost agricultural efficiency level and thus, productivity in the region. In this regard, we suggest improvement in extension services, introduction of incentives that encourage young, able and educated individuals with basic education to go into farming, and introduction of robust training program for farmers on modern technology through activities of extension should be seen as critical components of program that will enable smallholder farms, which dominate agriculture and food production in Africa to be more efficient in the region.

Reference

Alston, J. M., M. C. Marra, P.G. Pardey and T. J. Wyatt (2000). Research Returns Redux: A Meta-Analysis of the Returns to Agricultural R & D. *The Australian Journal of Agricultural and Resource Economics*, Vol.44 (2): 185-215.

Alene, A. D. (2010). Productivity Growth and the effects of R&D in African Agriculture. *Agricultural Economics,* Vol. 41: 223-238.

Asadullah, M. N, S. Rahman (2005). Farm productivity and Efficiency in Rural Bangladesh: The role of Education Revisited. Working paper CSAE WPS/2005-10, Center for the study of African Economies, University of Oxford.

Battese, G. E. (1992). Frontier production functions and technical efficiency: a survey of empirical applications in agricultural economics. *Agricultural economics,* Vol.7: 185-208.

Bravo-Ureta, B. E., D. Solis, V.H. Moreira Lopez, J. F. Maripani, A. Thiam and T. Rivas (2007). Technical Efficiency in Farming: A Meta-Regression analysis. *Journal of Productivity Analysis*, Vol. 27: 57-72.

Bravo-Ureta, B. E., and Pinheiro, A. E. (1993), 'Efficiency analysis of developing country agriculture: a review of the frontier function literature', *Agricultural Resources Economics Review*, Vol 22, pp 88–101.

Brümmer, B (2006). Food Policy to alleviate rural poverty: the potential contribution of productivity growth in Agriculture and agricultural trade linearization, *Quarterly Journal of international Agriculture,* Vol. 45(1): 1-6.

Chen, P-C., S-T. Chen and C-C. Chen (2012). Energy consumption and economic growth-New evidence from meta-analysis, *Energy policy,* Vol. 44: 245-255.

Coelli, T. J., Rao, D. S. P., O'Donnell, C. J., and Battese, G. E. (2005), *An Introduction to Efficiency and Productivity Analysis,* 2nd edition, Springer, New York.

Cox, C. (1996). Nonlinear quasi-likelihood models applications to continuous proportions. *Computational Statistics & Data Analysis* 21: 449-461.

Darku, A. B., S. Malla and K. C. Tran (2013). Historical review of Agricultural Efficiency Studies. CAIRN Research Network.

de Dominicis, L., R. J. G. M. Florax and H. L. F. de Groot (2008). A meta-analysis on the relationship between income inequality and Economic Growth. *Scottish Journal of Political Economy* Vol. 55(5): 654-682.

Florax, R. J. G. M, C.M. Travisi and P. Nijkamp (2005). A meta-analysis of the willingness to pay for reductions in pesticide risk exposure, *European Review of Agricultural Economics,* Vol. 32(4): 441-467.

Fried, H. O (2008). Efficiency and production. In Fried, H. O., C.A.K. Lovell and S.S. Schmidt (eds.), measurement of productive efficiency and productivity growth, Oxford University Press, New York.

Gallet, C (2010a). Meat Meets Meta: A quantitative Review of the Price Elasticity of meat. *American Journal of Agricultural Economics,* 92(1): 258-272.

Gallet. C.A (2010b). The income elasticity of meat: a meta-analysis. *The Australian Journal of agricultural and Resources Economics*, 54:477-490.

Gallet, C. A. (2007). The Demand for Alcohol: A Meta-Analysis of Elasticities. *Australian Journal of Agricultural and Resource Economics* 51(2): 121–35.

Gallet, C. A., and J. A. List. (2003). Cigarette Demand: A Meta-Analysis of Elasticities. *Health Economics* 12(10): 821–35.

Gallup, J., S. Radielet, and A. Warmer (1997). Economic growth and income of the poor. CAER Discussion paper No.36, Harvard Institute for International Development, Cambridge MA USA.

Hoff, A (2007). Second stage DEA: comparison of approaches for modeling the DEA score. *European Journal of Operational Research*, Vol. 181: 425-435.

Huffman, W. E (2001). Human capital: Education and Agriculture. In B.L. Gardner and G. C. Rausser (eds). *Handbooks of Agricultural Economics*, Vol. 1A, Elsevier, Amsterdam.

Josheski, D and D. Lazarov (2012). Exchange rate volatility and trade: a meta-regression analysis, *GRP International Journal of Business and Economics*, Vol. 1(2): 24-49.

Kieschnick, R and B. D. McCullough (2003). Regression analysis of variates observed on (0,1): percentages, proportions and fractions. *Statistical Modeling* 3: 193-213.

Kumbhakar, S. C., F. Asche and R. Tveteras (2013). Estimation and decomposition of inefficiency when producers maximize return to outlay: an application to Norwegian fishing trawlers. *Journal of Productivity Analysis.* DOI 10.1007/s11123-012-0336-5.

Kumbhakar, S. C., and Lovell, C. A. K. (2000), *Stochastic Frontier Analysis*, Cambridge University Press, Cambridge.

Longhi, S., Nijkamp, P. and Poot, J. (2005) A Meta-Analytic Assessment of the Effect of Immigration on Wages. *Journal of Economic Surveys* 19(3): 451-477.

Martin, W (2013). Productivity Growth, Trade and Poverty. Paper presented at the IARTC meeting Seville, 3rd June 2013.

Marshall, A (1920). *Principles of Economics*, 8th edition. London: Macmillan & Co Ltd.

Mekasha, T. J and F. Tarp (2013). Aid and Growth: What meta-analysis reveals. *The Journal of Development Studies*, 49 (4): 564-583.

McDonald, J (2009). Using least squares and Tobit in second stage DEA efficiency analysis, *European Journal of Operational Research*, Vol.197: 792-798.

Moore, W and C. Thomas (2010). A meta-analysis of the relationship between debt and growth, *International Journal of Development Issues*, Vol. 9(3): 214-225.

Nishimizu, M and J. Page (1982). Total factor productivity growth, technological progress, and technical efficiency change: dimensions of productivity change in Yugoslavia, 1965-1978, *Economic Journal*, 92: 920-936.

Oberhofer, H and M. Pfaffermayr (2009). Fractional response models-A replication exercise of Papke and Wooldridge (1996). *A working paper in Econometrics and Statistics, University of Innsbruck* No.2009-02.

O'Donnell, D. J (2010). Measuring and decomposing agricultural productivity and profitability change, *Australian Journal Agricultural Resource Economics*, Vol. 54: 527-560.

Ogundari, K. and A. Abdulai (2013). Examining the Heterogeneity in Calorie-Income Elasticities: A meta-analysis. *Food Policy*: Vol. 40: 119-128.

Ogundari, K., T. T. Amos and V.O. Okoruwa (2012). A review of Nigerian agricultural production efficiency literature, 1999-2011: What does one learn from frontier studies? *African Development Review*, Vol. 24(1): 93-106.

Ogundari, K and B. Brümmer (2011). Technical efficiency of Nigerian Agriculture: A meta-regression analysis. *Outlook on Agriculture*, Vol. 40 (2): 171-180.

Otsuka, K (2013). Food security, Income, Inequality and the Changing comparative Advantage in World Agriculture. *Agricultural Economics*, Vol. 44: 1-12.

Papke, L. S and J. M. Wooldridge (1996). Econometric methods for fractional response variables with an application to 401(K) plan participation rates. *Journal of Applied Econometrics*, Vol.11: 619-632.

Philips, J.M (1994). Farmer Education and farmer efficiency: a meta-analysis, *Economic Development and Cultural Change*, Vol. 4391): 149-165.

POSTnote (2006). Food security in developing countries, Published by Parliamentary office of Science and Technology, UK, Issues No. 274.

Pudasaini, S. P (1983). The effects of education in Agriculture: Evidence from Nepal. *American Journal of Agricultural Economics*, Vol. 65(3): 509-515.

Reimers, M and S. Klasen (2011). Revisiting the role of education for Agricultural productivity, Courant Research Center, Discussion paper No. 90, Georg-August University of Goettingen, Germany.

Romalho, E. A., J.J.S. Ramalho and P. D. Henriques (2010). Fractional regression models for second stage DEA efficiency analyses, *Journal of Productivity Analysis*, Vol. 34: 239-255.

Stanley, T. D and R. S. Rosenberger (2009). Are recreation values systematically under estimated? Reducing publication selection bias for benefit transfer. A paper presented at the 2009 MAER-Net Colloquium, Corvallis Oregon USA.

Sterne, J. A. C. (2009), *Meta-Analysis in Stata: An Updated Collection from the Stata Journal*, Stata Press, College Station, TX.

Thiam, A., Bravo-Ureta, B. E., and Rivas, T. (2001), 'Technical efficiency in developing country agriculture: a meta-analysis', *Agricultural Economics*, Vol 25, pp 235–243.

Weir, S. and J. Knight (2000). Education Externalities in Rural Ethiopia: Evidence from Average and Stochastic Frontier Production Functions. *Working Paper CSAE WPS/2000.4, Centre for the Study of African Economies*, University of Oxford.

Yu, B and A. Nin-Pratt (2011). Agricultural Productivity and Policies in sub Saharan Africa. IFPRI Discussion paper No. 01150 Washington DC.

Table 1: Summary statistics of variables used in meta-regression analysis (MRA)

Category	**Description**	**Variable**	**Mean**	**SD**
Efficiency Score	Average efficiency score reported *(Dependent variable)*	AVE_EFF	0.6879	0.1741
Data	Average year of the data that a primary study used	DATAYEAR	2005.0	5.5300
	Articles with panel data	D_PANELDATA	0.0523	0.2229
	Articles with cross-sectional data	D_CROSSDATA	0.9477	0.2229
	Degree of Freedom	DF	274.44	797.64
Output measure	Articles with single output measure/ un-aggregated output	D_OUTPUT	0.7757	0.4175
Publication	Journal Articles	D_JOURNAL	0.8785	0.3270
	Articles in top ranking journal	D_IMPACTFACTOR	0.1383	0.3456
Specification	Articles with Cobb-Douglas functional form	D_COBBDOUGLAS	0.7121	0.4532
	Articles with Translog functional form	D_TRANSLOG	0.2280	0.4199
	Articles with other Functional forms and with no functional form	D_NOFUNCTION	0.1009	0.3015
Methodology	Articles with parametric method	D_PARAMETRIC	0.8953	0.3064
	Articles with non-parametric method	D_NONPARAMETRIC	0.1047	0.3064
Technology	Articles with Primal Technology representation	D_PRIMAL	0.8822	0.3226
	Articles with Dual Technology representation	D_DUAL	0.0897	0.2860
Product	Articles with focus on Grain production	D_GRAIN	0.2935	0.4558
	Articles with focus on Food crop production	D_FOODCROP	0.7551	0.4304
	Articles with focus on Cash crop production	D_CASHCROP	0.1084	0.3112
	Articles with focus on non-crop production (livestock, fish etc.)	D_NONCROP	0.1551	0.3624
Region	Articles carried out in East Africa	D_EAST	0.1869	0.3902
	Articles carried out in Central Africa	D_CENTRAL	0.0168	0.1287
	Articles carried out in Southern Africa	D_SOUTHERN	0.0729	0.2602
	Articles carried out in North Africa	D_NORTH	0.0243	0.1541
	Articles carried out in West Africa	D_WEST	0.7009	0.4582

Table 2: Meta-regression analysis results

EXPLANATORY VARIABLES	ALL AFRICA: Without Regional Effects		ALL AFRICA: With Regional Effects		SSA REGION ONLY		PERIOD OF PUBLICATION 1984-2003		PERIOD OF PUBLICATION 2004-2013	
	Model 1		Model 2		Model 3		Model 4		Model 5	
	Coefficient	*Std. Error*	*Coefficient*	*Std. Error*	*Coefficient*	*Std. Error*	*Coefficient*	*Std. Error*	*Coefficient*	*Std. Error*
DATAYEAR	**-0.0202*** **	**0.0066**	**-0.0203*** **	**0.0064**	**-0.0253*** **	**0.0063**	**-0.0356*** **	**0.0075**	**-0.0208** **	**0.0099**
D_PANELDATA	0.0605	0.1334	0.0725	0.1386	-0.0092	0.1474	-0.4445	0.7045	0.0957	0.1349
DF	-0.0001*	0.0000	-0.0001*	0.0000	-0.0001	0.0000	-0.0005	0.0003	-0.0001**	0.0000
D_JOURNAL	0.4187***	0.1017	0.2845***	0.1108	0.2269**	0.1121	0.6260	0.4043	0.2867***	0.1130
D_IMPACTFACTOR	-0.2395**	0.1008	-0.1532	0.1066	-0.1689	0.1085	-0.9398***	0.1911	-0.0799	0.1230
D_COBBDOUGLAS	-0.2723*	0.1674	-0.3588***	0.1711	-0.3478**	0.1731	2.0351**	0.9054	-0.4514***	0.1759
D_TRANSLOG	-0.3136**	0.1552	-0.3673**	0.1559	0.3729**	0.1579	1.0570	0.8882	-0.3928***	0.1600
D_PARAMETRIC	0.4545**	0.2101	0.5099**	0.2105	0.5690***	0.2168	-0.7140	0.8586	0.4524***	0.2339
D_PRIMAL	0.2105*	0.1148	0.2324**	0.1130	0.2183**	0.1129	0.1815	0.4280	0.2949	0.1168
D_OUTPUT	0.2965***	0.1022	0.3009***	0.1028	0.3292***	0.1039	-0.3187*	0.1852	0.3060***	0.1061
D_GRAIN	-0.0943	0.0901	-0.0967	0.0899	-0.1091	0.0909	1.0739	0.3601	-0.0703	0.0933
D_FOODCROP	-0.0940	0.1304	-0.1031	0.1297	-0.1002	0.1304	-1.1033	0.7389	-0.0714	0.1296
D_CASHCROP	-0.1175	0.1486	-0.1460	0.1485	-0.1028	0.1515	-0.2861	0.7869	-0.0804	0.1476
D_EAST	-	-	-0.2742***	0.0949	-0.2851***	0.0952	-0.0865	0.2213	-0.3115***	0.0997
D_CENTRAL	-	-	-0.2347	0.2009	-0.2666	0.1929	-	-	-0.2927	0.2011
D_SOUTHERN	-	-	-0.1423	0.1327	-0.1499	0.1323	-0.8310***	0.3564	0.0217	0.1580
D_NORTH	-	-	-0.1078	0.2239	-	-	-	-	-0.1855	0.2129
CONSTANT	40.473***	13.193	40.914***	12.845	50.852***	12.633	72.408***	14.894	42.049***	19.986
LOG_LIKELIHOOD	-232.89		-232.36		-226.55		-16.48		-214.04	
DEVIANCE	73.09		72.03		70.35		1.85		66.52	
PEARSON	69.57		68.92		67.15		1.86		63.69	
1/DF DEVIANCE	0.1403		0.1393		0.1393		0.0638		0.1403	
1/DF PEARSON	0.1335		0.1333		0.1329		0.0641		0.1344	
AIC	0.9229		0.9359		0.9331		1.4178		0.9433	
BIC	-3199.97		-3175.89		-3089.77		-107.22		-2871.56	
# OBSERVATION	534		534		521		043		491	

Note: ****, **, * implies that the estimated parameters are significantly different from zero at 1%, 5%, and 10% significance level, respectively.*

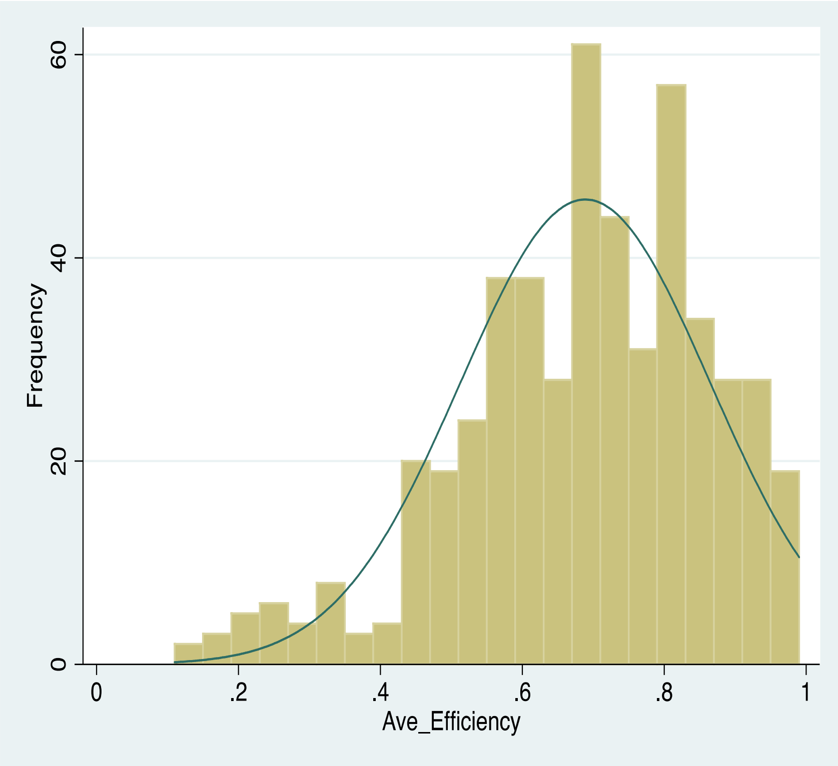

Figure 1: Distribution of Average Efficiency from the primary studies

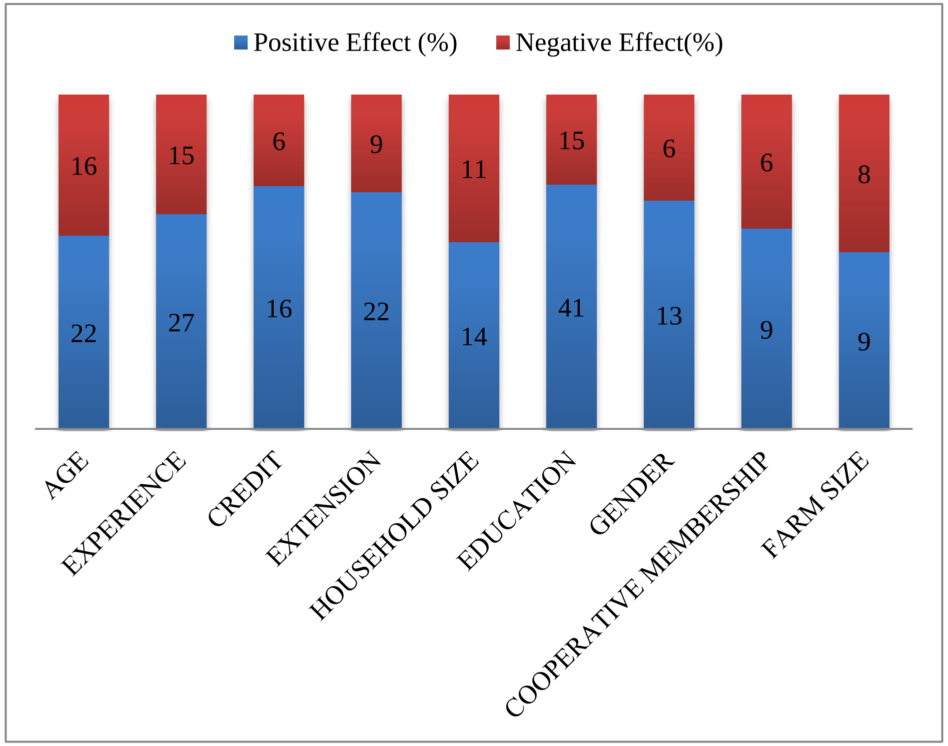

Figure 2: Distribution of identified key drivers African Agricultural Efficiency