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MEASURING TECHNICAL, ECONOMIC AND ALLOCATIVE EFFICIENCY OF MAIZE PRODUCTION IN SUBSISTENCE FARMING: EVIDENCE FROM THE CENTRAL RIFT VALLEY OF ETHIOPIA

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Abstract: *This study measured the technical, allocative and economic efficiencies of maize production in the central rift valley of Ethiopia using cross sectional data collected from randomly selected 138 sample households. The estimated result showed that the mean technical, allocative and economic efficiencies were 84.87%, 37.47% and 31.62% respectively. Among factors hypothesized to determine the level of efficiency scores, education was found to determine allocative and economic efficiencies of farmers positively while the frequency of extension contact had a positive relationship with technical efficiency and it was negatively related to both allocative and economic efficiencies. Credit was also found to influence technical and economic efficiencies positively and distance to market affected technical efficiency negatively. The model output also indicated that soil fertility was among significant variables in determining technical efficiency in the study area. The result indicated that there is a room to increase the efficiency of maize producers in the study area.*

Keywords: *Maize, Efficiency, Cobb-Douglas, Stochastic Frontier, Tobit*
(JEL Classifications: C67, D24, D61, L23, Q12, Q18)

1. INTRODUCTION

Ethiopia is one of the most populous counties in Africa with the population of 73.75 million in 2007 with an annual growth rate of 2.6% CSA (2008). The projected figure for the year 2012 was 84.32 million CSA (2012). This growing population requires better economic performance than ever before at least to insure food security. Yet achieving higher and sustained agricultural productivity growth remains one of the greatest challenges facing the nation Spielman *et al*. (2010) and the country is known for being the recipient of more food aid than any other country in the world Kirwan and Margaret (2007). As indicated by Goshu *et al*. (2012), the depth and intensity of food insecurity in the country are high.

In the country, agriculture contributes about 41% of GDP, employs 83% of total labor force and contributes 90% of exports EEA (2012). However, its performance has been disappointing and food production has been lagging behind population growth. For instance, from the late 1980's to 2005, population has grown by 97%, but production has increased only by 59% EEA (2006). This incompatibility in the growth clearly requires the import of food and/or food aid unless the country improves its productivity by applying improved agricultural technologies and increases production efficiency Haji (2007).

Nevertheless, as indicated by Torkamani and Hardaker (1996), in areas where there is production inefficiency, trying to introduce a new technology may not have the anticipated impact if the existing knowledge is not efficient. Because, improvement in efficiency is a potential source of productivity growth and embarking on new technologies is meaningless unless the existing technology is used to its full potential Kalirajan *et al*. (1996). Thus, increasing the efficiency in production assumes greater significance in attaining potential output at the farm level Anuradha and Zala (2010). Therefore, it is important to determine if the actual production process follows the economic rationality criterion and, if not, by how much farmers are operating off the efficiency frontier Bonabana-Wabbi *et al*. (2012).

In a poor country such as Ethiopia where technology introduction and increasing inputs are hardly possible, the identification of the extent of inefficiencies in production given the existing technology and input levels are crucial and relevant policy issues Haji (2007). In line with this, a large number of studies on farm productivity in Ethiopia have found that inefficiency exists. Seyoum *et al*. (1998); Arega, *et al*. (2006); Haji and Andersson (2006); Haji (2007); Kassie and Holden (2007); Gelaw (2013) and Ahmed *et al*. (2014) are few to mention. However, the majority of farm efficiency studies in agricultural economics focus on Technical efficiency, which is just one component of economic efficiency. In particular, no studies had been conducted in the area of economic efficiency of maize production in the study area. The extent, causes and possible remedies of inefficiency of smallholders are not yet given due attention. The purpose of this study is, therefore, to estimate the level of technical, allocative and economic efficiencies of maize producing farmers in Central Rift Valley of Ethiopia and to identify factors that determine efficiencies of smallholder farmers in maize production in the study area. This study also has policy implications because it not only provides empirical measures of different efficiency indices, but also identifies key variables that are determining the efficiency scores.

As far as maize production is concerned, it is a significant contributor to the economic and social development of the country. As indicated in CSA (2011) it is a cereal with the largest smallholder coverage with 7.96 million holders, as the vast majority of Ethiopian farmers are small-scale producers, it has a significant impact on the livelihood of smallholders in Ethiopia Rashid (2010). This role can be expanded as maize is the crop with the highest current and potential yield from available inputs, at 2.2 tons per ha in 2008/09 with a potential for 4.7 tons per ha according to field trials IFPRI (2010). According to CSA (2011), in 2010/11 production year, maize covered 1.96 million ha of land at national level. The total output of maize in the same year at national level was 49.86 million qt. This accounted for about 25% of the total crop production in the same year.

2. ANALYTICAL FRAMEWORK

2.1 Concept and Measures of Efficiency

Economic efficiency refers to the complete minimization of economic waste either, for any observed level of output, inputs are minimized, or for any observed level of inputs, outputs are maximized, or some combination of the two Coelli *et al.* (1998). Economic efficiency (EE) consists Technical and allocative efficiencies. Technical efficiency (TE) measures the ability of a farmer to produce the maximum feasible output from a given bundle of inputs or produce a given level of output using the minimum feasible amounts of inputs Bradley *et al.* (2014). According to Koopmans (1951) a producer is technically efficient if, and only if, it is impossible to produce more of any output without producing less of some other output or using more of some input. As indicated by Fraser and Cordina (1999), TE can also be defined in terms of the production function that relates the level of various inputs. It is a measure of a farm's success in producing maximum output from a given set of input. According to Farrell and Fieldhouse

Table 1. Recent Studies regarding the Efficiency of Agricultural Products

	Author(s)	Country	Mean Efficiency [a]	Data set	Approach
1	Udayanganie *et al*. (2006)	Sri Lanka	TE = 0.37	Cross Sectional	SFA
2	Karthick *et al*. (2013)	India	TE = 0.841	Cross Sectional	SFA
3	Hardwick (2009)	Malawi	TE = 0.53 AE = 46 EE= 0.38	Cross Sectional	SFA
4	Boubaker (2007)	Tunisia	TE =0.67	Cross Sectional	SFA
5	Berdikul *et al.* (2014)	US	TE = 0.84	Cross Sectional	SFA
6	Gelaw (2013)	Ethiopia	TE = 0.628	Cross Sectional	SFA
7	Stefanos *et al*. (2012)	EU	TE_{VRS} =0.664	Cross Sectional	DAE
8	Krishna *et al*. (2014)	Philippines	TE = 0.54.	Panel Data	SFA
9	Bonabana *et al.* (2011)	Uganda	TE = 0.697	Cross Sectional	SFA
10	Boubaker *et al*. (2012)	Tunisia.	TE = 0. 77	Cross Sectional	SFA
11	Kularatne *et al*. (2012)	Sri Lanka	TE = 0.72	Cross Sectional	SFA
12	Jean-Paul *et al*. (2005)	Gambia	TE =0.952 AE =0.567	Cross Sectional	DAE

Legend

AE, Allocative efficiency TE, technical efficiency EE, economic efficiency
DAE, Data Envelop Analysis SFA, stochastic frontier analysis
VRS, variable return to scale CRS, constant return to scale

(1962), Allocative efficiency (AE) involves the selection of an input mix that allocates factors to their highest valued uses and thus introduces the opportunity cost of factor inputs to the measurement of productive efficiency. TE and AE are then combined to give EE Coelli *et al.* (1998). A firm that is not efficient is wasting inputs and hence the possibility of reducing average costs Awudu and Hendrik (2007).

Parametric and nonparametric techniques are the two approaches that have been used to obtain estimates of farm efficiencies. The choice of which approaches to use is unclear Olesen *et al.* (1996). Studies on efficiency measurements argue that a researcher can safely choose any of the methods since there are no significant differences between the estimated results Abdourhmane *et al.* (2001).

The nonparametric method initiated as Data Envelopment Analysis (DEA) by Charnes *et al.* (1978) builds on the individual firm evaluation of Farrell (1957). In this case, Efficiency is defined in a relative sense, as the distance between observed input–output combinations and a best practice frontier Färe *et al.* (1994). DEA is nonparametric and does not require any parametric assumptions on the structure of technology or the inefficiency term Amin and Michael (2011). The nonparametric approach has the advantage of imposing no a priori parametric restrictions on the underlying technology. They also have some drawbacks: the traditional DEA approach does not have a solid statistical foundation behind it and is sensitive to outliers. Indeed, a deterministic frontiers statistical theory is currently accessible Simar and Wilson (2000) and Cazals *et al.* (2002) developed a robust nonparametric estimator.

The parametric approach consists of specifying and estimating a parametric production function representing the best available technology Jean-Paul *et al.* (2005). Stochastic frontier approach (SFA) is one of the parametric approaches used to measure farm efficiency. The primary characteristic of a stochastic frontier model is that it envelops rather than intersects data Kumbhakar and Knox Lovell (2000). While a typical least squares regression consists of a deterministic component and a random noise component, the stochastic frontier model is based on the premise that a production frontier cannot be generated from the deterministic component of a least squares linear regression because not all firms operate efficiently Matthew and Danny (2007). This approach provides a convenient framework for conducting hypothesis testing. Its main weakness is the assumption of an explicit functional form for the technology and the distribution of the inefficiency terms Hjalmarsson *et al.* (1996).

2.2 Specification and Estimation of the Empirical Model

This study employed stochastic efficiency decomposition method of Bravo-Ureta and Rieger (1991) to decompose TE, EE and AE. SFA was used for its ability to distinguish inefficiency from deviations that are caused by factors beyond the control of farmers. Farmers possess the potential to achieve both TE and AE in farm enterprises, but inefficiency may arise due to a variety of factors, some of which are beyond the control of the farmers Ogunniyi (2008). The assumption that all deviations from the frontier are associated with inefficiency, as assumed in DEA, is difficult to accept, given the inherent variability of agricultural production due to many factors like climatic hazards, plant pathology and insect Coelli (1995) and Kirkley *et al.* (1995).

SFA was first proposed in independent papers by Aigner *et al.* (1977) and Meeusen and van den Broeck (1977). This model can be Vanressed in the following form.

$$Y_i = F(X_i;\beta)\exp(V_i - U_i) \quad \text{i = 1, 2, 3... n} \qquad (1)$$

Where is the production of the i[th] farmer, X_i is a vector of inputs used by the i[th] farmer, is a vector of unknown parameters, V_i is a random variable which is assumed to be N () and independent of the U_i which is nonnegative random variable assumed to account for technical inefficiency in production. The variance parameters for Maximum Likelihood Estimates are expressed in terms of the parameterization

$\sigma_s^2 = \sigma_v^2 + \sigma^2$ and

$$\gamma = \sigma^2 / \sigma_s^2 = \frac{\sigma^2}{\sigma_v^2 + \sigma^2} \qquad (2)$$

Where,

σ^2 is the variance parameter that denotes deviation from the frontier due to inefficiency

σ^2_v is the variance parameter that denotes deviation from the frontier due to noise

σ_s^2 is the variance parameter that denotes the total deviation from the frontier

The g parameter has a value between 0 and 1. A value of g of zero indicates that the deviations from the frontier are due entirely to noise, while a value of one would indicate that all deviations are due to inefficiency. Battese and Coelli (1988) pointed out that in the prediction TE which is the best predictor of exp (-U_i) is obtained by:

$$E\left[\exp {(-U_i)}\Big/{e_i}\right] = \frac{1+\phi(\sigma_v + \gamma e_i/\sigma_v)}{1-\phi({\gamma e_i}/{\sigma_v})}\exp(\gamma e_i + {\sigma^2}/{2}) \qquad (3)$$

Where

$e_i = \ln(Y_i) - X_i b$

f(.) is the density function of a standard normal random variables.

2.3 Selection of the Functional Form

As SFA requires a prior specification of the functional form, given the assumption of self-duality Xu and Jeffrey (1998), Cobb-Douglas production function was selected. This nature of the Cobb-Douglas production and cost functions provides the computational advantage in obtaining the estimates of TA and EE. As indicated by Arega and Rashid (2005), inadequate farm level price data together with little or no input price variation across farms in Ethiopia precludes any econometric estimation of a cost function. A Cobb–Douglas production is also preferable due to collinearity and loss of degrees of freedom caused by the multiple interaction terms included in the translog function. In addition, variable returns to scale are likely to be rare in subsistence farming, making the homothetic assumption appropriate Catherine and Jeffrey (2013). As indicated by Bravo-Ureta and Evenson (1994) this functional form has also been widely used in farm efficiency analyses for both developing and developed countries. A study done by Kopp and Smith (1980) suggests that functional specification has only a small impact on measured efficiency. Ahmad and Bravo-Ureta (1996) also indicated that efficiency measures do not appear to be affected by the choice of the functional form.

Sharma *et al.* (1999) indicated that the corresponding dual cost frontier of the Cobb Douglas production function could be rewritten as:

$$C_i = C(W_i, Y_i^*; \alpha) \tag{4}$$

Where i refers to the i^{th} sample household; C_i is the minimum cost of production; W_i denotes input prices; Y_i* refers to farm output which is adjusted for noise v_i and α's are parameters to be estimated. To estimate the minimum cost frontier analytically from the production function, the solution for the minimization problem given in Equation 5 is essential Arega and Rashid (2005).

$$\underset{x}{Min}C = \sum_n \omega_n x_n$$

Subject to $$Y_k^{i*} = \hat{A}\prod_n x_n{}^{\hat{\beta}_n} \tag{5}$$

Where $\hat{A} = \exp(\hat{B}_0)$
ω_n = input prices
$\hat{\beta}$ = parameter estimates of the stochastic production function and
Y_k^{i*} = input oriented adjusted output level from Equation 1.

The following dual cost function will be found by substituting the cost minimizing input quantities into Equation 5.

$$C(Y_k^{i*}, w) = HY_k^{i*\mu}\prod_n \omega_n^{\alpha_n}$$

Where $\alpha_n = \mu\hat{\beta}_n$, $\mu = (\sum_n \hat{\beta}_n)^{-1}$, $H = \frac{1}{\mu}(\hat{A}\prod_n \hat{\beta}_n{}^{\hat{\beta}_n})^{-\mu}$ (5)

The economically efficient input vector for the i^{th} firmer derived by applying Shepard's Lemma and substituting the firms input price and adjusted output level into the resulting system of input demand equations.

$$\frac{\alpha C_i}{\alpha \omega_n} = X_i^e(\omega_i, Y_i^{i*}; \theta) \tag{6}$$

Where θ is the vector of parameters and n = 1, 2, 3, ..., N inputs.

The observed, technically and economically efficient cost of production of the i^{th} farm are equal to, $\omega_i^{'}X_i$, $\omega_i^{'}X_i^t$ and $\omega_i^{'}X_i^t$. Those cost measures are used to compute technically and economically efficient indices of the i^{th} farmer as follows:

$$TE_i = \omega_i^{'}X_i^t \big/ \omega_i^{'}X_i \tag{7}$$

$$EE_i = \omega^{'}X_i^t \big/ \omega_i^{'}X_i \tag{8}$$

Following Farrell (1957), allocative efficiency index of the i^{th} farmer can be derived from Equations 7 and 8 as follows;

$$AE_i = EE_i \big/ TE_i = \omega_i^{'}X_i^t \big/ \omega_i^{'}X_i^t \tag{9}$$

2.4 Determinants of Efficiency Scores

To determine the relationship between socioeconomic and institutional factors and the computed indices of efficiencies, a two-limit tobit model was utilized. The model was adopted because the efficiency scores are double truncated at 0 and 1 as the scores lie within the range of 0 to 1 Greene (1991). Estimation with OLS regression of the efficiency score would lead to a biased parameter estimate since OLS regression assumes normal and homoscedastic distribution of the disturbance and the dependent variable Greene (2003). The following relationship expresses the stochastic model underlying tobit Tobin (1958):

$$y_i^* = \beta_0 + \sum \beta_m z_{jm} + \mu_j \tag{10}$$

Where y_i^* = latent variable representing the efficiency scores of farm j,

β = a vector of unknown parameters,

Z_{jm} = a vector of explanatory variables m (m = 1, 2, ..., k) for farm j and

μ_j = an error term that is independently and normally distributed with mean zero and variance σ^2

Denoting y_i as the observed variables,

$$y_i = \begin{cases} 1 & if\, y_i^* \geq 1 \\ y_j^* & if\;\; 0 < y_i^* < 1 \\ 0 & if\;\, y_i^* \leq 0 \end{cases} \tag{11}$$

Following Maddala (1999), the likelihood function of this model is given by:

$$L(\beta, \sigma / y_j, .Z_j L_{1j}, L_{2j}) = \prod_{y_i - y_{1j}} \varphi\left(\frac{L_{1j} - \beta' Z_j}{\sigma}\right) \prod_{y_i - y^*_j} \frac{1}{\sigma} \phi\left(\frac{y_j - \beta' Z_j}{\sigma}\right) \prod_{y_i - L_{2j}} 1 - \varphi\left(\frac{L_{2j} - \beta' Z_j}{\sigma}\right)$$

(12)

Where $L_{1j} = 0$ (lower limit), $L_{2j} = 1$ (upper limit); and $\phi(.)$ and $\varphi(.)$ are normal and standard density functions. In practice, since the log function is monotonically increasing function, it is simpler to work with log of likelihood function rather than likelihood function and the maximum values of these two functions are the same Greene (2003).

2.5 Description of the Study Area

This study was undertaken in the central rift valley of Ethiopia, explicitly in Arsi Negelle district. Geographically, the district is located from 38^0 25' E to 38^0 54' E longitude and 07^0 09' to 07^0 42' N latitude. Except for the Southeastern part, most of the district's elevation is between 1500 and 2300 meters. The topography of the area is a gentle slope or flat and the soils of the area are lightweight, friable loam and clay loam. The main crops grown in the area include wheat, maize, teff, barley, sorghum, onion and potato. Annual crops accounted for 95% of all croplands in the district. *Andosol* soil type covers about 52.2% of the district, while *Nitosols* cover the remaining 47.8%. The temperature of the area ranges from 16^oc to 25^oc and annual rainfall ranges between 500-1150 mm. Livestock are an important component of the farming system and a source of intermediate products in the district. The area is intensively cultivated and private grazing land is unavailable. Communal pasture and straw from crops are the main source of feed for livestock production. According to CSA (2012), the district has a total population of 303,223 of which 150,245 are male and 152,978 are females. The average family size for the district was 5.2 (5.3 for urban and 5.1 for rural).

2.6 Sampling Technique and Sample Size

A two stage random sampling technique was used to select sample households for this study. In the first stage, three kebeles that produce maize were selected randomly. In the second stage, 138 sample farmers were selected using a simple random sampling technique from each kebeles proportional to the total number of households of the kebeles.

3. EMPIRICAL RESULT

3.1 Socioeconomic Characteristics of the Sample Respondent

The mean age of the sample farmers was about 42 years with a range of 22 to 70 years. The family size of the sample farmers ranged from one to 13 with a mean of 5.73 person per household. Concerning their literacy level, only 6.52% of the household heads were illiterate while the remaining 93.48% of the respondents were at least capable of reading and writing. Out of the total sample household heads, 63.04% have attained formal education while 30.43% of them were able to read and write though they did not attain formal education. Regarding the sex of respondents, 93.48% of the sample households were male-headed households.

The minimum land holding of the respondents was 0.50 ha while the maximum size was 4.25 ha. The mean land owned by the sample farmers was 1.81 ha. About 11% of the sample farmers owned land not more than 0.5 ha whereas 18.12% of the sample farmers had more than two ha of land.

The farming system in Ethiopia is mainly based on plough by animal draught power that has created complementarity between crop and livestock production for centuries. About 46% of the sample farmers had a pair of oxen and 12.32% of the sample farmers had two pair of oxen. On average, respondent farmers owned livestock of 8.07 TLU ranging from zero to 81.11 TLU.

The survey result showed that 44.20% of the sample farmers accessed credit from different sources. From the total of sample household interviewed for this study, 47.10% of them indicated that they have received training which is specific to maize production. All of the sample respondents reported that they received extension services though the frequency of contact differs. About 65% of respondents have indicated that they had extension contact on a weekly basis. While nearly a quarter of the sample respondents had contact with extension workers twice a month.

3.2 Econometric Results

3.2.1 Production and Cost Function Parameter Estimates

The dependent variable of the estimated model was maize output (qt) produced in 2011/12 production season and the input variables used in the analysis were area under maize (ha), animal draught power (oxen-days), labour (man-day in man-equivalent), quantity of seed (kg) and inorganic fertilizers specifically DAP and urea (kg). To include those farmers who did not apply DAP and urea in the estimation of the frontier a very small value that approach zero was assigned for non-users of fertilizer.

Prior to model estimation, a test was made for multicollinearity among the explanatory variables using the Variance Inflation Factor (VIF). In a production function analysis, correlation between some of the explanatory variables is expected and collinearity among economic variables is an inherent and age-old problem leading to problems of multicollinearity. However, the values of VIF for all variables entered into the models were below 10 (Appendix Tables 1 and 2), which indicate the absence of multicollinearity among the variables.

Efficiency score are sensitive to specification errors that may lead to hetroskedasticity. As measures of inefficiency in SFA are based on residuals derived from the estimation of a frontier, those residuals are sensitive to specification errors that may passed on to the efficiency scores Hadri *et al* (2003). Breusch-pagan test was then used to detect the presence of hetroskedasticity and the test indicated that there was no problem of hetroskedasticity in the models.

The result of the model showed that DAP, area under maize, oxen power, labour and seed had positive and significant effect on the level of output. The increase in these inputs would increase output of maize (Table 2).

Table 1. Estimates of the Cobb Douglas frontier production function

Variables	Coefficients	Std. Err.
DAP	0.05036***	0.0077
Urea	0.00471	0.0291
Seed	0.52897***	0.0843
Land	0.23204**	0.0906
Labour	0.12092*	0.0598
Oxen	0.17006**	0.0595
Constant	1.06943**	0.2988
Lambda	1.94304***	0. 0520
Sigma square	0.05976***	0.0125

Source: own data

****,** and * represents significant levels at 1%, 5% and 10% respectively*

The ratio of the standard error of u (σ_u) to the standard error of v (σ_v), known as lambda (λ), is 1.943. Based on λ, gamma (γ) which measures the effect of technical inefficiency in the variation of observed can be derived (i.e. $\gamma = \lambda^2 / [1+\lambda^2]$) Bravo-Ureta and Pinheiro (1997). The estimated value of γ is 0.7906 that indicates 79.06% of total variation in farm output is due to technical inefficacy.

The dual frontier cost function derived analytically from the stochastic production frontier shown in Table 2 using Equation 5 is given as:

$$\mathrm{h}\ C_i = 4.087 + 0.903\,\mathrm{h}\ Y_i^* + 0.2096\,\mathrm{h}\ \omega_{land} + 0.478\,\mathrm{h}\ \omega_{seed} + 0.0455\,\mathrm{h}\ \omega_{dap}$$
$$+ 0.004\,\mathrm{h}\ \omega_{uria} + 0.154\,\mathrm{h}\ \omega_{[illegible]} + 0.109\,\mathrm{h}\ \omega_{labour} \qquad (13)$$

Where C is the minimum cost of production of the ith farmer, Y* refers to the index of output adjusted for any statistical noise and scale effects and stands for input prices.

3.2.2 Tests of Hypothesis

Before proceeding to the estimation of the parameters from which individual level of efficiencies are estimated, it is essential to examine various assumptions related to the model specification. To do this, two hypotheses were tested. The first test was to verify whether there exists considerable inefficiency among farmers in the production of maize in the study area (to examine whether the average production function (OLS) best fits the data). The other hypothesis that was tested was that all coefficients of the inefficiency effect variables are simultaneously equal to zero. (i.e H_o: = δ_0 = δ_1 = δ_2 ... = δ_{13} = 0). The test was done based on the log likelihood ratio test (Table 3) which can be specified as:

$$LR = \lambda = -2\ln\left[L(H_0)/L(H_1)\right]$$
$$\lambda = -2\left[\ln L(H_0) - \ln L(H_1)\right] \qquad (15)$$

The λ value obtained from the log likelihood functions of the average response function and the SFA was found to be greater than the critical value. Hence, the null hypothesis that states the average response function (OLS) is an adequate representation of the data was rejected and the alternative hypothesis that stated there exists considerable inefficiency among sample farmers was accepted. The other hypothesis was also tested in the same way by calculating the λ value using the value of the log likelihood function under the SFA (without explanatory variables of inefficiency effects, (H_0)) and the full frontier model with variables that are supposed to determine the inefficiency level of each farmer, (H_1). The λ value obtained was again higher than the critical c^2 value at the degree of freedom equal to the number of restrictions. As a result, the null hypothesis is rejected in favour of the alternative hypothesis that the explanatory variables associated with the inefficiency effects model are simultaneously different from zero.

3.2.3 Efficiency Scores

The model output presented in Table 3 indicates that farmers in the study area were relatively good in TE than AE or EE. The mean TE was found to be 84.87%. This means in the short run there are opportunities for reducing input used for maize production proportionally by 15.13% to produce the current level of output.

Table 3. Summary of descriptive statistics of efficiency measures

Type of efficiency	Minimum	Maximum	Mean	Std. Deviation
TE	0.561	0.974	0.84868	0.0819
AE	0.187	0.553	0.37472	0.0555
EE	0.164	0.504	0.31620	0.0456

Source: own data

The mean AE of farmers in the study area was 37.47% indicating there is a need to improve the present level of AE. The estimates depicted that the farmers have ample opportunities to increase their AE. For instance, farmer with an average level of AE would enjoy a cost saving of about 32.24% derived from (1 – 0.37472/0.553)*100 to attain the level of the most efficient farmer.

The mean EE showed that there was a significant level of inefficiency in the production process. That is the producer with an average EE level could reduce current average cost of production by 68.38% to achieve the potential minimum cost level without reducing output levels. It can be inferred that if farmers in the study area were to achieve 100% EE, they would experience substantial production cost saving of

Table 4. Frequency distribution of efficiency estimates of sample farmers

Efficiency level	TE		AE		EE	
	N	Percent	N	Percent	N	Percent
00-09.999	0	0.00	0	0.00	0	0.00
10-19.999	0	0.00	1	0.72	3	2.17
20-29.999	0	0.00	5	3.62	44	31.88
30-39.999	0	0.00	94	68.12	87	63.04
40-49.999	0	0.00	35	25.36	3	2.17
50-59.999	1	0.72	3	2.17	1	0.72
60-60.999	8	5.80	0	0.00	0	0.00
70-79.999	22	15.94	0	0.00	0	0.00
80-89.999	62	44.93	0	0.00	0	0.00
90-99.999	45	32.61	0	0.00	0	0.00

Source: own data

68.38%. This implies that the reduction in cost of production through eliminating resource use inefficiency could add about 68.38% of the production cost to their annual income. The result also indicated that the farmer with an average level of EE would enjoy a cost saving of about 37.26% derived from (1-0.31620/0.504)*100 to attain the level of the most efficient farmer. From these results, it is observable that *EE* could be improved significantly, and that allocative inefficiency constitutes a more serious problem than technical inefficiency. The level of TE, AE and EE at which sample households operate is presented in Table 4.

3.2.4 Determinants of Efficiency Differentials among Farmers

After measuring levels of efficiency and determining the presence of efficiency difference among farmers, finding out factors causing efficiency disparity among them was the next most important step of this study. To see this, efficiency levels of sample farmers were regressed on factors that were expected to affect efficiency levels. These variables were selected based on previous studies and socioeconomic conditions of the study area (Table 5).

Table 5. Maximum likelihood estimates of the tobit model

Variables	TE		AE		EE	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Education	0.00448	0.00482	0.0087***	0.0032	0.00937***	0.00264
Family size(adult-eqt)	-0.00363	0.00323	0.0032	0.0022	0.00122	0.00177
Experience	0.00005	0.00062	0.0006	0.0004	0.00052	0.00034
Cultivated land	-0.00018	0.00769	-0.0051	0.0051	-0.00415	0.00421
Crop rotation	0.01337	0.01215	-0.0061	0.0081	0.00185	0.00665
Livestock (TLU)	0.00012	0.00090	0.0004	0.0006	0.00037	0.00049
Extension contact	0.00065*	0.00034	-0.0011**	0.0002	-0.00056***	0.00018
Training	-0.01153	0.01394	-0.0074	0.0093	-0.00989	0.00763
Credit	0.04747***	0.01490	0.0064	0.0100	0.02458***	0.00815
Distance to market	-0.00730**	0.00349	0.0021	0.0023	-0.00126	0.00191
Home to farm distance	0.00418	0.00663	-0.0023	0.0044	0.00002	0.00363
Off/non-farm activity	0.02416	0.01451	-0.0041	0.0097	0.00461	0.00794
Soil fertility	0.00731*	0.01661	0.0097	0.0111	0.00741	0.00909
Cons	0.79409***	0.03675	0.3806***	0.0246	0.29721**	0.02012

Source: own data
****,** and * represents significant levels at 1%, 5% and 10% respectively*

The coefficient for educational level was significant and was positively related to AE and EE at one percent. The positive sign indicates that an increase in human capital enhances the efficiency of farmers. Similar results were obtained in the works of Himayatullah and Imranullah (2011). Ahmed *et al.* (2001) indicated that education enhances farmers' ability to interpret and make good use of information about markets and prices in environments.

Frequency of extension contact had significant positive relationship with TE at 10% significance level. The frequent contact facilitates the flow of new ideas between the extension agent and the farmer, thereby giving a room for improvement in farm efficiency. Advisory service rendered to the farmers can help farmers to improve their average performance in the overall farming operation as the service widens the household's knowledge with regard to the use of productivity and input allocation. This result is also similar to those obtained by Jude *et al* (2011) and Mbanasor and Kalu (2008). However, the negative coefficient of extension contact, which is significant in AE and EE, indicates that efficiency in resource allocation is deteriorating as the frequency of extension contact increases. This may be due to the fact that extension workers are basically trained to solve the problem of food security and they have limited knowledge for appropriate resource allocation. In addition to this, as Haji (2007) indicated extension workers in the country devotes ample of their time for nonfarm activities such as credit application processing, input distributions and collection of loans and taxes.

The results also indicated that access to credit had a positive and statistically significant effect on both TE and EE at one percent significant level, which indicates that farmers with access to credit tend to exhibit higher levels of efficiency. Credit availability shifts the cash constraint outwards and enables farmers to make timely purchases of those inputs that they cannot provide from their own sources. This result is in line with the argument of Jude *et al.* (2011).

Distance from home to the nearest market was also significant in determining TE. Farmers far from markets are less technically efficient compared to their counterparts who reside nearby markets. This might be due to the fact that as farmers are located far from the market, there would be limited access to input and output markets and market information. Moreover, higher distance to market leads to higher transaction cost that reduces the benefits that accrue to the farmer. More importantly, longer distance from market discourages farmers from participating in market-oriented production.

The result also indicated that soil fertility was positively and significantly related to TE. This implies that farmers who allocated a land that was relatively fertile were good in TE. Therefore, decline in soil fertility could be taken as cause for significant output loss.

4. CONCLUSIONS AND RECOMMENDATIONS

The result of the analysis showed that maize producers in the study area are not operating at full TE, AE and EE levels and the result indicated that there is opportunity for maize producers to increase output at existing levels of inputs and minimize cost without compromising yield with present technologies available in the hands of producers. Those findings stresses the need for appropriate policy formulation and implementation to enable farmers reduce their inefficiency in production as this is expected to have multiplier effects ranging from farm productivity growth to economic growth and poverty reduction at the macro level.

Education was very important determining factor. Thus, government has to give due attention to training farmers through strengthening and establishing both formal and informal type of framers' education, farmers' training centers, technical and vocational schools, as farmer education would reduce both allocative and economic inefficiencies.

The study also revealed that distance to market has a significant influence on the TE of smallholders. Therefore, farmers have to get inputs easily and communication channels have to be improved to get a better level of TE.

Appropriate and adequate extension services should be provided. This could done by designing appropriate capacity building program to train additional development agents to reduce the existing higher ratio of farmers to development agents as well as to provide refreshment training for development agents.

Extension agents have to give due attention for appropriate input allocation and cost minimization in addition to their acknowledgeable effort to increase production. This calls for the need to more effective policy support for extension services and additional efforts need to be devoted to upgrade the skills and knowledge of the extension agents.

Better credit facility has to be produced via the establishment of adequate rural finance institutions and strengthening of the available micro-finance institutions and agricultural cooperatives to assist farmers in terms of financial support through credit are crucial to improve farm productivity.

Farmers have to work to improve the fertility status of the farm. Though it is difficult to achieve this in the short run, farmers can do this by applying fertilizers (organic or inorganic) that are suitable for the farm and practicing soil conservation practices.

Thus, the results of the study give information to policy makers and extension workers on how to better aim efforts to improve farm efficiency as the level and specific determinant for specific efficiency types are identified. This could contribute to compensation of high production cost, hence improve farm revenue, welfare and generally help agricultural as well as economic development. Those findings stresses the need for appropriate policy formulation and implementation to enable farmers reduce their inefficiency in production as this is expected to have multiplier effects ranging from farm productivity growth to economic growth and poverty reduction at macro level.

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Appendix Table 1. VIF for the variables entered in to the stochastic frontier model

Variable	VIF	1/VIF
Land	8.5	0.117647
Seed	8.32	0.120192
Oxen power	3	0.333333
Labour	2.84	0.352113
DAP	1.42	0.704225
Urea	1.29	0.775194
Mean VIF	4.228333	

Appendix Table 2. VLF for the continuous variables entered in to the efficiency model

Variable	VIF	1/VIF
cultivated land	2.26	0.442119
Livestock	2.2	0.454481
Family size	1.41	0.71001
Experience	1.27	0.784836
extension contact	1.22	0.820667
distance to mkt	1.22	0.820771
plot to home distance	1.07	0.933107
education	1.04	0.963307
Mean VIF	1.46	

Appendix Table 3. Contingency Coefficients of the dummy variables entered in to the efficiency model

	Crop rotation	Training	Credit	Soil fertility	Off/nonfarm activity
Crop rotation	1.0000				
Training	-0.0780	1.0000			
Credit	0.0104	-0.0341	1.0000		
Soil fertility	-0.0543	0.0923	0.1514	1.0000	
Off/nonfarm activity	-0.0950	0.0027	-0.1330	-0.1781	1.0000