Journal of Agricultural Science; Vol. 8, No. 2; 2016
ISSN 1916-9752 E-ISSN 1916-9760
Published by Canadian Center of Science and Education

Technical Inefficiency Effects in Agriculture—A Meta-Regression

Justice G. Djokoto[1], Francis Y. Srofenyoh[1] & Akua A. Afrane Arthur[1]

[1] Agribusiness Management Department, Central University College, Accra, Ghana

Correspondence: Justice G. Djokoto, Agribusiness Management Department, Central University College, Accra Ghana. Tel: 233-285-037-399. E-mail: dgameli2002@gmail.com.

Received: November 16, 2015 Accepted: December 24, 2015 Online Published: January 15, 2016
doi:10.5539/jas.v8n2p109 URL: http://dx.doi.org/10.5539/jas.v8n2p109

Abstract

A number of studies have examined the effect of study characteristics on mean technical efficiency as the dependent variable. This article departs from these earlier studies by using second-stage inefficiency covariates as key exploratory variables and study characteristics as control variables in a meta-regression. Unlike the vote count method of quantitative review, the parameters of the key variables have desirable properties and enable statistical inferences to be drawn. Additionally, the dependent variable employed is mean technical inefficiency. This is demonstrated using data on technical inefficiency of primary studies in Ghanaian agriculture, fitted to fractional regression models. The appropriate functional form of the fractional regression model is discussed with policy implications.

Keywords: agriculture, fractional regression, Ghana, meta-regression, technical inefficiency effects

JEL Classification: D24, Q12

1. Introduction

1.1 Background

Technical efficiency (TE) refers to how well a system or unit of production performs in the use of resources to produce outputs, given the available technology relative to a standard (frontier) production function (Fried, 2008). This is the ability of a decision-making unit (farm, in this case) to produce maximum output given a set of inputs (Farrell, 1957). The first step in improving efficiency is measurement. Measured relative to the production frontier, TE may be computed as the fraction of the observed output to the frontier output. In this way, the gap between the observed output and the frontier output becomes technical inefficiency. That is; technical inefficiency equals one less the TE measure.

1.2 Problem Statement

The traditional challenge in agriculture, which continues to remain a challenge in some parts of the developing world, has been to improve efficiency (Raj, 2011). The need to reduce inefficiency has motivated studies that estimated technical inefficiency and investigated the role of covariates (technical inefficiency effects) on estimated inefficiencies especially in agriculture. These covariates are usually farm and farmer characteristics such as age of farmer, sex, size of household, access to agricultural extension services, access to credit, access to road and other communication infrastructure among others. However, in meta-regressions of technical efficiency studies in agriculture, factors that account for variations in the mean technical efficiencies generated from primary studies did not include any of these principal determinants. For example Thiam et al. (2001), Bravo-Ureta et al. (2009), Ogundari and Brummer (2011), Ogundari (2014), Iliyasu et al. (2014) and Djokoto (2015) explored methodological, products and spatial effects. Bravo-Ureta et al. (2009) in addition to the above, examined the role of national income on mean technical efficiency. The question this paper seeks to address is; what is the effect of technical inefficiency effects on mean technical inefficiency? To address this question, a meta-regression is performed using primary studies on technical inefficiency studies on Ghana.

1.3 Theoretical Review

Among other reasons, the availability of several studies necessities meta-analysis which involves the combination of results of several homogenous studies into a unified analysis that provides an overall estimate of interest for further discussion (Sterne, 2009). Nelson and Kennedy (2009) identified six objectives of meta-analysis. The first objective is to provide a "combined" estimate of the effect-size. The second is to explain what determines the study-to-study variation or heterogeneity in effect-sizes. Third, to provide within-sample predicted values of the dependent variable under a particular set of conditions. Fourth, is to make an out of-sample prediction. Fifth, to summarise results of a single empirical study that has produced multiple estimates. Finally, study publication bias.

A general model for carrying out meta-regression is to relate a key (dependent) variable to some characteristics that are believed to explain that variable (Alston et al., 2000). It is of crucial importance that, this dependent variable is measuring the same concept across primary studies (Nelson & Kennedy, 2009). The study characteristics which include study designs, model specifications and econometric techniques, serve as moderator variables in the regression. Other covariates include valuation method, sample size, place and date of publication, data collection or data coverage (Nelson & Kennedy, 2009). In this article, unlike others, the moderators go into the meta-regression model as control variables whilst technical inefficiency covariates are key explanatory variables.

With its origins in the medical sciences, meta-analysis has gained widespread use in agricultural economics. Some studies include price and income elasticity of demand for alcohol (Gallet, 2007) and income and calorie intake (Ogundari & Abdulai, 2013). The first technical inefficiency meta-analysis in agriculture was by Thiam et al. (2001). Since then, meta-analysis by Bravo-Ureta et al. (2007), Moreira Lopez and Bravo-Ureta (2009), Ogundari and Brümmer (2011), Ogundari (2014), Iliyasu et al. (2014) and Djokoto (2015) have been published.

1.4 Empirical Review

Thiam et al. (2001), Bravo-Ureta et al. (2007), Moreira López and Bravo-Ureta (2009), Ogundari and Brümmer (2011), Ogundari (2014), and Iliyasu et al. (2014) investigated characteristics such as year of study, functional form, sample size, product analysed, number of variables and estimation technique. Others included geographical coverage and income level. Regarding time, the results differed. Thiam et al. (2001) and Iliyasu et al. (2014) found that, TE estimates have not increased in developing country agriculture over time. However, Ogundari and Brümmer (2011) and Ogundari (2014) reported increasing mean technical efficiency (MTE) over time in Nigerian agriculture and decreasing MTE over time in African agriculture respectively.

Increased number of variables in the technical inefficiency estimation model has implications for multicollinearity (Griffin et al., 1987). These may result in increased standard errors and invalidation of hypothesis tests. Since TE is a residual value; the influence of this theoretical position for technical efficiency is unclear. Thiam et al. (2001) did not find any significant effect of the number of variables on MTE. However, Bravo-Ureta et al. (2007), Iliyasu et al. (2014) and Ogundari and Brümmer (2011) found that, high number of terms in TE estimation model induced high TE estimates.

Since large sample size produces more efficient parameter estimates generally, the effect of sample size on MTE estimates may be important. Although Iliyasu et al. (2014) and Thiam et al. (2001) have shown that sample size did not distinguish MTEs; Ogundari and Brümmer (2011) and Moreira López and Bravo-Ureta (2009) however, found that, MTE increased with sample size.

Ogundari (2014) showed that TE estimation relations of other functional forms (distance functions) and without functional forms showed higher MTE than those with functional forms such as translog and Cobb-Douglas. However, Thiam et al. (2001), Bravo-Ureta et al. (2007) and Illyasu et al. (2014) suggested that MTE estimates obtained from translog production functions tended to record higher MTEs than those from Cobb-Douglas production functions. Ogundari (2014) showed that, for African agriculture, MTEs from parametric estimations such as SFA (Stochastic Frontier Analysis) were higher than non-parametric MTEs. However, Thiam et al. (2001) did not find any evidence for this, implying that the statistical noise embedded in TE estimates of non-parametric models in the studies investigated may have been small.

Geographical region may influence MTEs because agricultural output is highly dependent on environmental factors. Taking account of spatial coverage of studies is an attempt to account for climatic and other environmental variations associated with TE studies. Moreira López and Bravo-Ureta (2009) found that, studies conducted in North America and India posted higher MTE than the reference category. On the contrary, Eastern European studies showed decreases in MTE despite the greater attention Europe attracted from frontier researchers (Bravo-Ureta et al., 2007; Moreira Lopez & Bravo-Ureta, 2009). In Africa, countries in Eastern and Central parts showed lower MTEs than those in West Africa (Ogundari, 2014). Studies that focus on southern parts of Nigeria showed higher MTE than those otherwise (Ogundari & Brümmer, 2011).

Different products may have different yield capabilities. Thus, differences in their ability to attain their maximum potential would also exist. Empirically, conclusions have been made on products and product groups.

Studies on production (crops and livestock) showed higher average MTEs than others. Contrasting crops and animals in developing countries, animal production enterprises were more technically efficient than crops enterprises (Bravo-Ureta et al., 2007). Within crops subsector, cash crop production was more efficient than non-cash crop production in Nigeria (Ogundari & Brümmer, 2011). Turning to the African continent as a whole, there was no discernible difference among food crops, cash crops and non-crops enterprises (fish, livestock, poultry etc.). However, grain crops (rice, maize, wheat sorghum etc.) MTEs were significantly lower than MTEs of the other groups (Ogundari, 2014).

Ogundari (2014) showed that studies published in peer reviewed destinations showed higher MTEs than those in non-peer reviewed destinations (conference proceedings, working papers, thesis etc.). The statistical significance of the coefficient showed that MTEs from studies in peer reviewed sources differed from those in non-peer reviewed sources. However, Djokoto (2015) reported statistical indifference between the MTE of peer-reviewed publications and non-peer-reviewed publications (Note 1).

1.5 Relevance and Organisation of Study

Unlike Thiam et al. (2001), Bravo-Ureta et al. (2009), Ogundari and Brummer (2011), Ogundari (2014), Iliyasu et al. (2014) and Djokoto (2015) who examined the effect of study characteristics on mean technical efficiency as the dependent variable, this article departs from these earlier studies by using second-stage inefficiency covariates as key explanatory variables (Note 2) and study characteristics as control variables in a meta-regression. Unlike the vote count method of quantitative review (reference), the parameters of the key variables have desirable properties and enable statistical inferences to be drawn. Also, earlier studies used mean technical efficiency as dependent variable, in this article, the dependent variable in the meta-regression is mean technical inefficiency.

The rest of the article is sectioned into three. The collection of studies, extraction of data and analytical tools are described in section two. Section three presents and discusses the results. Section four concludes the article.

2. Method

2.1 Data

Databases and publishers websites such as AgEconsearch, Google scholar, Wiley online library, EmeraldInsight, EBSCOhost, oupjournals online among others were searched for literature. Relevant studies on technical inefficiency in agriculture obtained on Ghana numbered 34 yielding 49 observations up until June 2015 (Table 1). Though studies from non-peer reviewed studies may not be as reliable as peer reviewed ones, these have however been included for some reasons. First, to increase sample size of the analysis. Second, to test for the difference in MTEs from peer reviewed and non-peer reviewed sources in a single country case and third, to control somewhat for possible publication bias. The mean technical inefficiency (MTI) of the studies was extracted. The information on the statistical significance or otherwise of technical inefficiency effects was captured. These were identified and recognised as statistically significant positive or negative; or statistically insignificant. For statistically insignificant coefficients; these were not separated into positive and negative. Other study characteristics such as year of data collection, numbers of inputs in estimation model and number of observations were extracted. In the case of Data Envelopment Analysis (DEA) studies, the output-oriented MTI was used in order to conform to those of MTIs from SFA and distance function estimations. Others included products of agriculture, region of study and type of data as well as parameterisation.

Table 1. List of primary studies included in the metadata set

Author (year)	MTI	Formal education	SFA/DEA	Year of data	Number of variables	Region	Product	Sample size	Functional form	Peer reviewed status
Abatania et al. (2012)	0.17	SIGNEG	DEA	2006	3	NORTH	CROPS	189	Translog	Peer reviewed
Abbam (2009)	0.49	NS	SFA	2009	5	COSTL	CROPS	40	Cobb-Douglas	Non-peer reviewed
Abbam (2009)	0.45	SIGPOS	SFA	2009	5	COSTL	CROPS	80	Cobb-Douglas	Non-peer reviewed
Abdul-Malik & Mohammed (2012)	0.11	NS	SFA	2011	4	NORTH	Combined	48	Cobb-Douglas	Peer reviewed
Addai & Owusu (2014)	0.38	SIGNEG	SFA	2010	4	MID	CROPS	453	Translog	Peer reviewed
Addai et al. (2014)	0.27	NS	SFA	2010	4	ACROSS	CROPS	340	Translog	Peer reviewed
Adinku (2013)	0.16	SIGPOS	SFA	2011	5	COSTL	CROPS	356	Translog	Non-peer reviewed
Adzawla et al. (2013)	0.12	NS	SFA	2012	4	NORTH	CROPS	91	Translog	Peer reviewed
Al-hassan (2012)	0.66	NS	SFA	2003	5	NORTH	CROPS	220	Translog	Peer reviewed
Amoah et al. (2014)	0.76	NS	SFA	2013	5	MID	CROPS	250	Cobb-Douglas	Peer reviewed
Asante et al. (2014a)	0.15	NS	SFA	2009	5	MID	CROPS	103	Translog	Peer reviewed
Asante et al. (2014a)	0.11	SIGPOS	SFA	2009	5	MID	CROPS	272	Translog	Peer reviewed
Asante et al. (2014b)	0.31	SIGPOS	SFA	2010	5	ACROSS	CROPS	200	Cobb-Douglas	Peer reviewed
Asante et al. (2013)	0.22	SIGPOS	SFA	2011	10	ACROSS	CROPS	126	Cobb-Douglas	Peer reviewed
Awunyo-Vitor et al. (2013)	0.34	SIGNEG	SFA	2012	4	MID	CROPS	200	Cobb-Douglas	Peer reviewed
Bempomaa & Acquah (2014)	0.33	NS	SFA	2012	6	MID	CROPS	306	Cobb-Douglas	Peer reviewed
Besseah & Kim (2014)	0.52	NS	SFA	2006	4	ACROSS	CROPS	525	Cobb-Douglas	Peer reviewed
Besseah & Kim (2014)	0.52	NS	SFA	2006	4	ACROSS	CROPS	525	Cobb-Douglas	Peer reviewed
Besseah & Kim (2014)	0.52	NS	SFA	2006	4	ACROSS	CROPS	525	Cobb-Douglas	Peer reviewed
Besseah & Kim (2014)	0.52	NS	SFA	2006	4	ACROSS	CROPS	525	Cobb-Douglas	Peer reviewed
Bhasin et al. (2011)	0.4	SIGPOS	SFA	2009	3	COSTL	CROPS	100	Cobb-Douglas	Non-peer reviewed
Binam et al. (2008)	0.56	NS	SFA	2001	4	ACROSS	CROPS	1000	Translog	Non-peer reviewed
Cobbina (2014)	0.28	NS	SFA	2013		COSTL	CROPS	220	Translog	Non-peer reviewed
Crentsil & Essilfie (2014)	0.27	SIGNEG	SFA	2006	4	ACROSS	CROPS	124	Translog	Peer reviewed
Dadzie & Dasmani (2012)	0.75	SIGPOS	SFA	2012	2	COSTL	CROPS	360	Translog	Peer reviewed
Donkoh et al. (2013)	0.19	NS	SFA	2008	5	NORTH	CROPS	85	Translog	Peer reviewed
Donkoh et al. (2013)	0.29	NS	SFA	2008	5	NORTH	CROPS	100	Translog	Peer reviewed
Dzene (2010)	0.56	SIGPOS	SFA	2004	2	MID	CROPS	379	Cobb-Douglas	Non-peer reviewed
Dzene (2010)	0.56	SIGPOS	SFA	2004	2	MID	CROPS	379	Cobb-Douglas	Non-peer reviewed
Dzene (2010)	0.56	SIGPOS	SFA	2004	2	COSTL	CROPS	379	Cobb-Douglas	Non-peer reviewed
Dzene (2010)	0.56	NS	SFA	2004	2	MID	CROPS	379	Cobb-Douglas	Non-peer reviewed
Essilfie et al. (2011)	0.42	SIGNEG	SFA	2011	3	COSTL	CROPS	99	Cobb-Douglas	Peer reviewed
Etwire et al. (2013)	0.47	NS	SFA	2013	5	NORTH	CROPS	200	Translog	Peer reviewed
Johnson (2013)	0.42	NS	SFA	2012	5	COSTL	CROPS	128	Translog	Non-peer reviewed
Johnson (2013)	0.1	SIGPOS	SFA	2012	5	COSTL	CROPS	122	Translog	Non-peer reviewed
Johnson (2013)	0.23	NS	SFA	2012	5	COSTL	CROPS	250	Translog	Non-peer reviewed
Kuwornu et al. (2013)	0.49	NS	SFA	2010	6	MID	CROPS	226	Translog	Peer reviewed
Kyei et al. (2011)	0.5	NS	SFA		6	MID	CROPS	100	Cobb-Douglas	Peer reviewed
Nkegbe (2012)	0.37	NS	SFA	2010	4	NORTH	CROPS	445	Translog	Peer reviewed
Nkegbe (2012)	0.46	NS	SFA	2010	4	NORTH	CROPS	445	Translog	Peer reviewed
Nkegbe (2012)	0.27	NS	SFA	2010	4	NORTH	CROPS	445	Translog	Peer reviewed

Ofori-Bah & Asafu-Adjaye (2011)	0.14	NS	DF	2009	3	ACROSS	CROPS	80	Translog	Peer reviewed
Ofori-Bah & Asafu-Adjaye (2011)	0.53	NS	DF	2009	3	ACROSS	CROPS	80	Translog	Peer reviewed
Onumah & Acquah (2010)	0.17	SIGPOS	SFA	2009	5	COSTL	FISH	150	Translog	Peer reviewed
Onumah et al. (2010)	0.16	SIGPOS	SFA	2007	5	ACROSS	FISH	150	Translog	Peer reviewed
Onumah et al. (2013)	0.15	NS	SFA	2011	5	MID	CROPS	190	Translog	Peer reviewed
Oppong et al. (2014)	0.17	NS	SFA	2011	4	MID	CROPS	232	Translog	Peer reviewed
Peprah (2010)	0.25	SIGNEG	SFA	2008	4	COSTL	CROPS	1000	Translog	Non-peer reviewed
Shamsudeen et al. (2013)	0.23	NS	SFA	2011	5	NORTH	CROPS	360	Translog	Peer reviewed

Notes. MTI: Mean technical inefficiency; NS: not statistically significant; SIGPOS: statistically significantly positive; SIGNEG: Statistically significantly negative; SFA: Stochastic frontier analysis; DF: Distance functions; DEA: Data envelopment analysis; COSTL: coastal regions; MID: Middle regions; NORTH: Northern regions; ACROSS: Across country.

2.2 Model

The meta-regression model is specified as in Equation 1.

$$MTI = f(\mathrm{SIGNEG}_{ji},\ \mathrm{SIGPOS}_{ji},\ \mathrm{SFA}_i,\ \mathrm{DEA}_i,\ \mathrm{DATAY}_i,\ \mathrm{VAR}_i,\ \mathrm{SSIZE}_i,\ \mathrm{CD}_i,\ \mathrm{CROPS}_i,\ \mathrm{FISH}_i,\ \mathrm{COSTL}_i,\ \mathrm{MID}_i,\ \mathrm{NORTH}_i,\ \mathrm{PR}_i) \quad (1)$$

Where, $SIGNEG_j$ refers to study that reported statistically significant negative coefficients for the *j*th technical inefficiency effects and captured as 1 and 0 otherwise. The sign of this dummy variable is expected to be negative since the coefficients in the primary studies were negatively signed. $SIGPOS_j$ captured studies that reported statistically significant positive coefficients of the *j*th technical inefficiency effects and recognised as 1 and 0 otherwise. The studies that reported the statistically insignificant coefficient for the *j*th technical inefficiency effect is recognised as 0. The coefficients captured as $SIGPOS_j$ in this article were positively signed in the primary studies. Therefore, *a priori* the sign for this dummy variable is expected to be positively signed. The letter *i* represent observations in the metadata set.

A number of variables known to influence technical inefficiency were included in the model as control variables. Stochastic frontier approach (*SFA*) = 1 and 0 otherwise; data envelopment analysis (*DEA*) = 1 and 0 otherwise. The reference variable is distance functions (DF). Although distance functions are similar to SFA, they are distinguished here because they capture multiple outputs whilst the SFA uses single out (or aggregated multiple output). Year of data collection (*DATAY*) was represented as four digit year (YYYY). The number of production inputs included in the estimation relation was captured as *VAR*. This was not necessarily equal to the number of terms in the production function. Thus a translog function may not necessarily have more variables than a Cobb-Douglas function. *SSIZE* captured the number of observations or sample size of the case studies. Studies that used Cobb-Douglas (*CD*) production functions were represented as 1 and 0 otherwise; translog (*TL*). The translog functional form used by Ofori-Bah and Asafu-Adjaye (2011) in estimating their distance function is not different from the usual translog function. Hence this was not distinguished.

Ghana was segmented into three; coastal (Central, Greater Accra, Volta and Western Regions) (*COSTL*), middle (Ashanti, Eastern and Brong-Ahafo Regions) (*MID*) and north (Northern, Upper East and Upper West Regions) (*NORTH*). Five observations cut across the coastal and middle sections; therefore, these were grouped together with whole country studies as reference. Following previous studies, products were categorised as crops (*CROPS*), fish (*FISH*), and combination of crops and animals. All these were represented as 1 except crops and animal combinations which was the reference product and captured as 0. *PR* equals 1 if the study is peer reviewed and 0 if the study was not peer reviewed. This variable is used in place of a formal test for publication bias because many studies did not report standard deviations of the technical inefficiency estimates.

2.3 Estimation Procedure

Since technical inefficiency is generated as a fraction, fractional regression is employed to estimate Equation 1 (Papke & Wooldridge, 1996; Ramalho et al., 2010).

Let

$$E(y \mid x) = G(x\theta) \tag{2}$$

where, $G(\cdot)$ is some nonlinear function satisfying $0 \leq G(\cdot) \leq 1$. $G(\cdot)$ could be specified as any cumulative distribution function (Papke & Wooldrige, 1996; Ramalho et al., 2010) such as logit,

$$G(x\theta) = e^{x\theta} / 1 + e^{x\theta} \tag{3}$$

probit,

$$G(x\theta) = \Phi(x\theta) \tag{4}$$

or loglog,

$$G(x\theta) = e^{-e^{-x\theta}} \tag{5}$$

and complementary loglog (cloglog),

$$G(x\theta) = 1 - e^{e^{-x\theta}} \tag{6}$$

with partial effect for all specifications given as

$$\partial E(y \mid x) / \partial x = \theta_j g(x\theta) \tag{7}$$

These models were estimated by quasi maximum likelihood (QML) procedure.

2.4 Model selection

The appropriate specification of each functional form was tested by the use of Ramsey (1969) RESET test and goodness-of-functional form test (GOFF) (Ramalho et al., 2014). Although the RESET test was originally developed for use with linear functions, it is also applicable to any type of index models (Pagan & Vella, 1989; Ramalho et al., 2010, 2011; Cameron & Trivedi, 2013, p. 52). GOFF test note that the model is free of mis-specification if the null hypothesis cannot be rejected (Note 3). It is possible that more than one model would be selected by the RESET and GOFF tests. Therefore, the *P* test proposed by Davidson and MacKinnon (1981) provides an opportunity for one-on-one tests using the selected models from the first two stages as alternative hypotheses. Unlike RESET and GOFF tests for which failure to reject the null hypothesis selects the model, in the case of the *P* test, a model is selected if the null hypothesis is rejected.

3. Results and Discussion

3.1 Descriptive Statistics

Although 49 studies were found, not all of these reported many technical inefficiency effect results (Table 2). Specifically, 3 studies reported the effect of household income on technical inefficiency whilst 49 reported the effect of formal education on technical inefficiency. The number of studies that jointly reported at least 3 technical inefficiency effects was 23 whilst those that reported at least one were 49. Although it was desirable to use more technical inefficiency effects variables, doing so for variables more than one would severely limit degree of freedom for hypothesis testing of the parameters estimates. Therefore, only one; formal education was employed. Although the 49 observations are low compared to other technical efficiency meta-regressions, the resulting 34 degrees of freedom (to be shown shortly) is appreciable. Moreover, the principal contribution of this article is the estimation of technical inefficiency effects in a meta-regression environment, for which the 49 observations are not out of place.

3.2 Results of Vote Count

Out of the 49 parameters reported for formal education, 30 of these showed statistical insignificance whilst 13 showed statistically significant positive coefficients. The rest of the 6 showed statistically significantly negative parameters. Following the vote count method used by Ogundari and Brummer (2011), and Ogundari (2014), one would conclude that formal education has no statistically significant effect on technical inefficiency.

3.3 Results of Meta-Regression

3.3.1 Model Selection

Table 3 presents results of specification and model selection tests. The RESET test statistics are statistically insignificant. This implies the null hypothesis that the explanatory variables have powers not more than 1 cannot be rejected. Therefore, the models are well specified. With regards to the GOFF tests, the statistical insignificance of all the test statistics of all functional forms suggests all models are well fitted to the respective functional forms. Nevertheless, one model needs to be selected for discussion using the *P* test results (third panel of Table 3). Using logit, probit and loglog as alternative hypothesis; all the statistics are statistically insignificant.

This implies these functional forms are statistically indistinguishable from one another based on the data used. In the case of cloglog as alternative hypothesis, although the statistics are the highest, only that of loglog as null hypothesis is statistically significant. This implies that first; the cloglog is seemingly preferred to logit and probit functional forms. Second, cloglog is clearly statistically distinguished from the loglog functional form. Thus, the cloglog functional form is selected for discussion.

Table 2. Summary of reported technical inefficiency effects

Number of studies reporting the inefficiency effects	Inefficiency effects	Number of inefficiency effects reported at least		
		3	2	1
49	Formal education			
34	Age			
30	Gender			
28	Access to agricultural extension services			
26	Experience in farming			
25	Access to Credit			
24	Household size			
16	Farming as full time employment			
10	Membership of farmer-based organization			
4	Training in farming			
3	Household Income			
	Number of studies jointly reporting the shaded parameters	23	34	49

3.3.2 Discussion of Selected Model

The coefficients of the key variables and their marginal effects are statistically insignificant (Table 4). The statistical insignificance of the coefficients imply, combining evidence, studies that reported statistically significant negative, positive and statistically insignificant coefficients (control) are not statistically distinguished. Specifically, studies that reported statistically insignificant coefficients for the effect of formal education on technical inefficiency are not different from those that reported statistically significant coefficients. Although the conclusions are not different from the vote count method, the approach employed in this article is non-trivial. Additionally, the approach accounts for the influence of other factors and permits estimation of statistical properties of the parameters that informs the conclusion.

The statistically insignificant coefficient notwithstanding, the negative sign of coefficients of *EDUSSIGNEG* is in line with the negative sign of coefficients of formal education reported by primary studies. This shows seeming enhancing effect of formal education on technical efficiency. Formal education provides beneficiaries with reading and writing skills among others. Apart from offering exposure to practices that will enhance production outcomes, formally educated farmers will be able to read instructions on farm supplies such as fertiliser, pesticides, and poultry and livestock medications among others. Also, formally educated farmers have the opportunity to read extension bulletins. All these will contribute positively to their farm operations thereby resulting in high output, most likely close to expected output, thereby increasing efficiency.

Table 3. Results of Model selection for one technical inefficiency effect (Formal education) and dependent variable weighted by number of observations from each study

	Logit	Probit	Loglog	Cloglog
RESET	1.383	0.801	0.022	2.301
Goodness of functional form tests				
GOFF1	1.342	0.711	-	2.127
GOFF2	1.100	0.836	0.030	-
GGOFF	1.859	1.511	0.030	2.127
P test				
H_{ALogit}	-	1.863	2.000	0.708
$H_{AProgit}$	0.896	-	1.048	3.66
$H_{ALoglog}$	0.000	0.000	-	0.068
$H_{ACloglog}$	2.346	2.941	3.299*	-

Note. ***, **, * represents 1%, 5% and 10% levels of significance respectively.

The negative sign of the coefficient of *EDUSIGPOS* is contrary to the statistically significant positive signs reported by primary studies. This is because, the reported positive signs of coefficients showed that formal education exacerbated technical inefficiency. Therefore, combining these should show a positive sign of the coefficient. The contrary finding means that the findings of the primary studies are inconsistent with this, based on combined evidence. Additionally, the coefficients are not statistically significant. Therefore, unlike *EDUSIGNEG*, there is no conformation of the *a priori* sign.

Table 4. Results of Estimation of using dependent variable weighted by number of observations from each study

Loglog functional form estimation				
	Coefficients (Robust Standard errors)		dy/dx (Delta-method Standard errors)	
EDUSIGNEG	-0.1112503	(0.1653016)	-0.0377433	(0.0562509)
EDUSIGPOS	-0.1772271	(0.1850895)	-0.0601269	(0.0626637)
SFA	0.3708964	(0.2564704)	0.1258321	(0.0864182)
DEA	0.4521248*	(0.2387407)	0.15339*	(0.0803799)
DATAY	-0.027361	(0.0449429)	-0.0092826	(0.0152521)
VAR	0.0172320	(0.0573648)	0.0058462	(0.0194784)
SSIZE	0.0003493	(0.0004016)	0.0001185	(0.0001364)
CD	0.1760075	(0.1983732)	0.0597132	(0.0669128)
CROPS	0.5228971*	(0.2780098)	0.1774006*	(0.0945061)
FISH	0.1020492	(0.5383565)	0.0346217	(0.1826071)
COSTL	0.5129796	(0.3199687)	0.1740359	(0.1085653)
MID	0.0878041	(0.2024554)	0.0297888	(0.0687718)
NORTH	-0.0896533	(0.2163736)	-0.0304162	(0.0733051)
PR	0.6136983*	(0.3285888)	0.2082063*	(0.1108866)
CONSTANT	53.05793	(90.16688)	-	
Model statistics				
No. of observations	49			
R2-type measure	0.23256253		-	
Log- pseudolikelihood	-19.73997919		-	

Note. ***, **, * represents 1%, 5% and 10% levels of significance respectively.

The coefficients of three out of the twelve coefficients of the control variables are statistically significant. The statistically significant positive coefficient of *DEA* implies that technical inefficiencies measured using *DEA* are higher than those measured using *SFA* and distance functions. The random error in DEA models are sometimes picked up as technical inefficiency. Therefore, this finding is in line with theory. However, Ogundari and Brummer (2011), and Thiam et al. (2001) reported the contrary.

Although the coefficient and marginal effects of the *DATAY* is statistically insignificant, the negative sign of the parameter estimates suggests seeming (decrease) increase in (in)efficiency over time. Since Ogundari and Brummer (2011) found that MTE increased over time for Nigeria and did not increase for African and developing countries (Thiam et al., 2001; Iliyasu et al., 2014; Ogundari, 2014); increasing MTE in some countries such as Ghana and Nigeria among possible others may have been masked by some other poorly performing countries relative to MTE. The sources of this increase needs to be investigated in order to reinforce them for sustained decrease in technical inefficiency. This finding also calls for more individual country studies to identify countries regressing in MTE.

The statistically insignificant parameter estimates of *VAR* and *SSIZE* imply that number of variables and sample sizes employed in the primary studies are statistically indistinguishable. This suggests the numbers of sizes of these variables employed in the primary studies are adequate to estimate MTE. The finding for *VAR* is consistent with that of Thiam et al. (2001) but inconsistent with those of Bravo-Ureta et al. (2007), Iliyasu et al. (2014) and Ogundari and Brümmer (2011). The finding for *SSIZE* agrees with that of Iliyasu et al. (2014) and Thiam et al. (2001) but disagrees with that of Ogundari and Brümmer (2011) and Moreira López and Bravo-Ureta (2009).

Cobb-Douglas and translog are the popular functional forms for estimating SFA models. The results of the parameter estimates reveal that these have not distinguished MTE statistically. By implication, estimating SFA by either Cobb-Douglas or translog makes no difference for the size of the inefficiency estimates, given the data used in this article. Thus, although mean technical inefficiencies measured by DEA models are higher than those of SFA, mean technical inefficiency for Cobb-Douglas and translog models are similar. Thus, for SFA estimations specifically for Ghana, the choice between Cobb-Douglas and translog is immaterial as far as mean technical inefficiency is concerned (Note 4). This finding is inconsistent with those of Thiam et al. (2001), Bravo-Ureta et al. (2007), and Illyasu et al. (2014).

The statistically significant parameters for *FISH* means that technical inefficiency for fish products are similar to those of the reference products. In respect of *CROPS*, the result of the parameter estimates show that technical inefficiency for crops products are higher than those of fish and combination of crops and animals. Despite the large contribution of crop products to agricultural GDP in Ghana (ISSER, 2014), this subsector shows significant technical inefficiency. This certainly requires attention. Although Ogundari (2014) came to a similar conclusion for African agriculture, for Ghana, this finding calls for identification of the specific crops as well as the sources of these inefficiencies for redress. Achieving decrease in technical inefficiency in crops subsector of agriculture would create significant financial gains not only for the subsector but for the agriculture sector as a whole.

As noted in the review, geographical region may influence mean technical inefficiencies because agricultural output is highly dependent on environmental factors which may differ depending on location. However, the statistically insignificant parameter estimates of the location variables suggests otherwise. This finding does not support differential policy on technical inefficiency based on geography in Ghana. The finding for Ghana is inconsistent with that of Ogundari and Brümmer (2011) in respect of Nigerian agriculture.

The positive and statistically significant coefficient and marginal effects of *PR* means that the reference, studies that were not peer reviewed; produced lower mean technical inefficiencies than peer reviewed studies. By implication non-peer reviewed publications have been under-estimating mean technical inefficiency for Ghana. The causes of this under-estimation could be identified by comparing technical inefficiencies of studies prior to peer review and after peer review. Further research could examine this. This notwithstanding, policy makers must be mindful of publications that inform their decisions viz-a-viz technical inefficiency. Although the finding of this article is inconsistent with that of Ogundari (2014), a recent quantitative review by Djokoto (2015) in respect to organic agriculture is consistent with the findings of this article.

4. Conclusions

This article addressed the question: what is the effect of technical inefficiency effects on mean technical inefficiency? In order to address this question in this article, meta-regression of studies of technical inefficiency in Ghanaian agriculture was carried out using technical inefficiency effects variable(s) as explanatory variable in the meta-regression. Previous meta-regressions used study characteristics only, as explanatory variables. In this article, these are used as control variables and the statistical significance or otherwise and the sign of the statistically significant technical inefficiency effects are introduced as key explanatory variable. This approach builds on the vote count method which; whilst being simplistic, fails to provide a measure with statistical properties hence lacks statistical rigour. The computation of statistical properties of the parameters of the key explanatory variable provides greater reliability of the results while controlling for the effect of characteristics of the study. Therefore, this approach has merit over the vote count method although the conclusion of the vote count method using the current metadata and that of the enhanced approach are similar. Owing to data limitations, only one technical inefficiency effect, formal education was included in the meta-regression. Further research with larger metadata should consider equally important socio-economic variables such age of farmer, size of household, access to credit and agricultural extension services among others.

References

Abatania, L. N., Hailu, A., & Mugera, A. W. (2014). Technical efficiency of smallholder crop production in Ghana: An application of bootstrap DEA. *Recent Developments in Data Envelopment Analysis and Its Applications, 362*. Retrieved from http://www.researchgate.net/profile/Ali_Emrouznejad/publication/273706688_Recent_Developments_in_Data_Envelopment_Analysis_and_its_Applications/links/550996460cf2d7a2812d5046.pdf#page=378

Abbam, A. (2009). *Comparative study of technical efficiency of pineapple exporters and non-exporters in the central region of Ghana* (Unpublished Masters Dissertation, University of Cape Coast, Ghana).

Abdulai, S., Nkegbe, P. K., & Donkoh, S. A. (2013). Technical efficiency of maize production in Northern Ghana. *African Journal of Agricultural Research, 8*(43), 5251-5259. Retrieved from http://www.academicjournals.org/article/article1383904818_Abdulai%20et%20al.pdf

Abdul-Malik, A., & Mohammed, A. (2012). Technical efficiency of beekeeping farmers in Tolon-Kumbungu district of Northern region of Ghana. *Journal of Development and Agricultural Economics, 4*(11), 304-310. Retrieved from http://www.academicjournals.org/app/webroot/article/article1379426324_Abdul-Malik%20and%20Mohammed.pdf

Addai, K. N., & Owusu, V. (2014). Technical Efficiency of Maize Farmers across Various Agro Ecological Zones of Ghana. *Journal of Agriculture and Environmental Sciences, 3*(1), 149-172. Retrieved from http://jaesnet.com/journals/jaes/Vol_3_No_1_March_2014/11.pdf

Addai, K. N., Owusu, V., & Danso-Abbeam, G. (2014). Effects of farmer–Based-organization on the technical efficiency of maize farmers across Various Agro-Ecological Zones of Ghana. *Journal of Economics and Development Studies, 2*(1), 141-161. Retrieved from http://jaesnet.com/journals/jaes/Vol_3_No_1_March_2014/11.pdf

Adzawla, W., Fuseini, J., & Donkoh, S. A. (2013). Estimating technical efficiency of cotton production in Yendi Municipality, Northern Ghana. *Journal of Agriculture and Sustainability, 4*(1), 115-140. Retrieved from http://infinitypress.info/index.php/jas/article/download/316/194

Al-Hassan, S. (2012). Technical efficiency in smallholder paddy farms in Ghana: An analysis based on different farming systems and gender. *Journal of Economics and Sustainable Development, 3*(5), 91-105. Retrieved from http://www.iiste.org/Journals/index.php/JEDS/article/download/1590/1539

Asante, B. O., Villano, R. A., & Battese, G. E. (2014). The effect of the adoption of yam minisett technology on the technical efficiency of yam farmers in the forest-savanna transition zone of Ghana. *African Journal of Agricultural and Resource Economics, 9*(2), 75-90. Retrieved from http://ageconsearch.umn.edu/bitstream/176478/2/1.%20Asante%20et%20al.pdf

Asante, B. O., Wiredu, A. N., Martey, E., Sarpong, D. B., & Mensah-Bonsu, A. (2014). NERICA Adoption and Impacts on Technical Efficiency of Rice Producing Households in Ghana: Implications for Research and Development. *American Journal of Experimental Agriculture, 4*(3), 244-262. http://dx.doi.org/10.9734/AJEA/2014/7250

Awunyo-Vitor, D., Bakang, J., & Cofie, S. (2013). Estimation of farm level technical efficiency of small-scale cowpea production in Ghana. *American-Eurasian Journal of Agriculture and Environmental Sciences, 13*, 1080-1087. Retrieved from http://ir.knust.edu.gh/bitstream/123456789/6140/1/9.pdf

Bempomaa, B., & Acquah, H. D. G. (2014). Technical Efficiency Analysis of Maize Production: Evidence from Ghana. *APSTRACT: Applied Studies in Agribusiness and Commerce, 8*(2-3). 73-79. Retrieved from http://ageconsearch.umn.edu/bitstream/202884/2/9-Bempomaa.pdf

Besseah, F. A., & Kim, S. (2014). Technical Efficiency of Cocoa Farmers in Ghana. *Journal of Rural Development, 37*(2), 159-182. Retrieved from http://ageconsearch.umn.edu/bitstream/196615/2/37-2-techni cal.pdf

Bhasin, V. K., Harvey, S. K., & Fiawoyife, E. U. (2011). *Impact of cellular phones on technical and allocative efficiencies of commercial taxi and fishing boat firms in Ghana*. Retrieved January 16, 2013, from https://researcher.gdnet.org/CMS/getRepoDoc.php?community_group_document_id=415

Binam, J. N., Gockowski, J., & Nkamleu, G. B. (2008). Technical efficiency and productivity potential of cocoa farmers in West African countries. *The Developing Economies, 46*(3), 242-263. http://dx.doi.org/10.1111/j.1746-1049.2008.00065.x

Bravo-Ureta, B. E., Solís, D., López, V. H. M., Maripani, J. F., Thiam, A., & Rivas, T. (2007). Technical efficiency in farming: a meta-regression analysis. *Journal of productivity Analysis, 27*(1), 57-72. http://dx.doi.org/10.1007/s11123-006-0025-3

Cameron, A. C., & Trivedi, P. K. (2013). *Regression analysis of count data* (Vol. 53). Cambridge university press. http://dx.doi.org/10.1017/cbo9781139013567

Crentsil, C., & Essilfie, F. L. (2014). Measurement of technical efficiency of smallholder fish production in Ghana: A stochastic frontier approach. *Journal of Development and Agricultural Economics, 6*(5), 203-211. http://dx.doi.org/10.5897/JDAE12.146

Dadzie, S. K., & Dasmani, I. (2010). Gender difference and farm level efficiency: Metafrontier production function approach. *Journal of Development and Agricultural Economics, 2*(12), 441-451. Retrieved from http://www.academicjournals.org/app/webroot/article/article1379498064_Dadzie%20and%20Dasmani.pdf

Davidson, R., & MacKinnon, J. G. (1981). Several tests for model specification in the presence of alternative hypotheses. *Econometrica: Journal of the Econometric Society, 49*(3), 781-793. http://dx.doi.org/10.2307/1911522

Donkoh, S. A., Ayambila, S., & Abdulai, S. (2013). Technical efficiency of rice production at the Tono irrigation scheme in northern Ghana. *American Journal of Experimental Agriculture, 3*(1), 25-42. http://dx.doi.org/10.9734/AJEA/2013/1448

Donkoh, S. A., Tachega, M., & Amowine, N. (2013). Estimating technical efficiency of tomato production in Northern Ghana. *American Journal of Experimental Agriculture, 3*(1), 56-75. http://dx.doi.org/10.9734/AJEA/2013/1447

Djokoto, J. G. (2015). Technical efficiency of organic agriculture: a quantitative review. *Studies in Agricultural Economics, 117*(2), 61-71. http://dx.doi.org/10.7896/j.1512

Dzene, R. (2010). *What drives efficiency on the Ghanaian cocoa farm?* Retrieved January 20, 2013, from http://www.csae.ox.ac.uk/conferences/2010-edia/papers/498-Dzene.pdf

Essilfie, F. L., Asiamah, M. T., & Nimoh, F. (2011). Estimation of farm level technical efficiency in small scale maize production in the Mfantseman Municipality in the Central Region of Ghana: A stochastic frontier approach. *Journal of Development and Agricultural Economics, 3*(14), 645-654.

Etwire, P. M., Martey, E., & Dogbe, W. (2013). Technical Efficiency of Soybean Farms and Its Determinants in Saboba and Chereponi Districts of Northern Ghana: A Stochastic Frontier Approach. *Sustainable Agriculture Research, 2*(4), 106. http://dx.doi.org/10.5539/sar.v2n4p106

Farrell, M. J. (1957). The measurement of productive efficiency. *Journal of the Royal Statistical Society. Series A (General), 120*, 253-290. http://dx.doi.org/10.2307/2343100

Fried, H. O. (2008). Efficiency and production. In H. O. Fried, C. A. K. Lovell, & S. S. Schmidt (Eds.), *The measurement of productive efficiency and productivity growth*. New York: Oxford University Press. http://dx.doi.org/10.1093/acprof:oso/9780195183528.003.0001

Griffin, R. C., Montgomery, J. M., & Rister, M. E. (1987). Selecting functional form in production function analysis. *Western Journal of Agricultural Economics, 12*, 216-227.

Iliyasu, A., Mohamed, Z. A., Ismail, M. M., Abdullah, A. M., Kamarudin, S. M., & Mazuki, H. (2014). A review of production frontier research in aquaculture (2001-2011). *Aquaculture Economics and Management, 18*(3), 221-247. http://dx.doi.org/10.1080/13657305.2014.926464

ISSER (Institute of Statistical, Social and Economic Research). (2014). *State of the Ghanaian Economy Report in 2013*. ISSER, University of Ghana, Legon.

Johnson, E. N. (2013). *Adoption of improved technology and farm level technical efficiency of small-scale oil* *palm producers in the Western Region of Ghana* (Masters Dissertation, University of Ghana).

Kuwornu, J. K., Amoah, E., & Seini, W. (2013). Technical efficiency analysis of maize farmers in the Eastern Region of Ghana. *Journal of Social and Development Sciences, 4*(2), 84-99. Retrieved from http://ifrnd.org/Research%20Papers/S39.pdf

Kyei, L., Foli, G., & Ankoh, J. (2011). Analysis of factors affecting the technical efficiency of cocoa farmers in the Offinso district-Ashanti region, Ghana. *American Journal of Social and Management Sciences, 2*(2), 208-216. http://dx.doi.org/10.5251/ajsms.2011.2.2.208.216

Nkegbe, P. K. (2012). Technical efficiency in crop production and environmental resource management practices in Northern Ghana. *Environmental Economics, 3*(4), 43-51. Retrieved from http://www.researchgate.net/profile/Paul_Nkegbe/publication/235322172_Technical_efficiency_in_crop_production_and_environmental_resource_management_practices_in_northern_Ghana/links/0912f510bc4742daec000000.pdf

Ofori-Bah, A., & Asafu-Adjaye, J. (2011). Scope economies and technical efficiency of cocoa agroforesty systems in Ghana. *Ecological Economics, 70*(8), 1508-1518. http://dx.doi.org/10.1016/j.ecolecon.2011.03.013

Ogundari, K. (2014). The paradigm of agricultural efficiency and its implication on food security in Africa: What does meta-analysis reveal? *World Development, 64*, 690-702. http://dx.doi.org/10.1016/j.worlddev.2014.07.005

Ogundari, K., & Brümmer, B. (2011). Technical efficiency of Nigerian agriculture: A meta-regression analysis. *Outlook on Agriculture, 40*(2), 171-180. http://dx.doi.org/10.5367/oa.2011.0038

Onumah, E. E., & Acquah, H. D. (2010). Frontier analysis of aquaculture farms in the southern sector of Ghana. *World Applied Sciences Journal, 9*(7), 826-835.

Onumah, E. E., Brümmer, B., & Hörstgen-Schwark, G. (2010). Elements which delimitate technical efficiency of fish farms in Ghana. *Journal of the World Aquaculture Society, 41*(4), 506-518. http://dx.doi.org/10.1111/j.1749-7345.2010.00391.x

Onumah, J. A., Al-Hassan, R. M., & Onumah, E. E. (2013). Productivity and technical efficiency of cocoa production in Eastern Ghana. *Journal of Economics and Sustainable Development, 4*(4), 106-117.

Oppong, B. A., Onumah, E. E., & Asuming-Brempong, S. (2014). Stochastic Frontier Modelling of Maize Production in Brong-Ahafo Region of Ghana. *AGRIS on-line Papers in Economics and Informatics, 6*(2), 67-75. Retrieved from http://ageconsearch.umn.edu/bitstream/182492/2/agris_on-line_2014_2_oppong_onumah_asuming-brepong.pdf

Pagan, A., & Vella, F. (1989). Diagnostic tests for models based on individual data: a survey. *Journal of Applied Econometrics, 4*(0), S29-S59. http://dx.doi.org/10.1002/jae.3950040504

Papke, L. E., & Wooldridge, J. M. (1996). Econometric methods for fractional response variables with an application to 401(k) plan participation rates. *Journal of Applied Economics, 11*, 619-632. http://dx.doi.org/10.1002/(SICI)1099-1255(199611)11:6%3C619::AID-JAE418%3E3.0.CO;2-1

Peprah, J. A. (2010). *Access to credit and technical efficiency of vegetable growers in Mfantsiman District of Ghana*. http://dx.doi.org/10.2139/ssrn.1805218

Raj, S. P. (2011). Inaugural Editorial. *Journal of Agribusiness in Developing and Emerging Economies, 1*. http://dx.doi.org/10.1108/jadee.2011.52401aaa.002

Ramalho, E. A., Ramalho, J. J., & Henriques, P. D. (2010). Fractional regression models for second stage DEA efficiency analyses. *Journal of Productivity Analysis, 34*(3), 239-255. http://dx.doi.org/10.1007/s11123-010-0184-0

Ramalho, E. A., Ramalho, J. J., & Murteira, J. M. (2011). Alternative estimating and testing empirical strategies for fractional regression models. *Journal of Economic Surveys, 25*(1), 19-68. http://dx.doi.org/10.1111/j.1467-6419.2009.00602.x

Ramalho, E. A., Ramalho, J. J., & Murteira, J. M. (2014). A generalised goodness - of - functional form test for binary and fractional regression models. *The Manchester School, 82*, 488-507. http://dx.doi.org/10.1111/manc.12032

Notes

Note 1. This conclusion however related to organic agriculture.

Note 2. Ogundari and Brummer (2011) and Ogundari (2014) attempted this but used summary statistics and made conclusions based on 'vote count'.

Note 3. See Ramalho et al. (2010) for details on GOFF tests: formulation, testing and distributional assumptions.

Note 4. In the literature, translog functions have been chosen a priori for their flexibility or contrasted with Cobb-Douglas based on likelihood ratio test.