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The Paradigm of Agricultural Efficiency and its Implication on Food Security in Africa: What Does Meta-analysis Reveal?☆

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Summary. — The study investigates whether African agricultural efficiency levels have been improving or not and what drives them over the years based on 442 frontier studies using meta-regression analysis. The results show that the mean efficiency estimates from studies decrease significantly as year of survey in the primary study increases. Also studies published in Journals, with parametric specification and with panel data produced significantly higher efficiency estimates, while those with a focus on grain crops reported 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.

Key words — agriculture, efficiency, meta-analysis, food security, fractional regression, Africa

1. 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). The key to boosting food security in the region cannot be divorced from agricultural total factor productivity (TFP) growth. As noted by Brümmer (2006), 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.

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 important input for better informed policy decisions around the globe (Ogundari, Amos, & Okoruwa, 2012; Thiam, Bravo-Ureta, & Rivas, 2001).

According to Gallup, Radielet, and Warmer (1997), increase in the 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 levels provides opportunities for farmers to produce more at same level of resources, while 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 lead to a 1.6% rise in income of the poorest. Likewise, Martin (2013) argued that the poverty impact of increase in agricultural productivity growth is much larger than for industry or services sector.

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). Meanwhile, recent empirical findings by Thiam *et al.* (2001), Bravo-Ureta *et al.* (2007) and Ogundari and Brümmer (2011) have shown that the mean efficiency estimates of agricultural and food production reported in the primary studies differ across many study attributes (or dimensions) such as methodology, data type, model specification, and location among others.

In addition, two recent cross-country analyses of agricultural productivity growth in Africa based on FAOSTAT data by Alene (2010) and Yu and Nin-Pratt (2011) provided evidence that change in efficiency levels over time contributed negatively to the TFP growth of the sector over the years. Subsequently, both authors concluded that the decline in efficiency levels is a major cause of poor TFP growth in African agriculture and food production, while both studies also identified

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

technical progress (technological change) as main driver of agricultural TFP growth in the region. [1] This observation contradicts Fugile and Wang's (2012) argument that the future challenge to the global food security as in the past does not appear to be related to technical constraints, but rather to uneven access to resources (i.e., poor resource use efficiency level).

Furthermore, recent study by Ogundari (2013) has shown that there are a 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. In this respect, it will be interesting to understand what literature revealed about the trends (or development) in the African agricultural efficiency levels and what drives the efficiency levels over the years as an important input in agricultural policy decisions in the region. In other words, 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 noted by Ogundari *et al.* (2012), lessons/policy implications drawn from previous studies on agriculture and food production, could be very useful as guides to agricultural policymakers in designing effective food security programs and policies. Thus, arising from the foregoing, the present study addresses the following research questions:

RQ1. How did the relationship between reported mean efficiency estimates and year of survey from the selected frontier studies develop (i.e., rise or decline) over the years?

RQ2. Are there differences in reported mean efficiency estimates driven by study-specific attributes such as methodology used, model specification, publication outlet, data type, location etc. from the selected frontier studies?

RQ3. What factors (policy variables) have driven agricultural efficiency levels most over the years from the selected frontier studies?

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 the mean efficiency scores from primary studies 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 using just 2 studies from Africa, Bravo-Ureta *et al.* (2007) examined efficiency estimates from both the developing and developed agriculture using 14 studies from Africa, and Ogundari and Brümmer (2011) focused exclusively on efficiency estimates from Nigeria with 124 studies involved.

The present study contributes to existing literature in three ways. *First*, unlike previous studies that include few numbers of observations from Africa, the present study focuses exclusively on the efficiency estimates from Africa with broader geographical coverage that would produce a better understanding of the link between these estimates in African agriculture and attributes of studies reporting these estimates in the region. *Second*, unlike previous studies that used Tobit, OLS, and truncated regressions, believed to yield biased result as argued by McDonald (2009) and Ramalho, Ramalho, and Murteira (2011), the current study makes a significant contribution in terms of methodology employed by using fractional regression model for the meta-regression analysis (MRA). *Third,* unlike previous studies with the exception of Ogundari and Brümmer (2011), we extend our discussion to include drivers of agricultural efficiency level over the years in Africa.

The paper is structured as follows. The next section provides overviews of frontier efficiency and meta-analysis. Section 3 provides detailed description of the meta-dataset used for the analysis. In Section 4, meta-regression model specification is provided. Section 5 presents the results and discussion, while conclusions are provided in Section 6.

2. AN OVERVIEW OF FRONTIER EFFICIENCY AND META-ANALYSIS

(a) *An overview of frontier efficiency*

Efficiency 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). The efficiency of a decision-making unit (DMU) can be assessed as technical, cost or profit or allocative efficiency. When producers face input–output mix, efficiency of DMU, called technical efficiency, is measured relative to production frontier, using primal technology specification (i.e., production function). Also, when producers face input price mix and output price mix, efficiency of DMU is measured relative to cost and profit frontiers, respectively. In this regard, cost and profit efficiencies are estimated using dual technology specification (referred in the literature as alternative representation of the production function) such as cost and profit functions, respectively. Since, the measure of cost or profit efficiency can be decomposed into technical and allocative efficiencies (see for detail, Coelli, Rao, O'Donnell, & Battese, 2005; Kumbhakar & Lovell, 2000), allocative efficiency is derivable from the combination of either the production and cost frontiers or production and profit frontiers estimates. [2] Thus, following Farrell's (1957) definition, technical efficiency is defined as the ability of a DMU (e.g., a farm) to produce maximum output given a set of inputs, while allocative efficiency is the ability to produce a given level of output using cost-minimizing input ratios – in recognition that a technically efficient producer could choose an inappropriate input mix given the input prices it faces. But profit efficiency is viewed as the highest possible profit achieved by DMU relative to the frontier profit, given the optimum combination of output and factor prices (Kumbhakar & Lovell, 2000).

Meanwhile, economic theory offers numerous procedures for evaluating efficiency of a DMU (Hoff, 2007), as methodologies employed in estimating efficiency level of agriculture and food production have evolved over the years. This however, ranges from when simple indexing method and mathematical programing (or nonparametric method-Data Envelopment Analysis – DEA) were used, the use of simple and sophisticated econometrics (or parametric method such as stochastic frontier analysis – SFA), the introduction of theoretically consistent functional forms, the introduction of dynamic and spatial econometrics and systems of equations, use of multi-output technology estimation to the introduction of meta-frontier technology among others (for detail discussion see, Kumbhakar & 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 Kumbhakar and Lovell (2000), a major feature of panel data is the ability to decompose TFP growth into four distinct components such as technical change or technological change (which could be outward or inward shift of production frontier) and efficiency change (which could be movement toward (catching up) or away from (lagging behind) the production frontier and until lately into scale efficiency change (change in variety of inputs available) and allocative efficiency change in inputs and output and mix-efficiency change (Kumbhakar & Lovell, 2000; O'Donnell, 2010). This decomposition makes it possible to study the sources of TFP growth from different points of view (Nishimizu & Page, 1982) and this is very useful for designing agricultural policy program.

Generally speaking, frontier efficiency model does not only serve as a benchmark, which efficiency levels of DMU are estimated, but it is also very useful in identifying determinants of efficiency levels for policy inference (Kumbhakar & Lovell, 2000). In this case, the approach used to incorporate the determinants of efficiency into frontier model has evolved over the years from two-stage approach to one-stage approach that enables joint estimation of efficiency and its determinants (Kumbhakar & Lovell, 2000; Coelli *et al.*, 2005). Even within the one-stage approach, the methodology has also evolved from when mean of the pre-truncated distribution of the inefficiency error term is modeled as a function of exogenous variable that represents determinants of efficiency levels to when variance of the pre-truncated inefficiency error term is model as a function of exogenous variables. The latter is believed to have the possibility of solving two problems at once, namely to correct for heteroskedasticity in the inefficiency error terms, while incorporating exogenous variables to investigate inefficiency effects in the production process.

A search of literature 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 Darku, Malla, and Tran (2013). The conclusions from these studies highlight the efforts that have been devoted to measuring efficiency in agriculture using different frontier methods and models over the years. In addition, the general conclusion from many of these studies show 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. This observation 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).

(b) *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) 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, Marra, Pardey, & Wyatt, 2000). With reference to the present study, mean efficiency estimates (which could be technical, allocative, 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.

Although, MA is quite popular in medical, education, pharmaceutical, and marketing researches as noted by Thiam *et al.* (2001), a review of the literature, 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 times. This includes effect of immigration on wages (Longhi, Nijkamp, & Poot, 2005), income and calorie intake (Ogundari & Abdulai, 2013), income inequality and economic growth (de Dominicis, Florax, & de Groot, 2008), effect of aid on economic growth (Mekasha & Tarp, 2013), energy consumption and economic growth (Chen, Chen, & Chen, 2012), effect of currency unions on trade (Havranek, 2010), price and income elasticity of demand for meat (Gallet, 2010a, 2010b), price and income elasticity of demand for alcohol (Gallet, 2007), income elasticity of demand for cigarette (Gallet & List, 2003), exchange rate volatility and trade (Josheski & Lazarov, 2012), debt and economic growth (Moore & Thomas, 2010), Willingness to pay for reduction in pesticide risk exposure (Florax, Travisi, & Nijkamp, 2005), and many more.

3. META-DATASET

Meta-analysis requires a thorough search of literature that provides a complete description of study-specific characteristics or attributes of interest for the MRA. To this end, a variety of sources were used to compile the selected case 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 were that the study reports mean efficiency estimates, data year or year of survey, and sample size. Based on this, we selected 442 frontier studies published from 1984 to 2013 for the current analysis. Because some of the retrieved studies reported more than one efficiency estimate, a total 612 farm-level efficiency estimates were used for the MRA in the present study. [4] The selected studies cut across the entire region in Africa namely West Africa, East Africa, Central Africa, Southern Africa, and Northern Africa with a total of 30 countries represented in the meta-dataset.

Thus, using previous studies by Thiam *et al.* (2001), Bravo-Ureta *et al.* (2007), and Ogundari and Brümmer (2011) as guides, we extracted and coded study-specific attributes of interest for the MRA presented in Table 1. Conversely, an overview of the database shows that the number of farm-level efficiency estimates (or frontier studies) obtained across the West Africa, East Africa, Central Africa, Southern Africa, and North Africa regions are 418 (314), 114 (78), 12 (5), 43 (27), and 25 (18), respectively. This perhaps shows that the substantial number of studies on the performance of Africa agriculture focuses their research interest on the efficiency of agricultural and food production in West Africa region. In addition, we provide evidence that the selected studies covered a range of products starting from grain crops such as maize, rice etc., tubers such as cassava, yam, cocoyam, potatoes, cash crops (cocoa, coffee etc.) to noncrop products such as egg production, poultry, livestock, fish etc.

Meanwhile, the list of the selected studies for the meta-analysis containing information regarding the authors, the publication outlet for the primary study, year of publication, the product under investigation, sample size, and reported efficiency from the studies is available in an unpublished appendix.

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

Category	Variable	Description	Mean	SD
Efficiency Score	EFF_EST	Mean efficiency score reported	0.6822	0.1749
Data	DATAYEAR	Year of the data that a primary study used	2005.5	5.5349
	D_PANELDATA	Equal to 1 if article used panel data	0.0507	0.2195
	D_CROSSDATA	Equal to 1 if article used cross-sectional data (*reference*)	0.9493	0.2195
	DF	Degree of Freedom	261.28	749.57
Output measure	D_OUTPUT	Equal to 1 if article is with single output measure/un-aggregated output and *0 otherwise*	0.7941	0.4047
Publication	D_JOURNAL	Equal to 1 if article is published in journal and 0 if working papers, conference proceed, thesis	0.8839	0.3205
	D_IMPACTFACTOR	Equal to 1 if article is published in journal with impact factor and *0 otherwise*	0.1258	0.3319
Specification	D_COBBDOUGLAS	Equal to 1 if article used Cobb-Douglas functional form	0.7075	0.4553
	D_TRANSLOG	Equal to 1 if article use Translog functional form	0.2239	0.4172
	D_NOFUNCTION	Equal to 1 if article used other Functional forms and with no functional form (*reference*)	0.1046	0.3062
Methodology	D_PARAMETRIC	Equal to 1 if article used parametric method	0.8922	0.3104
	D_NONPARAMETRIC	Equal to 1 if article used nonparametric method (*reference*)	0.1078	0.3104
Technology	D_PRIMAL	Equal to 1 if article used primal Technology representation	0.9036	0.2935
	D_DUAL	Equal to 1 if article used Dual Technology representation (*reference*)	0.0964	0.2954
Product	D_GRAIN	Equal to 1 if article focused only on grain crop production (e.g., rice, maize, wheat, sorghum, etc.)	0.2942	0.4560
	D_FOODCROP	Equal to 1 if article focused on food crop production (e.g., tubers, cereals, vegetable etc.)	0.7467	0.4352
	D_CASHCROP	Equal to 1 if article focus on cash crop production (e.g., cocoa, rubber, etc.)	0.1160	0.3205
	D_NONCROP	Equal to 1 if article focused on noncrop production, e.g., fish, livestock, poultry etc. (*reference*)	0.1519	0.3593
Region	D_EAST	Equal to 1 if article is published in countries in East Africa	0.1863	0.3896
	D_CENTRAL	Equal to 1 if article is published in countries in Central Africa	0.0212	0.1443
	D_SOUTHERN	Equal to 1 if article is published in countries in Southern Africa	0.0686	0.2530
	D_NORTH	Equal to 1 if article is published in countries in North Africa	0.0408	0.1981
	D_WEST	Equal to 1 if article is published in countries in West Africa (*reference*)	0.6846	0.4650

4. THE META-REGRESSION MODEL AND EMPIRICAL MODEL

(a) The meta-regression model

To provide answers 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

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

where EFF_EST_{ir} represents mean efficiency estimate(s) from the i-th primary study, conducted in r-th region in Africa and ψ_0 is intercept; $DATAYEAR_{ir}$ is the year of survey used in the primary study, which starts from 1967, 1981, 1989, …, 2012.[5] This is included in Eqn. (1) to investigate the 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 a proxy indicator of efficiency change over time in absence of reliable panel data. X_{kir} is a vector of other study attributes also considered in the MRA model as control variables. This however includes, a continuous variable *DF* representing the degree of freedom in each study and fourteen dummy variables *D_attributes* representing study-specific attributes such as data used, output measure, publication outlet, specification, methodology, technology, products, and region where these studies were carried out (for detailed description of the variables see Table 1). Meanwhile, the dummy variables considered in MRA 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 nonaggregated output (studies with an aggregated output served as reference)[6]; *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 journals with impact factor[7]; *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 nonparametric method served as reference); *D_PRIMAL* representing articles that employed primal technology (articles with dual technology served as reference)[8]; *D_GRAIN* representing studies that focused on grain crops such as maize, rice etc. (articles with a focus on nongrain products served as reference); *D_FOODCROP* and *D_CASHCROP* represent studies with a focus on food crops and cash crops, respectively (noncrop 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_i, and α_k are parameters to be estimated and the sign of β_i 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 effect on the *EFF_EST*$_{ir}$, a negative sign would suggest otherwise.[9] 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, Asche, & Tveteras, 2013). In this regard, McDonald (2009) and Ramalho, Ramalho, and Henriques (2010), argued that the DGP for *EFF_EST*$_{ir}$ is a fractional/proportional data bounded between zero and 1 and not censored data by construction. McDonald (2009) showed that consequently, the use of linear models such as ordinary least square (OLS) and Tobit models may not provide accurate estimates of the effects of explanatory variables on the dependent variable of Eqn. (1). For example, if the explanatory variables in Eqn. (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 Ramalho *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 (Ramalho *et al.*, 2010).

Intuitively, MRA of Eqn. (1) is synonymous with 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. As noted by Kumbhakar and Lovell (2000), these factors often include managerial characteristics such as age, educational attainment, and experience of the producers or DMU, and access to credit among others. Guided by this, the present study uses fractional regression model to estimate the parameters of Eqn. (1). As earlier mentioned, this is a departure from previous studies on meta-analysis of efficiency 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 the Truncated regression model by Ogundari and Brümmer (2011). The fractional regression model is subsequently discussed below.

(b) *Empirical model*

Papke and Wooldridge (1996) highlighted the drawbacks of linear models for fractional data that are analogous to the drawbacks of the linear probability model for binary data. Likewise, Kieschnick and McCullough (2003) argued that since fractional data are only observed over a closed interval, it 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, however 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.[10]

The fractional response model is estimated using Quasi-Maximum Likelihood Estimation (QMLE) method and is a nonlinear model. QMLE is asymptotically efficient and consistent compared to either OLS or Tobit or Truncated or transformed logistic normal often used by researchers 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 used the following Bernoulli Log-likelihood specification.

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

where, $0 \leqslant y_i \leqslant 1$ 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 $\beta \ or \ \alpha$ in Eqn. (1) is obtained by simply maximizing Eqn. (2) [that is, $\max_{\beta \, or \, \alpha} \sum_{i=1}^{N} L_i(\beta \, or \, \alpha)$]. 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 is 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 achieved 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. But, 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.[11]

QMLE is estimated by weighted nonlinear allowing for heteroskedasticity and testing procedures, which are asymptotically efficient within a class of estimators (Oberhofer & Pfaffermayr, 2009).[12]

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

$$E(EFF\_EST_{ir}|Z) = G\left(\psi_0 + \beta_i DATAYEAR + \sum_{k=1}^{K} \alpha_k X_{kir} + \varepsilon_{ir}\right) \times t = 1967, \ldots 2012 \tag{3}$$

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

Because many of the studies reported more than one efficiency estimate, Espey and Shaw (1997) argued that lack of independence in the values of the dependent variable across observations is one of the problems of meta-regression analysis (MRA), which is likely to bias the standard errors of Eqn. (3). In this regard, Nelson and Kennedy (2009) suggested the use of weighted regression technique to eliminate lack of independence in the values of the dependent variable of MRA, which Stanley (2008) also argue can potentially be used to lessen publication bias in MRA. In addition, Stanley and Doucouliagos (2013) argued that weighted regression-MRA offers the best of both fixed effect and random effect MRA.

However, unlike un-weighted regression, which gives equal weight to each observation, weighted regression also corrects for outliers and measurement errors by giving less weight to such outliers so as to ensure that potentially more reliable estimates are not confounded by observations subject to a larger variance.

In view of this, we estimate Eqn. (3) by taken sample sizes from the primary study as proxies for the weight following the work of Stanley (2008) and Nelson and Kennedy (2009).

5. RESULTS AND DISCUSSION

(a) *RQ1: What is nexus between mean efficiency estimates and year of survey?*[13]

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. The figure on the left hand side (LHS) shows that the mean efficiency scores from all the selected primary study have a right-skewed distribution with most observations ranging from 0.52 to 0.99 and with an average of about 0.68 (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 & Pinheiro, 1993; Ogundari *et al.*, 2012; Thiam *et al.*, 2001). Meanwhile, for the institution responsible for agricultural and food policy design in Africa, it is very important to note that 0.68 average mean efficiency levels obtained in the present study is an indication that there is ample room for improvement of efficiency in agriculture and food production in Africa. In addition, the results imply that there is need to focus attention on investments that will push African agriculture toward the existing frontier. Hence, the average mean efficiency estimate obtained in the present study is lower than the estimate between 0.74 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, while it is not different from 0.69 reported by Ogundari (2013) from 379 published frontier studies from Africa.

Also, closely related, the distribution of the reported mean efficiency estimates are allowed to vary across the regions where the selected case studies were carried out, which is presented on the right hand side (RHS) of Figure 1. In this case, the figure shows that studies from West Africa reported highest efficiency estimates within the range 0.50–0.90 and with a mean score of about 0.71, followed by North Africa (0.66), Southern Africa (0.65), East Africa (0.63), and Central Africa (0.54) countries in that order.

Furthermore, in an attempt to provide answers to the first research question, we also present in Figure 2 the scatter plot of univariate relationship between the reported mean efficiency estimates and year of survey (or year of data) in the primary study. Using the fitted line as a guide, the figure on LHS of Figure 2 shows a negative linear correlation relationship between reported mean efficiency estimates per study and year of survey for the whole sample under consideration. But when the relationship is allowed to vary across the regions as presented on the RHS of Figure 2, we uncover evidence of linear negative correlation in the studies carried out in the West Africa, East Africa, and Central Africa regions and positive linear correlation in the studies carried out in the Southern Africa and Northern Africa regions.

Also, we augment the results of the scatter plot by using MRA based on Eqn. (3) to further investigate the first research question and result is presented in Tables 2A and 2B. While Table 2A presents estimates from un-weighted fractional regression model, Table 2B presents the results from weighted fractional regression model with number of observations from the primary study as weight. As for each of the results in the tables, we estimate 5 different models to provide robustness check to the result of the coefficient of $DATAYEAR_{ir}$, which happens 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

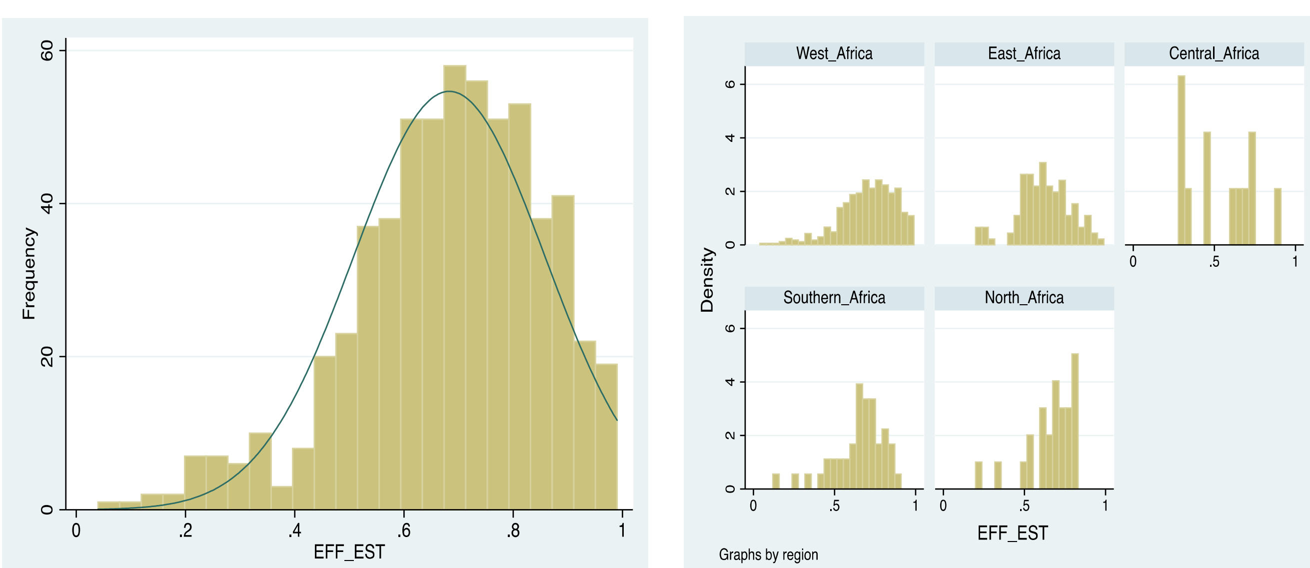

Figure 1. *Distribution of mean efficiency estimates from the selected case studies for the whole sample and also across the regions in Africa.*

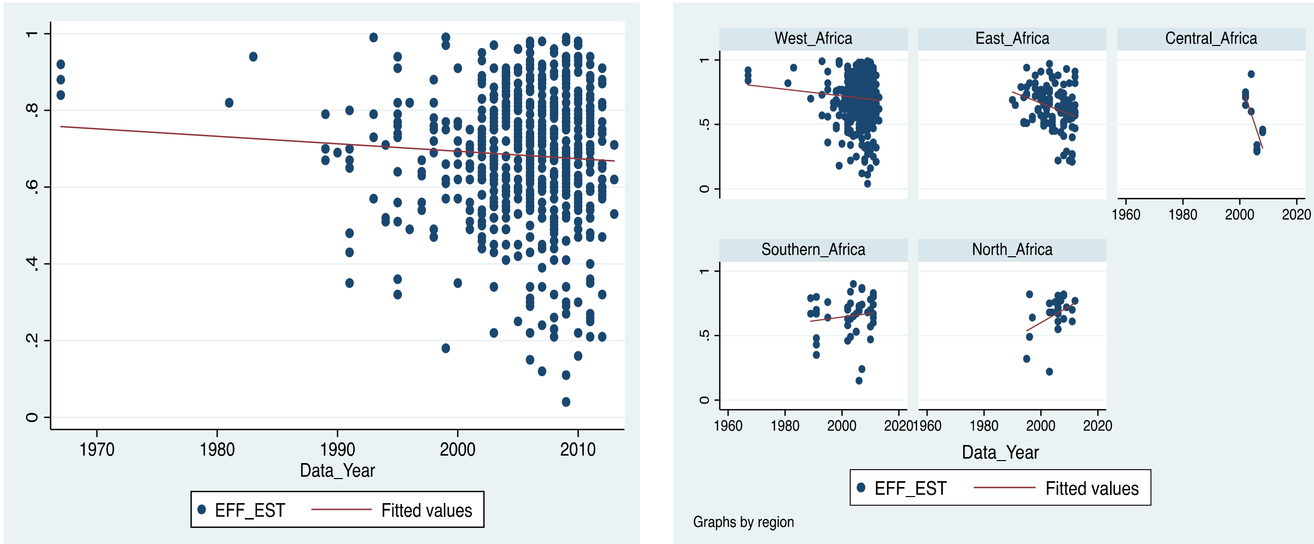

Figure 2. *Scatter plot of the univariate relationship between the mean efficiency estimates and year of survey for the whole sample and the regions in Africa.*

Table 2A. *Meta-regression results without weight*

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	**−0.0198*****	**0.0061**	**−0.0205*****	**0.0059**	**−0.0266*****	**0.0059**	**−0.0356*****	**0.0075**	**−0.0215****	**0.0087**
D_PANELDATA	0.4884	0.2006	0.1028	0.1304	0.0115	0.1389	−0.4445	0.7045	0.1371	0.1279
DF	−0.0001*	0.0000	−0.0001*	0.0000	−0.0001*	0.0000	−0.0005	0.0003	−0.0001**	0.0000
D_JOURNAL	0.3426**	0.0962	0.1988**	0.1020	0.1716*	0.1044	0.6260	0.4043	0.2062**	0.1042
D_IMPACTFACTOR	−0.1784*	0.0963	−0.0746	0.1003	−0.1039	0.1024	−0.9398***	0.1911	0.0198	0.1146
D_COBBDOUGLAS	−0.2313	0.1652	−0.3641**	0.1681	−0.3442**	0.1708	2.0351**	0.9054	−0.4452***	0.1732
D_TRANSLOG	−0.2637*	0.1535	−0.3538**	0.1545	−0.3644**	0.1573	1.0570	0.8882	−0.3784**	0.1593
D_PARAMETRIC	0.4884**	0.2006	0.5549***	0.1995	0.6357***	0.2065	−0.7140	0.8586	0.5275***	0.2154
D_PRIMAL	0.2094**	0.1059	0.2504**	0.1029	0.2293**	0.1031	−0.1815	0.4280	0.2945***	0.1057
D_OUTPUT	0.2288**	0.0966	0.2609***	0.0953	0.2961***	0.0969	−0.3187*	0.1852	0.2588***	0.0994
D_GRAIN	−0.0781	0.0817	−0.0993	0.0809	−0.1156	0.0829	1.0739***	0.3601	−0.0788	0.0833
D_FOODCROP	−0.0667	0.1157	−0.0376	0.1150	−0.0323	0.1157	−1.1033	0.7389	−0.0019	0.1149
D_CASHCROP	−0.1113	0.1417	−0.0914	0.1422	−0.0199	0.1484	−0.2861	0.7869	−0.0319	0.1429
D_EAST	–	–	−0.3135***	0.0854	−0.3122***	0.0860	−0.0865	0.2213	−0.3504***	0.0891
D_CENTRAL	–	–	−0.7127***	0.2139	−0.7109***	0.2011	No case study		−0.7904***	0.2187
D_SOUTHERN	–	–	−0.1923	0.1243	−0.1884	0.1249	−0.8310***	0.3564	0.0693	0.451
D_NORTH	–	–	−0.2351	0.1567	Not part of SSA		No case study		−0.2855*	0.1519
CONSTANT	39.783***	12.121	41.295***	12.029	53.468***	11.757	72.408***	14.894	43.257***	17.480
LOG_PSLIKELIHOOD	−268.82		−267.45		−255.99		−16.48		−249.11	
DEVIANCE	85.00		82.25		79.08		1.85		76.71	
PEARSON	80.80		78.69		75.49		1.86		73.46	
(1/DF) DEVIANCE	0.1421		0.1385		0.1387		0.0638		0.1392	
(1/DF) PEARSON	0.1351		0.1325		0.1325		0.0641		0.1333	
AIC	0.9243		0.9328		0.9301		1.4178		0.9388	
BIC	−3752.20		−3729.29		−3554.68		−107.22		−3418.77	
# OBSERVATION	612		612		587		043		569	

Note: Standard errors reported are robust standard errors.
*The estimated parameters are significantly different from zero at 10% significance level.
**The estimated parameters are significantly different from zero at 5%, significance level.
***The estimated parameters are significantly different from zero at 1% significance level.

among others (Bravo-Ureta *et al.*, 2007; Ogundari & Brümmer, 2011; Thiam *et al.*, 2001). The first and second models focus on the primary studies from Africa but without and with the regional specific effects, respectively. The third model focuses on the selected case studies from sub-Saharan Africa (SSA), while fourth and fifth models focus on the

Table 2B. *Meta-regression results with weight*

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	**−0.0339*****	**0.0096**	**−0.0342*****	**0.0095**	**−0.0393*****	**0.0099**	**−0.0368*****	**0.0077**	**−0.0416*****	**0.0141**
D_PANELDATA	0.2881	0.1829	0.2815*	0.1649	0.2579	0.1684	-0.4544	0.5653	0.3255**	0.1649
DF	−0.0001*	0.0000	−0.0001**	0.0000	−0.0001**	0.0000	−0.0003	0.0004	−0.0001**	0.0000
D_JOURNAL	0.3577***	0.1303	0.2666**	0.1269	0.2521**	0.1275	0.8957***	0.2680	0.2844***	0.1265
D_IMPACTFACTOR	−0.1591	0.2225	−0.1087	0.2165	−0.1309	0.2197	−0.8619***	0.1679	−0.0606	0.2329
D_COBBDOUGLAS	−0.1139	0.2132	−0.2819	0.2239	−0.2741	0.2278	2.2007**	0.8827	−0.4137*	0.2168
D_TRANSLOG	−0.0233	0.1683	−0.1507	0.1769	−0.1618	0.1807	1.3875	0.8686	−0.2869*	0.1647
D_PARAMETRIC	0.9377***	0.3315	1.1102***	0.3354	1.1663***	0.3392	−0.7710	0.8578	1.2862***	0.3658
D_PRIMAL	−0.1886	0.1946	−0.1322	0.1829	−0.1304	0.1795	−0.2226	0.3305	−0.1267	0.1817
D_OUTPUT	0.3322**	0.1501	0.3383**	0.1518	0.3667**	0.1536	−0.3442**	0.1073	0.3641**	0.1560
D_GRAIN	−0.3927***	0.1249	−0.3979***	0.1258	−0.4192***	0.1525	0.8650***	0.3413	−0.3995***	0.1289
D_FOODCROP	−0.0376	0.1414	−0.0257	0.1478	−0.0209	0.1492	−0.4193	0.5049	0.0022	0.1514
D_CASHCROP	−0.2737	0.1916	−0.2896	0.2069	−0.2420	0.2176	0.4695	0.5728	−0.2909	0.2151
D_EAST	–	–	−0.3367***	0.1368	−0.3369***	0.1366	−0.1269	0.1650	−0.3575***	0.1440
D_CENTRAL	–	–	−0.5456***	0.1993	−0.5634***	0.1965	No case study		−0.5884***	0.2101
D_SOUTHERN	–	–	−0.1064	0.2343	−0.1078	0.2300	−0.5809**	0.2698	−0.1142	0.2529
D_NORTH	–	–	−0.0363	0.2214	Not part of SSA		No case study		−0.0675	0.2355
CONSTANT	67.749***	19.100	69.212***	19.284	78.488***	19.697	73.546***	15.324	84.506***	28.409
LOG_PSLIKELIHOOD	−275.18		−273.75		−262.15		−17.40		−254.97	
DEVIANCE	72.16		69.31		65.85		1.04		65.46	
PEARSON	67.64		65.55		62.30		0.97		62.14	
1/DF DEVIANCE	0.1207		0.1167		0.1155		0.0360		0.1188	
1/DF PEARSON	0.1131		0.1104		0.1093		0.0335		0.1128	
AIC	0.9450		0.9534		0.9511		1.4607		0.9595	
BIC	−3765.05		−3742.22		−3567.91		−108.03		−3430.02	
# OBSERVATION	612		612		587		043		569	

Note: Standard errors reported are robust standard errors. Weight is the size of observation in the primary study.
*The estimated parameters are significantly different from zero at 10% significance level.
**The estimated parameters are significantly different from zero at 5% significance level.
***The estimated parameters are significantly different from zero at 1% significance level.

selected case studies published from 1984 to 2003 and 2004 to 2013, respectively.

Thus, a closer look at the results obtained from both the unweighted (i.e., Table 2A) and weighted (i.e., Table 2B) regressions shows that the mean efficiency estimates EFF_EST_{ir} from the selected case studies decrease significantly as survey year $DATAYEAR_{ir}$ in the primary study increases across all the models judging by the coefficient of $DATAYEAR_{ir}$. This probably implies that on average, the efficiency levels of African agriculture and food production have declined over the years, while agricultural and food production is lagging behind or farther from the frontier level.[14] Alternatively, this can be an indication that relative efficiency over time contributes negatively to the TFP growth of African agriculture and food production over the years, which lends support to Mugera and Ojede's (2013) argument that in the context of African agriculture, declines in efficiency over time and negative growth of TFP are possible.

To sum up, we find that the MRA result in the present study conforms with the results of the scatter plot earlier discussed and agrees with the findings of two recent cross-country analysis of TFP growth of African Agriculture and food production based on FAOSTAT data from 1961 to 2008 by Alene (2010) and Yu and Nin-Pratt (2011). The authors found evidence that change in efficiency contributes negatively to agricultural productivity growth over the years in the region. Given this, 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.[15] The implication of this is that if food insecurity problem in Africa is to be addressed, then a major policy challenge would be to identify factors driving efficiency levels in African agriculture and food production that can be explored to improve its growth (or development) in the region. These drivers will be discussed in Section 5(c) of this paper.

(b) *RQ2: Are there differences in mean efficiency estimates across other study attributes?*

Before we address the second research question, it is important to mention that looking through the results presented in Tables 2A and 2B, there are significant differences between the two. Nevertheless, because of the potential advantage of weighted regression as earlier discussed, we address the second research question of the study using results of Table 2B. In this regard, the parameters of models 1 through 3 have similar significant results with similar pattern, while models 4 and 5 gave slightly different results due to different time period covered, especially model 4, as model 5 strongly aligns with the results of models 1–3. That said, the results show that studies published in journals (D_JOURNAL), with parametric method

(D_PARAMETRIC), with panel data (D_PANELDATA), with single output or un-aggregated output (D_OUTPUT) yield significantly higher mean efficiency estimates than studies not published in journals, with nonparametric, with cross-sectional data, and aggregated output, respectively across. The coefficient of panel data (D_PANELDATA) is insignificant in models 1, 3 and 4 but significant in models 2 and 5, while coefficient of D_JOURNAL, D_PARAMETRIC, and D_OUTPUT are statistically significant in all the models with the exception of the coefficient of D_PARAMETRIC, which is not significant in model 4. 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, and is therefore in agreement with the result of the present study. Bravo-Ureta *et al.* (2007) also found evidence those studies with nonparametric specification report higher efficiency estimates, which contradict the present finding.[16]

Furthermore, we find that studies with large degree of freedom (DF) shows significantly lower mean efficiency estimates in all the models with exception of model 4. Likewise, our findings show that studies with Cobb-Douglass (D_COBBDOUGLAS) and Translog (D_TRANSLOG) functional forms were insignificantly different from those that use other functional forms and with no functional forms, especially in all the models with exception of model 4. Also, we find that studies published in journals with impact factor (D_IMPACTFACTOR) reported insignificantly lower mean efficiency estimates in all the models with exception of model 4 that gives significant result, compared to studies with no impact factors.

Studies with a focus on grain crops (D_GRAIN) reported significantly lower efficiency estimates, compared to nongrain crops' studies, while studies with a focus on food crops (D_FOODCROP), and cash crops (D_CASHCROP) yield insignificantly lower mean efficiency estimates compared to studies with nonfood crops, respectively across all the models. By contrast, studies with a focus on cash crop were found to have higher and significant efficiency estimates by Ogundari and Brümmer (2011). But similar to the finding of the present study, Bravo-Ureta *et al.* (2007) found consistently lower mean efficiency scores for studies with a focus on grain crops.

While, no regional effects were considered in model 1, the empirical results show that countries in the East Africa (D_EAST) and Central Africa (D_CENTRAL) regions report significantly lower mean efficiency estimates, while countries in the Southern Africa (D_SOUTHERN), and North Africa (D_NORTH) yield insignificantly lower mean efficiency estimates compared to countries in the West Africa (D_WEST) region especially in models 2, 3, and 5. The implication of this finding is that regional differences to some extent play a significant influence in the systematic heterogeneity that exists in the reported mean efficiency estimates conditional on study-specific attributes in the study. Interestingly, Bravo-Ureta *et al.* (2007) found significant differences in reported efficiency estimates across the region and income groups considered in their study.[17]

(c) *RQ3: What drives African agriculture and food production efficiency over the years?*

In an attempt to provide answers to the third research question, we specially construct a database by focusing on the studies that investigate the determinants of efficiency/or sought to explain the source of variation in the efficiency level. This is important to be able to identify variables that are associated with the decision-making units (i.e., farmers) from the primary studies. Specifically, we carefully coded variables that had positive or negative significant effects on African agriculture and food production efficiency level over the years from the selected studies. The idea is to be able to synthesize important socio-demographic variables of the decision-making units (DMU) or farmers that are key to improving/increasing agricultural efficiency levels, which could serve as guide to agricultural policy design and implementation in the continent in the future. In recognition of this, Bravo-Ureta *et al.* (2007) stressed 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). And, Fugile and Wang (2012) broadly labeled these variables as the enabling environment essential to enhance agricultural productivity in terms of dissemination of new technologies and practices to the farmers. Literature identifies these variables such as age, years of experience, educational level, extension, credit etc. as the underlying causes of deviation from the frontier (Coelli, Rao, O'Donnell, & Battese, 2005; Kumbhakar & Lovell, 2000).[18]

To this end, our database shows that out of the 612 farm-level mean efficiency estimates from the 442 selected frontier studies, only 439 estimates and 341 studies sought to explain the sources of variation in the efficiency level (often referred to as determinant of efficiency) from the primary study, respectively. In addition, the database shows that the variable postulated to affect the efficiency levels of the respondents in the primary studies vary from region to region and these include age, years of experience, educational level, health, occupation (farming as a major occupation), and gender (male) of the farmers in the primary study. Others are 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 etc. Figure 3 shows the distribution of the socio-demographic variables of the farmers identified as the key drivers of African Agricultural efficiency over the years by the number of studies that included these variables and the percentage of occurrence of the effect of the variables on the reported efficiency estimates in the primary studies.

However, before we proceed on the discussion of Figure 3, it is important to mention that in many of the 341 case studies or 439 estimates that investigated determinants of efficiency level, the variables in the figure were not jointly considered or included by the primary researchers. Thus, the left hand side (LHS) of the figure shows the number of studies that included each of the variables in the primary study.[19] It shows the number of studies that obtained positive and significant coefficient, negative and significant coefficient, and the total number of studies that included these variables in their respective analysis. The right hand side (RHS) contains estimates with highest percentage of occurrence for the variable with 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 statistically significant effect in Figure 3.

The figure on the RHS of Figure 3 shows that a total of 213 studies considered age as an important driver of efficiency level, while 78 of these studies reported positive and significant coefficients. Likewise, we found that 197, 162, 217, 212, 275, 134, 154, and 161 studies identified experience, credit, extension, household size, education, gender, cooperative membership, and farm size respectively as important drivers of efficiency level; with 96, 51, 74, 53, 139, 39, 29, and 31, of these

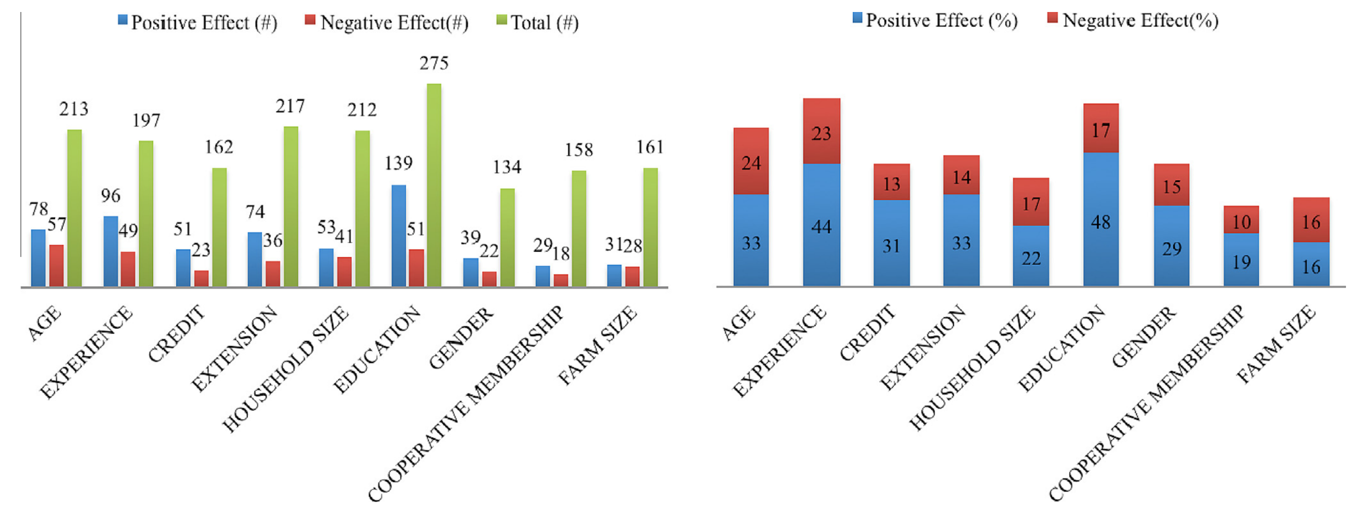

Figure 3. *Distribution of identified drivers of African agricultural efficiency levels by number of studies (LHS) and percentage of the estimates (RHS).*

studies, respectively reporting positive significant effect. Since frontier studies often report more than one efficiency estimate as earlier mentioned, it is very unlikely that the number of studies (i.e., the LHS figure) would give accurate statistics of the variables with highest occurrence of positive significant or negative significant effect on the reported efficiency estimates from the primary studies. In this regard, we present on the RHS, the percentage of the variables conditional on the number of efficiency estimates per variable.[20] The figure shows that 48% of the estimates identify education as a major driver of efficiency level of African agriculture over the years. This was followed by year of farming experience (44%); contact with extension agents (33%), age of the farmer (33%), credit (31%), gender-male (29%), household size (22%), membership of cooperative society (19%), and farm size (16%). Other analysis shows that 27%, 39%, and 31% of the estimates recognized joint significant coefficient of the following pair of variables; education and experience, education and extension, and education and age, respectively on the efficiency level of African agriculture and food production over the years.

The highest ranking of education agrees with Philips' (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's (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. Also, closely related, the ranking of age as also important driver of efficiency levels of agriculture and food production 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.

Furthermore, identification of extension service (a proxy for agricultural education) as third most important factor driving efficiency levels in African agriculture, underscores the policy relevance of extension as an important vehicle for disseminating breakthrough technologies and innovation to farmers that should be vigorously intensified in Africa.

Thus, we believe the findings have a number of policy implications. First is the policy relevance of education in increasing agricultural production and productivity in Africa. Second, 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 Pudasaini (1983) argued that education contributes to agricultural production and productivity much higher in a modernized environment, highlighting 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. Otsuka argued further that the vision of the appropriate technologies and their dissemination strategies are still missing or at best weak in SSA. While we acknowledge that the findings from the present study have been established in the literature on the efficiency of developing agriculture (see; Asadullah & Rahman, 2005; Ogundari & Brümmer, 2011; Ogundari *et al.*, 2012; Weir & Knight, 2000), 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 plays in increasing agricultural production. *First*, education helps farmers become better managers of limited resources 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 better. *Fourth*, education helps farmers to adopt riskier production technologies since they are able to evaluate adequately the implied opportunities.

6. CONCLUSIONS

The paper attempts to investigate whether African agricultural efficiency levels have been improving or not and what drives them over the years. We employed meta-regression analysis (MRA) on a total of 442 studies resulting in 612 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 30 countries represented.

Taken together, the overall mean farm-level efficiency estimate of about 0.68 was obtained from the case studies, which indicates that there is scope to improve the efficiency level of African agriculture as about 32% cost saving could be achieved if agricultural production is on the frontier level in the region. The results of MRA showed that the mean efficiency estimates of African agriculture from the primary studies decrease significantly as year of survey increases in the selected case study. This implies that over the years, negative efficiency change has characterized development of African agriculture and food production. The results also showed that studies published in journal, with parametric method and with panel data report significantly higher mean efficiency estimates, while studies with a focus on grain crops and with higher degree of freedom yield significantly lower efficiency estimates. The variation in reported efficiency estimates is significantly lower among countries from the Eastern and Central Africa regions, compared to countries from Western Africa region.

Other results identify key drivers of efficiency levels 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. In addition, the results could be very useful for researchers and academicians to enable them 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 aligned with the identified drivers of efficiency of African agriculture obtained in the present study. This points to the needs for programs and policies that will boost agricultural efficiency levels and therefore productivity in the region. In this case, we suggest policies that focus on improvement in extension services, introduction of incentives that will encourage young, able, and educated individuals with basic education to go into farming, and introduction of robust training program for farmers on the usage of modern technology. These policies should be seen as critical components of program that will enable smallholder farms to be more efficient in the region.

NOTES

1. Generally speaking, total factor productivity growth (TFP) measures the change in the total output net of the change in total input use in any production process. And, TFP growth is driven by four distinct components namely, technical change (TC), change in efficiency levels (EC), scale efficiency change (SE), and change in allocative efficiency (AE) in inputs and outputs (Kumbhakar & Lovell, 2000). Mathematically, TFP equals the sum of TC, EC, SE, and AE.

2. Alternatively, in recognition of Farrell (1957) definition of efficiency measures, cost or profit efficiency is also referred to as economic efficiency in the literature since both measures can be decomposed into technical and allocative efficiency (Kumbhakar & Lovell, 2000), while allocative efficiency mathematically equals technical efficiency estimates divided by cost (or profit) efficiency estimates.

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.

4. Although, the number of selected literature is not an exhaustive case study on frontier efficiency estimates from Africa, nevertheless we believe this is a good representative list of frontier literature from the continent since all the sub regions are fully represented.

5. For the studies that use cross-sectional data, the year of survey denotes directly the DATAYEAR, while for studies that use panel data or with multiple year of survey; the DATAYEAR is computed as the mid point of the years of the panel data in the primary study.

6. Here we refer to studies using nonaggregated dependent variable, that is, efficiency estimate from the primary study is based on a single type of product-dependent variable in the regression such as let us say, yam, or cassava etc. and not a combination of two or more products. Conversely, aggregated dependent variable means efficiency estimate computed using monetary value of different agricultural produces produced by the farmers as dependent variable in the primary research.

7. In this regard, journals with impact factor are scored one for the dummy and zero otherwise (see Table 1).

8. Whenever, behavioral assumption is not assumed, efficiency of a decision-making unit (DMU) can be investigated using primal technology specification such as production function from which technical efficiency estimates could be derived. On the other hand, when behavioral assumption is imposed, efficiency of a DMU can be investigated using dual technology specification such as cost or profit function from which cost or profit efficiency is derivable. Thus, a dummy D_PRIMAL represents studies that used production function, while studies that employed either cost or profit functions are taken as reference.

9. With regard to the parameter of interest β_i – 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.

10. In this regard, the problem in using OLS on fractional dependent variable is that it is not asymptotically efficient estimator but rather unbiased and consistent estimator.

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

12. QMLE accommodates naturally, nonconstant variances and skewness (Oberhofer & Pfaffermayr, 2009).

13. As earlier mentioned, efficiency estimates in our case study comprises of technical, allocative, cost, and profit efficiencies.

14. 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.

15. TFP growth is driven by four distinct components namely efficiency change, technical change (or technology change), scale efficiency, and allocative efficiency change inputs and outputs (Kumbhakar & Lovell, 2000).

16. Since most if not all the previous studies highlighted in the text employed un-weighted regression, it is most likely difficult to compare the result of the present study that is based on weighted regression to many of these previous studies. For example, we find that many of the significant results in Table 2A actually align strongly with the significant results reported in many of the previous studies.

17. Bravo-Ureta *et al.* (2007) employed efficiency studies from both the developed and developing agriculture, which probably explain the significance of the regional dummies in their study.

18. In most empirical studies, educational level represents the average years of formal educational attainment of the farmers, while extension refers to frequency of contact with/visit by extension or whether the farmers had former contact with extension agent.

19. We thank the anonymous referee for bringing our attention to this point.

20. Because not all efficiency studies include these variables simultaneously in their respectively analysis, the total number of efficiency estimates (or observations) that sought to explain sources of variation in the efficiency level likely to vary across each variable. For example, in the present study, the total number of studies that include age and education in their respective analysis are 213 and 275, while the total number studies that produce significant positive and negative coefficients are 78 and 57, respectively for age and 139 and 51, respectively for education. However, our meta-data also show that the total number of efficiency estimates for age and education are 293 and 378, respectively, while the total number of efficiency estimates with significant positive and negative coefficient are 97 and 70 for age, respectively and 181 and 66, respectively for education. In this respect, the short fall of total number of 213 frontier studies that include age in their analysis from the 314 frontier studies that sought to explain sources of variation in the efficiency level could be linked to studies that did not include age in their respective analysis. Conversely, the short fall of total 78 and 57 frontier studies that produce significant positive and negative coefficient of age from the total number of 213 frontier studies that include age in their analysis could also be linked to studies that did not produce significant result. The same interpretation goes for the number of efficiency estimates per variable. Meanwhile, the implication of this is that total number of efficiency estimates varies across each variable, as percentage of occurrence of these variables should be conditional on total number of efficiency estimate per variable as we did in the RHS of Figure 3.

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APPENDIX A. SUPPLEMENTARY DATA

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.worlddev.2014.07.005.