ADITUM
Journal of Agricultural Research Pesticides and Biofertilizers
Open Access
Research Article

Technical Efficiency of Ethiopian Agriculture: A Meta-Analysis

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Article Info

Received: May 08, 2021
Accepted: May 17, 2021
Published: June 02, 2021

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Citation: Firomsa.M.Tekalign. (2021) "Technical Efficiency of Ethiopian Agriculture: A Meta-Analysis.", Journal of Agricultural Research Pesticides and Biofertilizers, 1(3); DOI:http;//doi.org/05.2021/1.1012.

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Abstract

Meta-analysis allows combining the outcomes of several studies into a combined analysis that delivers an overall estimate of attention for policymaking. A meta-dataset generated from existing frontier studies with a focus on Ethiopian agricultural production systems and covering the period 2010-2018 is employed to provide answer to which of the farmers' socioeconomic variables most influence the technical efficiency level of the primary respondents from the case studies? With the objectives of reviewing, the empirical estimates of the determinants of Technical efficiency of Agriculture in Ethiopia from several studies and analyzing the variation of these estimates based on differences across studies as explanatory variables in a regression model. The frontier studies used were compiled from different sources, including economic databases such as Web of Science, Google Scholar, AgEcons search and other online databases using relevant keywords. Twenty studies were considered for the analysis using the statistical methods are which is based on standard fixed or random effects models. From a total of papers used for the meta-analysis, labor, fertilizer, extension, number of owned, land, age, offarm activity, education, Gender, credit and farm size were used as explanatory variables in most of the studies and only labor, fertilizer, land, education and farm size were found to have significant relationship with technical efficiency. The Econometric result reveal that the sample size, year of study, range and region were the study undertakes reported significantly affect TE estimates across studies. Therefore, further meta-analysis research of TE seems warranted more accurate TE estimates in guiding policy decisions were recommended.

Keywords: technical efficiency; agriculture; Ethiopia; meta-analysis

1. Introduction

Meta-analysis allows researchers to combine the outcomes of several studies into a combined analysis that delivers an overall estimate of attention for policymaking (Sterne, 2009). Specifically, meta-regression analysis is the use of regression models to appreciate changes quantitatively in the study-specific effect of interest by the difference in a number of moderator variables associated with homogeneous studies such as methodology used, size of observation, location of the study, etc.

Given the number of efficiency studies used to increase policy debates on the performance of the Ethiopian agricultural sector over the years, meta-regression analysis will, furthermore, make a valuable contribution to Ethiopian agricultural efficiency literature in general.

It is important not only to estimate the efficiency level of a given firm, but also to understand clearly the factors responsible for efficiency distinction (determinants) at individual firm level or the causes of deviation from the frontier technology among the producing units.

In the case of agricultural production, the literature identified education, age, years of experience, credit, market access, off-farm income and extension activities, among other factors, as controllable variables explaining the variation in efficiency with respect to frontier (Kumbhakar and Lovell, 2000; Coelli et al, 2005). This observation may indicate why many frontier studies contain quantitative results on sources of technical efficiency differences in addition to the estimated production frontier either in a single step or in a two-step method.

Against this background, we take a closer look at those studies that estimate determinants of efficiency level in addition to the estimated efficiency scores from the primary studies for further policy inferences. This is done by identifying which farmers' socioeconomic/ demographic variables most influence the technical efficiency level of Ethiopian agricultural producers (overwhelmingly smallholder farmers) over the years from the chosen studies.

Therefore, a meta-dataset generated from existing frontier studies with a focus on Ethiopian agricultural production systems and covering the period 2010-2018 is employed to provide answers to the following research questions proposed in this analysis:

- Which of the farmers' socioeconomic/demographic variables most influence the technical efficiency level of the primary respondents from the case studies?
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Objective of Conducting Meta-Analysis:

The primary objective of this meta-analysis is to:

- ➢ Review empirical estimates of the determinants of Technical efficiency of Agriculture in Ethiopia from several studies.
- ➢ Analyze the variation of these estimates based on differences across studies as explanatory variables in a regression model.

Significance of Meta-Analysis:

Undertaking analysis of efficiency and performance of firms are becoming vital areas of researches in applied economics. Efficiency measurement has received considerable attention by both theoretical and applied economists. It is regarded as one of the most indispensable researchable areas in production economics. In most least developing countries (like Ethiopia), where farmers are not well educated, resources are scarce, market is imperfect, labor is abundant, extension trainings are inadequate, and agricultural capital is limited, such studies on resource use efficiency will benefit the producers in the study area. This is because the ability of farmers to adopt modern technologies and achieve sustainable production depends on their level of efficiency. This will again play a crucial role at large in fastening economic growth of the country in terms of rising rural income, achieving food security, increasing employment, and accelerating poverty reduction without injecting new investment on modern technologies.

Limitation of Meta-Analysis:

Meta-analysis has been used extensively in education, psychology and health sciences. More recently, some economists have used this technique (e.g. Espey et al., 1994; Phillips, 1994). However, there appears to be no application of this methodology to the analysis of TE. First, we consider different approaches to estimating TE. Next, we present a summary of TE measures reported in the literature for a wide range of developing countries. We then present the empirical model and discuss, on the basis of our results, some key methodological issues that arise from the empirical analysis of TE using frontiers.

2.Methodology:

Data Source:

The frontier studies used in this paper were compiled from different sources, including economic databases such as Web of Science, Google Scholar, AgEcons search and other online databases using relevant keywords. This was followed by an exhaustive search in reference lists for relevant papers. The studies are mostly from journal publications.

The initial search yielded a total of 41 studies covering 2010–2018. While 21 studies were excluded because of a limited number of dual and non-parametric (that is, DEA) studies, and studies that did not include full information on all the potential explanatory variables considered for MRA, such as year of the survey, location of the studies and sample size, among other factors.

A total of 20 studies was considered for the analysis. None of the frontier studies employed panel data. In a meta-analysis, each study constitutes a single observation with a sufficiently large number of independent observations. Because some of the studies reported more than one ATE.

From the case studies, we extracted and coded information on the reported ATE score and a number of potential explanatory variables that represent based on the theoretical framework. The information extracted includes sample size, number of variable and year of publication. Other items included stochastic frontier analysis and deterministic model.

Model Specification:

The Random Effect Model Estimation:

The statistical methods are generally based on standard fixed or random effects models. The random effects model was discussed as follow.

Consider a collection of k studies, the i th of which has estimated effect size Yi and true effect size θi. A general model is then specified by:

$$Y_i = \theta_i + e_i \quad \text{where } e_i \overset{d}{=} \mathrm{N}(0, \sigma_i^2), \quad i = 1, 2, \ldots, k$$

The **ei** indicate random deviations from the true effect size and are assumed independent with mean zero and variance δ^2 i. This implies that the estimated effect size Yi is normally distributed with mean θi and variance δ^2 i. **Yi** can be any measure of effect, provided the assumption of normality is (at least approximately) appropriate. Common examples are a log-odds ratio or difference in means.

In general, the parameter of interest is the overall effect, denoted by μ. the fixed effects model assumes θi = μ for i = 1, 2 … k, implying that each study in the meta-analysis has the same underlying effect. Note that even if θi are assumed to be the same, the Yi are not identically distributed due to the possibility of differing δ^2 i. The estimator of μ is generally a simple weighted average of the Yi, with the optimal weights proportional to **w_i =1/var (Yi).** In practice the variances are not known so estimated variances δ ˆ2 i are used to estimate both μ and var (μ ˆ). Any effect of this is generally ignored in practice, but to indicate this estimation we use the notation δ ˆ2 i throughout. Hence, we define wˆi =1/ δ ˆ2 i giving:

$$\hat{\mu} = \frac{\sum \hat{w}_i Y_i}{\sum \hat{w}_i} = \sum \frac{Y_i}{\hat{\sigma}_i^2} \Big/ \sum \frac{1}{\hat{\sigma}_i^2} \quad \text{and} \quad \widehat{\mathrm{var}}(\hat{\mu}) = 1 \Big/ \sum \frac{1}{\hat{\sigma}_i^2}$$

In contrast to the fixed effects model, the random effects model does not assume that θi are equal, but that they are normally distributed. This gives the two-stage model

$$\left.\begin{array}{ll} Y_i = \theta_i + e_i & \text{where } e_i \stackrel{d}{=} \mathrm{N}(0, \hat{\sigma}_i^2) \\ \theta_i = \mu + \varepsilon_i & \text{where } \varepsilon_i \stackrel{d}{=} \mathrm{N}(0, \tau^2) \end{array}\right\} \quad (1)$$

The error terms ei and εi are assumed to be independent. In this case, the true effect for study **i** is centered on the overall effect, allowing individual studies to vary both in estimated effect and true effect. The random effects variance parameter τ^2 is a measure of the heterogeneity between studies. Note that the fixed effects model is a special case of the random effects model, with $\tau^2 = 0$. The random effects model given in (1) can also be written:

$$Y_i = \mu + \varepsilon_i + e_i \quad \text{where } e_i \stackrel{d}{=} \mathrm{N}(0, \hat{\sigma}_i^2) \quad \text{and} \quad \varepsilon_i \stackrel{d}{=} \mathrm{N}(0, \tau^2)$$

Relating the **Yi** directly to the overall measure of effect**μ**. By the independence of ε_i and e_i we then have $Y_i \stackrel{d}{=} \mathrm{N}(\mu, \hat{\sigma}_i^2 + \tau^2)$.

A weighted average is again used to estimate**μ**, giving:

$$\hat{\mu}_\tau = \frac{\sum \hat{w}_i(\tau) Y_i}{\sum \hat{w}_i(\tau)}$$

With variance $\mathrm{var}(\hat{\mu}_\tau) = \frac{1}{\sum \hat{w}_i(\tau)}$

Empirical Model:

The basic hypothesis of this paper is that the variation in the TE indices reported in the literature can be explained by the attributes of the studies, including functional form, sample size, product analyzed, number of variables in the model, and estimation technique. To investigate this issue formally, the following model is estimated:

TE = f (YRSTUD, REGION, STO, SIZE, NVAR, RANGE)

Where TE is the average technical efficiency reported in a study; YRSTUD is the year the study was published; REGION is a categorical variable equal to one if for Oromia, 2 for Amhara, 3 for Tigray, 4 for SNNP and 5 for Ethiopia in general; STO is a dummy variable equal to one if the model is a stochastic frontier and zero otherwise; SIZE is the number of observations used in the study and NVAR, represent the number of variables used, the. The last variable, RANGE, stands for the difference between the minimum and the maximum TE scores reported in the study. No variable was included to account for the distinction between parametric and non-parametric frontiers because of the limited number of non-parametric studies. The model is estimated using ordinary least squares (OLS) estimates.

3.Results and Discussion:

Random (Mean) Effect Result of the Variables:

The statistical methods, which are random effects models are generally based on collecting the coefficient and standard errors of independent variables that different studies were used and calculated using the method, discussed in section 3.2. The mean effect of variables was given in Table 1 and discussed

VARIABLES	COEFFICIENT	STD.ERROR
LABOR	0.133***	0.018
FERTILIZER	0.029***	0.003
EXTENSION	-0.035	0.0497
OXEN	0.003	0.0028
LAND	0.095***	0.011
AGE	-0.001	0.001
OFFARM	9.87E-05	5.99E-05
EDUCATION	-0.002***	0.0008
GENDER	0.0001	0.0005
CREDIT	-0.0001	6E-05
FARM SIZE	0.038*	0.021

Table 1: Random (Mean) Effect Result of the Variables.

Source: Computation from the studies result, 2019

(***, ** and * refer to the statistical significance of variables at 1 %, 5 % and 10 % level of significance, respectively)

In this meta-analysis, from a total of 20 selected papers, labor was used as explanatory variables in most of the studies and they found positive relationship with technical efficiency. Most of the results are in line with the hypothesis that increase in labor usage will lead to increment in value of output, holding other factors constant. So, the studies conducted by Beyan (2012), Shumet (2016), Zewdie (2015), Shumet (2011), Getachew (2018) and Musa (2014) found positive and statistically significant relationship between labor and the probability of being technically efficient.

Fertilizer was used as explanatory variables in almost all of the studies and they found positive relationship with technical efficiency. Most of the results are in line with the hypothesis that increase in fertilizer usage will lead to increment in value of technical efficiency. The result is in line with the studies conducted by Beyan (2012), Shumet (2016), Zewdie (2015), Shumet (2011), Getachew (2018) and Musa (2014).

Education was used as explanatory variables in most of the studies and they found negative relationship with technical efficiency. Most of the results are in line with the argument that when a farmer gets access to better education, he or she may get better opportunities outside the farm sector to pursue other income earning activities. Ultimately, this reduces labor availability for a farm production in the household thereby lowering efficiency. Nevertheless, it could be argued that access to better education enables farmers to better manage their resources in order to sustain the environment and produce at optimum levels. The result is in line with the studies conducted by Beyan (2012), Shumet (2016), Zewdie (2015), Shumet (2011), Getachew (2018) and Musa (2014).

Land and Farm size was used as explanatory variables in most studies, and it have highest significant and positive effect on farmers' productivity and technical efficiency. Most of the results are in line with the hypothesis that increase in labor usage will lead to increment in value of output.

Empirical Results:

According to the estimates, OLS results presented in Table 1, the parameter estimates of the year of the study positively and statistically significant. This suggests that reported average TE indices have increased significantly over time

Number of Obs = 20			
F (6, 13) = 11.34			
Prob > F = 0.0002			
R - Squared = 0.5428			
Root MSE = 0.13384			
		Robust	
TE	Coef.	Std.Err.	p > |t|
YRSTUD	0.035*	0.019	0.087
SIZE	0.0001*	0.00006	0.099
NVAR	0.012	0.008	0.16
RANGE	-0.556**	0.189	0.012
REGION	-0.091**	0.033	0.017
STO	0.027	0.094	0.778
_cons	0.893***	0.143	0.000

Table 2: OLS estimate for Average TE reported in the study.
Source: Own computation, 2019
(***, ** and * refer to the statistical significance of variables at 1 %, 5 % and 10 % level of significance, respectively)

Models using stochastic frontiers do not generate significantly different TE indices than deterministic models. This finding contradicts a priori expectations that inefficiency scores are higher for deterministic models than stochastic frontiers. Moreover, in an empirical analysis, Ekanayake and Jayasuriya (1987) found that deterministic procedures have a tendency to overestimate the average level of technical inefficiency and that the extent of the bias is unknown.
Further, these authors concluded that even though stochastic frontiers enable the separation of random noise from deviations arising from technical inefficiency, the smaller this noise, the closer the efficiency estimates from these two procedures would be.
The Econometric result shown in Table 1 also reveal that the sample size and the range of TE reported significantly affect TE estimates across studies. But, and the number of variables in the model do not reported that significantly affect TE across studies.

4.Summary and Conclusion:

A total of 20 frontier studies using farm level data from Ethiopia were analyzed. The farm level TE scores from all the studies reviewed range from 40 to 99% with an average of 72.3%. The key results of this study, which have implications for future efficiency work, relate to the impact of the independent variables under study such as labor, fertilizer application, extension access, land, education, farm size and family size. The empirical result also shows that sample size used in each study, the region, the year of study has a significant effect on the overall technical efficiency of the product.
As concluded by Bauer (1990) in a review of new developments in frontier function methodology, additional empirical as well as theoretical work is needed to arrive at a clearer picture of the effects that alternative methodological assumptions might have on measures of efficiency.
From a policy standpoint, more accurate TE estimates are crucial in guiding policy decisions dealing with farm extension and training programs, among others. Finally, further meta-analysis research of TE seems warranted. In our view, additional work that incorporates a larger set of studies with broader geographical and/or sectoral coverage would produce a better understanding of the association between measures of TE and the attributes of the studies reporting these measures.

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