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Measurement of Technical Efficiency of Resettled Farm Households in Western Ethiopia

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Abstract: *The study brought new estimates of technical efficiency of resettled farm households in Western Ethiopia using 2015/16 farm household survey data. Multi-stage proportionate random sampling technique was used to collect farm data of 420 farm households of which 285 farm households are resettled and the remaining 135 farm households are existing crop producers. The result of maximum likelihood estimation of stochastic frontier Cobb-Douglass production function shows that land, labor, local seed, oxen, improved seed, manure and herbicide were found to have enhancing effect on the productivity of farm households in the study area. The stochastic frontier approach shows that the mean TE scores of resettled and existing farmers were found as 0.738 and 0.713, respectively and hence they forgone a total income of 8,746.53 Birr and 17,249.25 Birr due to their inefficiency, respectively. The result of spearman rank correlation test reveals that significant agreement was found between stochastic frontier approach and data envelopment approach in estimating technical efficiency. Therefore, the study recommended the government, NGOs, and private sectors to promote local best farming practices accompanied by timely supply of improved inputs in fair price. In addition, strengthening livelihood assets of farmers is, therefore, vital to enlarging opportunities for their food security.*
Keywords: *DEA, Farm Households, productivity, SFA, Technical Efficiency, Western Ethiopia*

I. Introduction

Around 2.5 billion people in the world engage on agriculture sector directly or indirectly as their principal sources of livelihood and from this, 1.3 billion people are smallholder farmers and landless laborers. Almost 75 % of world's poorest people reside in rural areas and 86 % of them work in agricultural sector for their livelihood. Similarly agriculture sector plays a principal role in the African countries in terms of economic growth, employment and food security. Two-thirds of the population of Sub-Saharan Africa (SSA) still lives in rural areas and nearly half of SSA's rural population is economically active in agriculture (ECG, 2011). According to Schultz (1964), farmers in developing economies are poor but efficient. This famous hypothesis has made researchers and policy makers to believe that increment in production hence productivity could not be realized at the given resources and technology rather should focus on investing in new technologies to shift the frontier upward. However, this could not be realized because investments in new technologies require huge resources which the developing countries lack.

Agriculture sector, which is the backbone of Ethiopian economy, is characterized by traditional technologies and dominated by smallholder farmers who produced 95 % of total agricultural output from around 95 % of country's arable land. It accounts 45 % of gross domestic product (GDP); 87 % of export earnings; and 85 % of employment. Ethiopia is ranked third in the world and first in SSA in regards to the share of GDP that generates from agriculture sector. Achieving productivity gains in agriculture sector has been an important challenge for the country and hence needs considerable attention. With a fast-growing population (2.8 % per year which ranked the country to be thirteenth in the world and the second in Africa next to Nigeria), it has been so far challenging for the economy to satisfy its domestic food requirements (EEA, 2012; Beyan et al., 2013; and EGP, 2014).

Though agriculture sector has been grown by 5.4 % so far and remained to be significant sector of Ethiopian economy, yet the increasing population pressure, weak infrastructure, and decreasing productivity have been critical problems in the country. These in turn have aggravated the food insecurity and inflation situation in the country by widening the gap between demand for and supply of food grains. Despite the incidence of frequent drought and poor cultivation practices prevailing in the country, Ethiopia has amble agricultural potential because of its unexploited 74 million hectares of arable land, diverse agro-ecological zones (Dega, Weyna-Dega, and Kolla), adequate rainfall, ample labor force and huge livestock resource (NBE, 2009 and Davis et al., 2010).

After the down fall of the Derge regime in 1991, the country has undertaken series of structural adjustment programs (SAP) to facilitate transition from a command economy to a market oriented. In the process of implementing SAP for achieving Millennium development goals (MDGs), Ethiopia developed the Interim Poverty Reduction Strategy Program (IPRSP) in 2000 and launched Sustainable Development and Poverty Reduction Program (SDPRP) in 2002. Because of the agrarian nature of the economy, SAP was backed by Agricultural Led Development Industrialization (ADLI) in 1993 aiming at reducing poverty and achieving a self-sustained economic growth through increasing agricultural productivity. To realize this, the government has been trying to transform the economy, and thereby to identify large investments targets in roads, education, health and agricultural technology (Moller and Dorosh, 2010).

II. Rationale of Study

The success stories in the Ethiopian economy so far and the common words like famine, hunger, poverty have been related to contemporary agricultural performance. And hence, it is true that agriculture sector, though potentially promising, is structurally traditional and mainly managed by smallholder farmers who make non-separable consumption and production decisions under asymmetric information, market imperfection, high weather risk, liquidity constraint, bottlenecks in supply of improved and modern inputs, and poor infrastructure. It is, thus, simple to observe that any technical, institutional, economic and/or natural bottlenecks that farm households have faced are translated to food insecurity, vulnerability to poverty, and lack of structural transformation. Between 1990 and 1997, yields of cereal crops increased by only 0.3 % per annum. However, in spite of the sharp increase in fertilizer and other improved inputs, there has not been significant improvement in yields since 1994. This could be attributed to inefficient use of the agricultural inputs and productivity-enhancing technologies (Devereux and Guenthe, 2009; Andersson et al., 2009).

In developing countries, empirical researches on estimating farm specific level of technical efficiency of farm households using Stochastic Frontier Analysis (SFA) and Data Envelopment Approach (DEA) are too scarce. Similarly in Ethiopia, empirical studies on the areas of productivity and technical efficiency are not extensive. A common features of the previous empirical studies are: (1) most of them employed SFA alone which might not depict the robustness of the efficiency results; (2) they did not address the issue for resettled farm households; and (3) majority of the them were conducted to specific crops while a few studies conducted using total value of crops at either district or zonal level. Given various advantageous and drawbacks of the SFA and DEA approaches, it is the main objective of this study to compare empirical performance of these approaches using the same observation and data set. To best of our knowledge, no similar studies had been conducted so far in the same topic of this study. Therefore, to fill the above gaps and to add stock of knowledge in review of literature this study brought new estimates of technical efficiency scores of crop producing resettled farm households in the study area in Western Ethiopia using both Stochastic Frontier Analysis (SFA) and Data Envelopment Approach (DEA) as comparative analysis.

III. Working Hypotheses

Farm households in developing countries in general and Ethiopia in particular are characterized by heterogeneity in resource endowments, knowledge of farming practices, and other socio-economic factors which could lead to variation in their technical, allocative and economic efficiency. According to Coelli (1995) stochastic frontier analysis (SFA) has an advantage over data envelopment approach (DEA) in undertaking inferential statistical hypothesis testing. The following hypotheses were tested using the generalized likelihood ratio test: LR = -2[L(H0)-L(H1)], where L(H0) and L(H1) are the values of log likelihood functions under the null and alterative hypothesis, respectively (Greene, 1980).

1. The hypothesis that chooses the appropriate functional form for stochastic frontier model (SFA) that can adequately represent the data between Cobb-Douglas (C-D) and Translog frontier (TF) function was tested. In fact the choice of functional form has insignificant effect on the overall results and limited effect on empirical efficiency measurement in particular (Kopp and Smith, 1980).

H_0: $\beta_{11} = \beta_{12} = \ldots = \beta_{65} = 0$. The coefficient restrictions imposed on the squared and interaction terms of convectional input variables in translog frontier function are equal to zero simultaneously meaning that the restricted type of the translog frontier function, Cobb–Douglas frontier function, is an adequate representation of the model.

H_1: the above coefficients of squared and interaction terms of input variables in translog frontier function are statistically significantly different from zero meaning that the more flexible type of the translog frontier function is an adequate representation of the model.

2. The hypothesis that shows the appropriateness of employing parametric stochastic frontier analysis (SFA) model in the above chosen function over traditional average production function (OLS) or not was tested. The test is based on the statistical significance of the parameter gamma, γ.

H_0: $\sigma_u^2 = \gamma = 0$ refers to the absence of one-sided inefficiency effect error term (u) from the data and hence the data are better analyzed using the deterministic frontier or traditional average production function, ordinary least square (OLS).

H_1: $\sigma_u^2 = \gamma > 0$ refers gamma is statistically significantly different from zero which shows the presence of significant inefficiency and hence the data can adequately be analysed using parametric stochastic frontier analysis, SFA.

3. If the above hypothesis supports SFA, then the next hypothesis that specifies whether the half-normal distributional assumption for the one-sided inefficiency effect error term (u) of SFA is appropriate or not was tested.

H_0: one-sided inefficiency effect error has half-normal distribution (H_0: $\mu = 0$).

H_1: inefficiency effect error term has truncated-normal distribution (H_1: $\mu \neq 0$).

In addition if σ^2 is statically significantly different from zero, then it reveals a good fit of the model and correctness of distributional form assumed for the composite error term (i.e. normal distribution for stochastic random error term (v) and truncated - normal distribution for one-sided inefficiency effect error term (u) (Coelli et al, 2005; Zalkuwi et al.,2010).

4. The hypothesis that specifies whether the stochastic production frontier function is characterized by constant returns to scale or not was tested. This helps us to know whether the prevailing nature of production of farm households in the study area is characterized by constant returns to scale (CRS) or variable returns to scale (VRS) technology.

H_0: the stochastic production function is characterized by constant returns to scale (H_0: $\sum_{j=1}^{10} \beta_j = 1$ for all j) i.e., no scale inefficiency in the production.

H_1: the stochastic production function is characterized by variable returns to scale (H_1: $\sum_{j=1}^{10} \beta_j \neq 1$ for all j) i.e., there is scale inefficiency.

IV. Contribution of Study

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 indispensible researchable areas in production economics. In most least developed countries (like Ethiopia), where farmers are not well educated, resources are scarce, market is imperfect, labour 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 to optimize their production by not wasting their scarce resources via solving resource allocation problem at a given technology. 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. In addition, since there are no previous studies on technical efficiency of resettled farm households using stochastic frontier analysis and data envelopment approach, this study will contribute in reducing the dearth of literatures on productivity and efficiency of farm households by adding stock of knowledge on these empirical techniques which are modern and appropriate methodologies commonly used for agricultural efficiency evaluation.

V. Review of Literature

Theoretically, production function can be defined as the highest possible output attainable from a given bundle of factors of production and fixed technology. This is regarded as estimated average production function. This definition assumes that technical inefficiency is absent from the production function. Following the independent works by Aigner et al. (1977) and Meeusen and van den Broeck (1977), serious attention has been given to the possibility of estimating the so-called frontier production functions, in an effort to bridge the gap between theory and empirical work. The Stochastic frontier production function is developed to bridge the above gap by including the concept of technical inefficiency which is defined as the amount by which the observed output falls short of the frontier output (Kumbhakar, 1988 and Ajibefun et al., 2006). Classical production theory assumes that producers in an economy always operate efficiently and any observed output discrepancy from the frontier is due to external shocks which are entirely out of the control of firms. Accordingly, performance of any firm may depend on differences in production technology, differences in the effectiveness of production process, and/or differences in the production environment. However, at particular period of time, even when production technology, production environment and effectiveness of production process are given same, farm households may exhibit different productivity levels due to differences in their production efficiency (Korres, 2007).

Technical or productive efficiency measures the relative ability of the farm household to obtain the maximum frontier output from given set of inputs. Technically efficient farm households are those who operate on the production possibility frontier which represents maximum possible output attainable from each input level. All feasible points below the production possibility curve are technically inefficient points. This concept involves assessing each farm household's actual production performance compared to a best-practice farm household. The best-practices production frontier is established by the practices of the most efficient farm households. Thus, the gap of the individual farm household from the frontier production measures technical efficiency. Technical inefficiency reveals the reason of the cost difference among farm households due to inefficient use of the given input bundle. From time series point of view, the best-practice frontier is the maximum potential output for the best practice year. Thus, the technical efficiency of farm household in this case, is the deviation between the actual output for any particular year and the maximum potential output of the best-practice year (Coelli et al., 2002 and Djokoto, 2012).

Farrell (1957) described technical efficiency as a perspective of output expansion and input contraction , i.e., the ability of farm household to produce as large as possible level of output from the given the bundles of inputs and production technology (output-oriented technical efficiency) or to use as small as possible inputs to produce a given set of outputs (input-oriented technical efficiency). A production plan of individual decision making unit (xo, yo) is said to be technically efficient if yo = f(xo), where yo is actual output and f(xo) is maximum attainable frontier output, and a production plan of farm household (xo, yo) is said to be technically inefficient if yo < f(xo); yo > f(xo) is assumed to be impossible. One measure of the technical efficiency of production plan can be represented by $0 \leq \frac{y^0}{f(x^0)} \leq 1$. The technical inefficiency is occurred due to the presence of excessive input usage which is costly and since cost is not minimized then the profit is also not maximized (Vicente, 2004).

The primary purpose of this section is to explore a number of commonly-used modern efficiency measurement techniques and to illustrate how they can be used to compute relative efficiency of farm households on the prevailing production technology that is represented by some form of production frontier functions. The discussion of efficiency measurement began with Farrell's work (1957), since then there was a growing demand to develop scientific methodologies to be applied for measurement of efficiency. Among many authors, Coelli et al. (1995) present the most recent frontier techniques used for efficiency measurement like parametric stochastic frontier approach (SFA) and non-parametric data envelopment approach (DEA) including their limitations and strengths.

Table 1: Summary of Strengths and Weaknesses of Technical Efficiency Estimation Methods

No	Techniques	Strength	Weakness
1	**SFA**	• Capturing stochastic noises • Permits hypotheses testing • Estimating parameters of the functions • Being less sensitive to outliers and number of observations	• Imposing explicit functional form • Imposing distributional assumption for the composite error terms • Being not appropriate for multi-output case • Cannot directly decompose technical efficiency in to pure technical and scale efficiency.
2	**DEA**	• Avoids functional specification • No distributional assumption of the composite error terms • Being appropriate for multi-inputs and multi-outputs • Enabling to decompose TE into overall technical efficiency, pure technical efficiency and scale efficiency	• Does not capture stochastic noises • Sensitive to measurement errors • Does not permit hypotheses testing • Being more sensitive to outliers and observations • Does not allow parameter estimation

The choice of efficiency estimation method has been an issue of debate, with some researchers preferring the parametric and others the non-parametric approach. To fill this gap, this study uses both parametric stochastic frontier and non-parametric data envelopment approaches to bring new estimates of crop producing resettled farm households' technical, allocative and economic efficiencies and hence to investigate whether these approaches give statically different technical efficiency results or not.

VI. Methodology of Study

6.1. Description of Study Area

Ethiopian is a sovereign state located in the horn of Africa. It is divided into nine regional states which are further structured into zones and woredas. The woredas are further classified into peasant associations/ kebeles. Benishangul-gumuz is one of the nine regional states established in 1994. The region is divided into 3 administrative zones and 20 woredas. Metekel zone, which is the area of the study, consists of seven woredas, namely: Pawe, Bulen, Dangur, Dibate, Guba, Mandura, and Wombera. This zone has an area of about 26,560 km2 with altitude ranging from 600 to 2800 meters above sea level (masl). About 80 % of the zone is characterized by having sub-humid and humid tropical climate. It has a total population of around 403,216 people; of this 81,919 are farm household heads. The average family size of zone is six. The population density of the zone is about 15.48 persons/square kilometer (CSA, 2013). This zone is located 550 km west of the Ethiopian capital city, Addis Ababa. Like most of other rural areas, this zone is dominated by lowland agro-ecology with the traditional mixed crop–livestock production system. Dominantly grown annual crops in the study area are: maize, sorghum, rice and millet, sesame, niger seed, groundnuts, haricot beans, chickpeas, and soya beans (Solomon et al., 2014).

During the mid of 1980s, Ethiopian government considered resettlement program as a feasible solution to the sever famine problem occurred during that time. As a result, from 1984-1986 the government relocated about 600,000 people from drought-affected and over-populated regions , majorly from Northern Ethiopia and some from Southern Ethiopia, to different resettlement sites, namely, Metekel, Metema, Assosa, Gambella, and Kefa, located in the western and south western parts of Ethiopia. Of the total figure, over 82,000 people moved to Pawe special woreda, Metekel zone (Gebre, 2002 and World Factbook, 2004). In addition, the regional government has undertaken intra-regional resettlement program from 2010-2013 particularly in two of the study districts, Mandura and Dangure. This resettlement program was done voluntary based on public consensus for sake of having common public institutions like farmers training center (FTC), education, health and public administration institutions in the form of villagization program.

6.2. Sources and Methods of Data Collection

The study used multi-stage random sampling technique to collect farm household data in 2015/16 crop production mehar season. The study used pre-tested structured questionnaire and three extension workers (DAs) for each chosen kebele in the three districts as enumerators. The study selected 30 farm households from each kebele using systematic random sampling. As a result, the study collected data of a total 420 farm households in 2015/2016 production season. From the total respondents, 119 (28.33 %) farmers are old resettled farmers, 166 (39.52 %) are newly resettled farmers and the remaining 135 (32.14 %) are existing farmers.

6.3. Sampling Design

Sample size is determined based on standard sample size determination formula given by Israel (1992).

$$\mathbf{n} = \frac{z^2 P(1-P)}{e^2} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\mathbf{(1)}$$

Where,

n= total number of respondents,

z= z value at 95 % confidence interval which equals to 1.96,

P= estimated proportion of an attribute that is present in the population. With the assumption that there is large population but we do not know the variability in the population, p = 0.5 was considered as suggested by Israel (1992), and

e =level of precision (i.e., 5 %).

6.4. Empirical Model Specification and Data Analysis

To analyze the data, the study used econometric tool (SFA) via Coelli FRONTIER 4.1c and mathematical linear programming tool (DEA) via DEAP version 2.1 computer programs to measure the extent of technical efficiency of resettled farm households (Coelli, 1996).

6.4.1. Parametric Stochastic Frontier Approach (SFA)

Most empirical studies interchangeably used either Cobb-Douglas(C-D) or translog function. However, C-D has been more commonly used due to its self-dual nature of production and cost functions as well as due to its computational advantage in estimating efficiency scores. Technical efficiency can be measured by using input or output-oriented approaches. Under constant returns to scale (CRS), the input-oriented approach has the same result with output-oriented. However, the case is different when variable returns to scale (VRS) is chosen. Since the farm households in the study area have relatively more control on inputs and faced resource shortages so the study gets input-oriented approach more appropriate. Furthermore, in many instances, the selection of such orientation has only minor effect on efficiency measurement (Coelli et al., 2005 and Begum et al., 2010).

Technical Efficiency

After specifying input and output variables, the Cobb-Douglas production function can be specified , which is consistent with the empirical works of Aigner et al.(1977) and Meeusen and van den Broek (1977) , as:

$$\ln(\text{Output})_i = \beta_0 + \beta_1\ln(\text{Land})_i + \beta_2\ln(\text{Local seed})i + \beta_3\ln(\text{Improved seed})i + \beta_4\ln(\text{Labor})_i + \beta_5\ln(\text{Herbicide})_i + \beta_6\ln(\text{Pesticide})_i + \beta_7\ln(\text{Ox})_i + \beta_8\ln(\text{Urea})_i + \beta_9\ln(\text{DAP})_i + \beta_{10}\ln(\text{Manure})_i + v_i - u_i \quad \ldots\ldots\ldots\ldots\mathbf{(2)}$$

Where,
ln **:** it refers to the natural logarithm ,
$(Output)_i$ **:** it refers to the total value of crop outputs produced by the i^{th} farm household in the study area for 2015/16 production season in Birr, Ethiopian currency,
β_0**:** it refers to the constant term (intercept),
β_j**:** it refers to a vector of j unknown parameters to be estimated by MLE method,
$X_{j:}$ it refers to the vector of inputs of i^{th} the farm household, and
$v_i - u_i$: it refers to a two-component error term which captures the deviation of the observed value of output from its corresponding frontier output of i^{th} farm household attributed to the effect of uncontrollable factors and technical inefficiency, respectively.

6.4.2. Non-Parametric Data Envelopment Approach (DEA)

The DEA method constructs a non-parametric piecewise linear surface of a production frontier over the data. The strength of DEA is that it does not require any restricted assumptions about the functional form and distribution of the error term. Being deterministic is the major weakness of DEA, i.e., it does not take in to account random shocks. In addition DEA is sensitive to measurement errors, number of observations and outliers in the data set. Charnes et al. (1978) proposed input-orientated CRS DEA to simultaneously construct frontier with the aim of maximizing output by minimizing cost. The TE (θ_i) of i^{th} the DMU is obtained by solving the following DEA model (Coelli et al., 2005):

$$\min_{\theta,\lambda} \theta_i$$
$$\text{Subject to} \quad -y_i + Y\lambda \geq 0 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \mathbf{(3)}$$
$$\theta x_i + X\lambda \geq 0$$
$$\lambda \geq 0$$

Where,
θ_i **:** it refers to a TE measure of the i^{th} DMU under CRS,
λ **:** it refers to an N x 1 vector of weights attached to each of the efficient DMUs,
y_i **:** it refers to total value of crop output produced by i^{th} the DMU ,
x_i **:** it refers to the vector of inputs , $x_1, x_2,\ldots,x_{10,}$ used by the i^{th} DMU
Y : it refers to the (1xN) vector of outputs of all N DMUs in the sample , and
X : it refers to the (M x N) matrix of inputs of all N DMUs in the sample.

The CRS assumption is only appropriate when all DMUs are operating at an optimal scale. Imperfect competition, government regulation, credit constraints, etc., may cause a DMU to be not operating at optimal scale. Banker et al. (1984) suggested an extension of the CRS DEA model to account for variable returns to scale (VRS). The use of VRS DEA model enables to calculate TE devoid of this SE effect. Note that the farm households in the study areas have relatively direct control on inputs and faced resource shortages so the study gets input-oriented approach. In addition, VRS is found to be more appropriate than its CRS counterpart for measuring efficiency. The CRS linear programming problem can be easily relaxed to take in to account for VRS technology by adding the convexity constraint: $N1' \lambda = 1$ to equation (3) as follow:

$$\min_{\theta,\lambda} \theta_i$$
$$\text{Subject to} \quad -y_i + Y\lambda \geq 0 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \mathbf{(4)}$$
$$\theta x_i - X\lambda \geq 0$$
$$N1' \lambda = 1$$
$$\lambda \geq 0$$

Where,
θ_i : it refers to the technical efficiency score of the i^{th} DMU,
$N1' \lambda = 1$: it refers to a convexity constraint which ensures that an inefficient farm household is only benchmarked against farm household of a similar size,
N1 **:** it refers to an N x 1 vector of ones,
Y**:** it refers to the output matrix for the farm households,
y_i **:** it refers to the total value of output of i^{th} DMU in Birr ,
X : it refers to the input matrix of convectional inputs for the farm households,
x_i **:** it refers to the vector of convectional inputs , and
λ **:** it refers to a Nx1 constants.

VRS DEA forms a convex hull plane which envelops the data points more tightly than the CRS and thus provides efficiency scores which are greater than or equal to CRS DEA. DEA is also used to evaluate the returns to scale of each DMU. Estimating TE under CRS DEA model gives overall TE, while VRS DEA model calculates only pure TE which captures the management practices of DMUs. The overall technical inefficiency can be decomposed into two components: one is due to scale inefficiency and the other due to pure technical inefficiency (Coelli et al., 2002). Mathematically it can be expressed as:

$$SE = \frac{TE_{CRS}}{TE_{VRS}} \quad \text{...} \quad \mathbf{(5)}$$

VII. Results and Discussions

7.1. Testing Hypotheses of the Study

According to Coelli (1995), SFA has a comparative advantage over DEA in inferential hypothesis testing. The results of the hypotheses tested are presented as follow:

Table 2: Summary statistics of Tests of Hypotheses:

Null Hypothesis	$\chi 2_{Cal}$	df	$\chi 2_{tab}$	Decision
$H_0: \beta_{11} = \beta_{12} = \ldots = \beta_{65} = 0$ $H_0: \beta_{11} \neq \beta_{12} \neq \ldots \neq \beta_{65} \neq 0$	230.52	65	94.42	H_0 is rejected at 1 % critical value meaning that translog function is more appropriate than Cobb-Douglass
$H_0: \sigma_u^2 = \gamma = 0$ $H_1: \sigma_u^2 = \gamma > 0$	11.96	2	8.27	H_0 is rejected at 1 % critical value meaning that SFA is more appropriate than ordinarily least square(OLS)
$H_0: \mu = 0$ $H_1: \mu \neq 0$	5.8	1	5.41	H_0 is rejected at 1 % critical value meaning that truncated-normal distribution is more appropriate than half-normal
$H_0: \sum_{j=1}^{10} \beta_j = 1$ $H_1: \sum_{j=1}^{10} \beta_j \neq 1$	154	10	22.53	H_0 is rejected at 1 % critical value meaning that VRS is more appropriate than CRS

Source: Critical values were obtained from Kodde and Palm (1986)

7.2. Empirical Results of Stochastic Frontier Analysis (SFA)

1. Multicollinearity, Heteroscedasticity and Omitted Variable Tests

The first test used is multicollinearity test which had been undertaken using variance inflation factor (VIF). The result of VIF for Cobb-Douglass production function was found as 1.76 while for translog function it was found as 282.36. Since there is sever multicollinearity problem in translog function, the study used Cobb-Douglass function as best fit of the data. The second test used is heterosckedasticity test using Breusch-Pagan test. According to Battese and Coelli (1995), one-sided error term (u_i) is i.i.d with truncated-normal distribution and constant variance (μ, σ^2u) while random error term (v_i) is i.i.d with normal distribution and constant variance (0, σ^2v). Since this test failed to reject the null hypothesis that claims constant variance at 1 %, we used robust of the OLS regression result as remedy solution for this problem. The third test undertaken is omitted variable test via Ramsey test. Since the p-value of this test was found to be insignificant even at 10 %, then null hypothesis that claims as the model has no omitted variables could not be rejected.

2. Productivity of Farm Households

The MLE result shows that all convectional inputs, except DAP fertilizer which is inconsistent with our prior expectation, were found to have the expected positive signs. In addition, expect pesticide, urea and DAP fertilizers, other input variables were found as significant determinants of productivity.

Table 3: MLE and OLS Estimation of Cobb-Douglas SFA Production Function:

	SFA Results			**OLS Results**		
Variables	**Coef.**	**Sd.error**	**t-ratio**	**Coef.**	**Rob Sd. error**	**t-ratio**
Constant	6.55	0.416	15.73***	5.99	0.50	11.90***
Ln(Land)	0.58	0.059	9.71***	0.57	0.069	8.26***
Ln(Local)	0.13	0.018	6.98***	0.14	0.043	3.3***
Ln(Improved)	0.03	0.007	4.18***	0.03	0.006	5.29***
Ln(Labor)	0.36	0.071	5.08***	0.38	0.083	4.55***
Ln(Herbicide)	0.03	0.012	2.45**	0.03	0.012	2.31**
Ln(Pesticide)	0.009	0.016	0.56	0.01	0.014	0.75
Ln(Ox)	0.05	0.012	4.06***	0.05	0.015	3.32***
Ln(Urea)	0.008	0.010	0.75	0.006	0.010	0.64
Ln(DAP)	-0.004	0.010	-0.40	-0.003	0.010	-0.230
Ln(Manure)	0.03	0.007	3.74***	0.03	0.007	3.75***
σ^2	1.10	0.218	5.10***	0.63	-	-
γ	0.81	0.035	23.39***	-	-	-
MU=μ	-1.89	0.709	-2.67***	-	-	-
LL	-347.43	-	-	-353.41	-	-
$\Sigma\beta_i$ (RTS)	1.22	-	-	1.24		

Source: Own Computation Using Rural Farm Household Survey of 2015/16

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

Land was found to have highest significant and positive effect on farmers' productivity at 1 % significance level in line with our prior expectation. This shows that a 1% raise in size of land will lead to a 0.58 % increment in value of crop output, holding other factors constant. As a result of alarmingly rising population and declining in agricultural productivity, the country has faced challenges in balancing demand for and supply of foods. Therefore, the feasible solution to this serious problem is raising land productivity via intensive farming and applying environmentally friendly technology that can raise land fertility in subsistence farming. This result is in agreement with studies like Wadud (2003), Arega et al. (2006) and Musa (2013).

Labor was found, in line with our prior expectation, to have positive and significant effect on farmers' productivity at 1 % significance level. This implies that a 1 % increase in labor usage will lead to a 0.36 % increment in value of output, holding other factors constant. This reveals the fact that agriculture is labour intensive not only in the study area but also in the country in general. This result was found in agreement with studies like Arega et al (2006), Musa (2013), and Opaluwa et al. (2014).

Local seed was found to have positive and significant effect on farmers' productivity at 1 % significance level consistent with our prior expectation. This implies that a 1 % increase in the use of local seed will lead to a 0.13 % increment in value of output, holding other factors constant. Although improved seed was found to have positive and significant effect on output with elasticity of 0.03, 257 (61.2 %) farm households did not use it because of its high price. This result is in line with empirical studies like Opaluwa et al. (2014) and Hassen et al. (2015).

Oxen drought power was also found to have significant and positive effect on farmers' productivity at 1% significance level. This implies that a 1% increase in the usage of oxen will lead to a 0.05% increment in output, holding other factors constant. This result is consistent with the findings of empirical studies like Endrias et al (2013) and Hassen et al (2015). In addition, herbicide (at 5%) and manure (at 1%) were found to have same significant and positive effect on farmers' productivity. This implies that, holding other factors constant, a 1% increase in the usage of herbicide and manure will lead to only 0.03 % increment in value of crop output, respectively. This result is consistent with studies like Ogundari (2008) and Mburu et al (2014).

Importantly the value of gamma (γ = 0.81**)** was found as significantly different from zero at 1% significance level. This figure reveals that 81 % of the variation of observed crop output from frontier level is due to farmers' technical inefficiency. However, the remaining 19 % is due to stochastic noises. This result is in line with the findings of studies like Ogundari (2008). In addition, sigma square (σ^2 =1.10) was found as significant at 1% which assures the goodness of fit of the model used and the validity of the distribution assumption used for the composite error terms (in line with studies like Zalkuwi et al., 2010).

3. Technical Efficiency Scores of Farm Households

The average TE score of the resettled farmers equals to 73.84 %. The mean actual output of a resettled farmer equals to 24,675.45 Birr while the average frontier output equals to 33,421.98 Birr. The actual yield of a resettled farmer equals to 5,765.29 Birr per hectare and the frontier yield equals to 7,808.87 Birr per hectare. This implies that he/she has forgone a total income of 8,746.53 Birr due to its considerable technical inefficiency. Using input-oriented approach, resettled farmers could decrease their inputs, on average, by 19.12 % if they could achieve the TE level of their most efficient counterparts [i.e., 1- $(\frac{0.7384}{0.9130}) * 100]$ but still producing the same level of output with the given technology. A similar calculation for the most technically inefficient resettled farmers shows 84.19 % cost saving, [i.e., 1- $(\frac{0.1443}{0.9130}) * 100$], at the existing technology. We can conclude that the mean TE score of the resettled farmers is comparable with the finding of Musemwa et al. (2013).

The mean TE score of the existing farmers equals to 71.31 %. This implies that an average existing farmer has lost a total income of 17,249.25 Birr due to his/her inefficiency. Using input-oriented approach, existing farmers could decrease their inputs, on average, by 22.65 % if they could achieve the TE level of their most efficient counterparts but still producing the same level of output with the given technology. A similar calculation for the most technically inefficient existing farmer shows 87.34 % cost saving, [i.e., 1- $(\frac{0.1167}{0.9219}) * 100$], at the existing technology. All in all, this result is found to be similar with the finding of studies like Ajibefun (2008) and Mokgalabone (2015).

7.3. Empirical Results of Data Envelopment Analysis (DEA)

1. Technical Efficiency Scores of DMUs

The average TE score of the resettled DMUs under VRS DEA was found as 74 % and72.3 %, respectively. The average actual value of crop output of the given DMU was found as 24,675.45 Birr while his/her average potential output equals to 33,345.20 Birr. The actual yield of a typical DMU equals to 5,765.29 Birr per hectare and the potential yield equals to 7,790.93 Birr per hectare. This implies that an average DMU has lost a total income of 8,669.75 Birr. According to input-oriented approach, the average resettled DMU in the study area could reduce his/her inputs and hence costs by 26 % , [i.e., 1- ($\frac{0.74}{1.00}$) $* 100$], if he/she could achieve the TE level of his/her most efficient counterpart but still producing the given level of crop output with the existing production technology. A similar calculation for the most technically inefficient resettled DMU shows that he/she could achieve 72.1 percent cost saving, [i.e., 1- ($\frac{0.2790}{1.00}$) $* 100$] , at the existing technology.

The mean TE score of the existing DMUs was found as 72.3 %. This implies that an average existing DMU has lost a total income of 16,427.31 Birr due to his/her inefficiency. According to input-oriented approach, the average existing DMU could reduce his/her inputs and hence cost by 27.7 % [i.e., 1- ($\frac{0.7230}{1.00}$) $* 100$] if he/she could achieve the TE level of his/her most efficient counterpart but still producing the given level of crop output with the existing technology. A similar calculation for the most technically inefficient existing DMU shows that he/she could achieve 68.6 % cost saving, [i.e., 1- ($\frac{0.3140}{1.00}$) $* 100$], at the existing technology.

2. Scale Efficiency Scores of DMUs

The mean SE score of the resettled DMUs was found to be 89 % which shows that resettled DMUs were 11 % scale inefficient. Regarding to the nature of returns to scale, 179(62.80 %) resettled DMUs had IRS, 54 (18.95 %) resettled DMUs had DRS and the remaining 52(18.25 %) resettled DMUs had CRS. This reveals that majority of the resettled DMUs had IRS consistent with the result of SFA. The mean SE score of the existing DMUs was found as 76.5 % which shows that existing DMUs were 25.5 % scale inefficient. In addition, 101 (74.81 %) existing DMUs had IRS, 18 (13.34 %) existing DMUs had DRS and the remaining 16 (11.85 %) DMUs had CRS. From this we can conclude that majority of the existing DMUs had IRS. This result is consistent with the findings of the studies like Javed (2009) and Charyulu (2010).

7.4. Comparative Analysis of SFA and DEA

According to the result the mean TE scores of resettled farmers (0.738) and existing farmers (0.713) under SFA were found to be ,more or less, similar with their respective figures under VRS DEA (0.740 and 0.723, respectively) but significantly higher than the corresponding figures under CRS DEA (0.659 and 0.553, respectively). Since VRS DEA approach is more flexible and hence encloses the data tighter than the CRS DEA approach, the estimated TE scores of DMUs under VRS DEA (0.629) were found significantly higher than the TE scores estimated under CRS DEA (0.510) at 5% significance level. In addition, greater variability in TE scores was found in DEA more than SFA. These results are consistent with previous studies like Sharma et al. (1999), Wadud and White (2000), Minh and Long (2009), and Theodoridis and Anwar (2011).

Table 4: Spearman Rank Correlation Coefficient Matrix:

Correlation		VRS SFA	CRS DEA	VRS DEA
VRS SFA	Correlation Coefficient	1.00	0.671**	0.531**
	Sig. (2-tailed)	-	0.00	0.00
	N	420	420	420
CRS DEA	Correlation Coefficient		1.00	0.775**
	Sig. (2-tailed)	0.00	-	0.00
	N	420	420	420
VRS DEA	Correlation Coefficient	0.531**	0.775**	1.00
	Sig. (2-tailed)	0.00	0.00	-
	N	420	420	420

** = correlation is significant at 1 % level

Source: Own Computation using Rural Farm Household Survey of 2015/16

Although we used the same data set, SFA and DEA brought different TE results mainly due to different returns to scale specifications. However, the spearman rank correlation shows that significant agreements were found between the results of SFA, VRS DEA and CRS DEA at 1 % significance level. And hence, integrating both approaches for efficiency estimation will bring robust results. This result is found to be consistent with studies like Wadud and White (2000), Wadud (2003), and Theodoridis and Anwar (2011).

VIII. Conclusion and Policy Implications

The results of MLE of SFA shows that the mean TE of resettled and existing farm households were found as 0.738 and 0.713 and hence they forgone a total income of 8,746.53 Birr and 17,249.25 Birr due to their technical inefficiency, respectively. Therefore, this implies that they could reduce their usage on average by 19.12 % and 22.65 % if they could achieve the technical efficiency level of their most efficient counterparts but still producing the same output with the existing technology, respectively.

The results of VRS DEA show that mean TE score of the resettled and existing DMUs were found as 0.740 and 0.723 and hence they lost a total income of 8,669.75 Birr and 16,427.31 Birr due to their technical inefficiency, respectively. Therefore, this implies they could reduce their input usage on average by 26 % and 27.7 % if they could achieve the technical efficiency level of their most efficient counterparts but still producing the same output with the existing technology, respectively. The mean SE scores of the resettled and existing DMUs were found to be 0.890 and 0.765 which reveal that the DMUs the technology used by the DMUs in the study area was dominantly IRS consistent with the result of SFA.

Although we used the same observation and data set, SFA and DEA brought different TE results mainly due to different returns to scale specifications. However, the result of spearman rank correlation test reveals that their results are found to be in agreement at 1 % significance level. And hence, integrating both approaches for efficiency estimation will bring robust results. Therefore, the study recommended the government, NGOs and private sectors to promote local best farming practices accompanied by timely supply of improved inputs in fair price. In addition, the concerned bodies should develop new pro-poor agricultural development approaches and strengthening livelihood assets of farmers is, therefore, vital to enlarging opportunities for food security in the study area.

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