Economic Efficiency and its Determinants of Smallholder Sorghum Producers: The Case of Hidabu Abote District, Ethiopia

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Abstract

In Ethiopia, increasing productivity and efficiency in crop production could be taken as an important step towards attaining food security. This study was aimed to measure economic efficiency and its determinants of smallholder sorghum producers in Hidabu Abote District, Ethiopia. Two stage sampling technique was used to select 153 sample farmers to collect primary data for 2020/21 production year. Cobb-Douglas stochastic frontier and a two-limit Tobit model were used for data analysis. The result of the stochastic frontier model revealed a statistically significant positive elasticity of labour and oxen power. The estimated mean values of technical, allocative, and economic efficiency were 65.2%, 79.8%, and 51.9%, respectively. On average, there was a yield gap of 8.58 quintals/hectare due to inefficiency. A two-limit Tobit model indicates that education, soil fertility, frequency of extension contacts, sex, farm experience, and livestock ownership contributed significantly and positively to efficiency, while striga weeds and distance from home to farmland had a significant and negative effect on efficiency. Therefore, due attention should be paved to improve soil fertility, livestock rearing, supply, striga resistance varieties, increasing the frequency of extension contact, and expanding of roads to improve the efficiency of sorghum farmers.

Key words: Economic Efficiency, Ethiopia, sorghum, stochastic frontier, two-limit Tobit

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1. Introduction

Agricultural sector contributes about 35.8% to Ethiopia's GDP and around 79% of the national export earnings were obtained from this sector (CIA, 2018). Cereals are the major food crops in Ethiopia. Sorghum is one of the major traditional food crops and ranks third in terms of national production following *teff* and maize in Ethiopia. However, the mean national productivity of sorghum was 27.26 qt/ha (CSA, 2018), which is very low as compared with a yield potential of the crop and far from the vision of the success of sorghum research, which is to attain 60 qt/ha (EIAR, 2014).

In countries like Ethiopia, where access to capital is fatally limited, it is desirable to benefit from increased productivity by improving the efficiency (Kinde, 2005). Hence, working to improve production efficiency through efficient use of production inputs is the best option on hand. Hidabu Abote District Agriculture and Natural Resource Office (HADANRO) annual crop assessment year of 2020/21 showed that from the total cereal crops cultivated (26046 ha), sorghum accounted for 28.16% and its productivity was 19.2 qt/ha. This showed that the productivity of sorghum was very low which is below the average productivity of the country (27.26 qt/ha), (CSA, 2018). Many researchers have done efficiency studies in Ethiopia. However, many of them focused on the analysis of technical efficiency (TE). Examination of the TE alone understates the benefits that could be derived by producers from improvements in overall performance. Moreover, it may not provide satisfactory information for decision-makers and policy interventions.

A number of studies indicated that factors that could affect productivity might vary across areas and over time. Hence, the policy implications drawn from the study might not be relevant to designing policy in another area due to socio-economic and agro-ecological variations. Thus, this study aims to fill this gap by investigating the economic efficiency (EE) of sorghum in Hidabu Abote district, Oromia, Ethiopia, where there was no such study before. In addition, previous studies overlooked yield gaps.

2. Materials and Methods

2.1. Description of the Study Area

Hidabu Abote district is located in North Shoa Zone, Oromia, Ethiopia. There are 19 *kebeles* and 1 urban *kebele* in the district. The district capital town, Ejere, is located 42 km far from Fitche town and 147 km from Addis Ababa. Altitude in Hidabu Abote ranges from 1160m to 3000m meters above sea level (masl). Most parts of the district lay between 1387 and 1543; and 1849 and 2067m a.sl. Astronomically, Hidabu Abote district extends from $9^{0}47'15''$- $10^{0}\,0'45''$north latitudes and $38^{0}26'\,15''$-$38^{0}38'45''$ east longitudes (HADNRO, 2021).

2.2. Sources of data, Sampling techniques and sample size determination

The current research utilized data obtained from primary (structured questionnaire) and secondary sources. Two stage sampling technique was used to get a representative sample. First, from 9 *kebeles*, 3 *kebeles* were selected randomly. Secondly, 153 farmers were selected using simple random sampling from Adaboneya, Gidabojema, and Adanacho kebeles. Since the producers have homogeneous characteristics, Yamane (1967) was employed. Accordingly,

$$n = \frac{N}{1 + N(e)^2} = \frac{6896}{1 + 6896(0.08)^2} = 153 \quad (1)$$

Where, n = sample size, N = Total sorghum producers in the study area (6896), e = Level of precision considered (8%), 1 is for designated the probability of events occurring.

2.3. Method of Data Analysis

A stochastic frontier approach was used to estimate the level of economic efficiency of sorghum producers and a two-limit Tobit model was applied to identify the determinants of the level of farmers' efficiency. Following Aiger *et al.* (1977) and Meeusen and Van den Broeck (1977), the stochastic frontier model for this study was specified as follows:

$$Y_z = f(X_z; \beta_z) + \varepsilon_z \quad (2)$$

Where z = 1, 2, 3... n; Y_z represents the observed output level of the z^{th} sample farmer; f (X_z; β_z) is the convenient frontier production function; X_z denotes the actual input vector by the z^{th} farmer; β_z stands for the vector of unknown parameters to be estimated; ε_z is a composed disturbance term made up of two error elements (V_z and U_z) and n represents the number of farmers involved in the survey. The test conducted showed that Cobb-Douglas production functional form best fits the data. Accordingly, specification:

$$Y_z = AX_1^{\beta 1}X_2^{\beta 2}..X_n^{\beta n} \quad (3)$$

The Cobb-Douglas production function for this study is defined as:

$$ln\, ln\, (Y_z) = \beta o + \sum_{j=1}^{4} \beta_j lnX_{jz} + \varepsilon_z \quad (4)$$

$$ln\, (Y_z) = \beta o + \beta 1\, ln\, ln\, (SEED) + \beta 2\, ln\, ln\, (LAB) + \beta 3\, ln\, ln\, (OXEN) + \beta 4\, ln\, ln\, (LAND) + \varepsilon_z$$

$$\varepsilon_z = V_z - U_z$$

Where, ln denotes the natural logarithm; j represents the number of inputs used; z represents the z^{th} farm in the sample; Y_z represents the observed sorghum output of the z^{th} sample farmer; X_{jz} denotes the z^{th} farm input variables will be used in sorghum production of the z^{th} farmer; β_0 represent intercept; $\beta_1 - \beta_4$ stands for the vector of parameters; $\mathcal{E}_z$ is a composed disturbance term made up of two error elements (V_z and U_z); the symmetric component (V_z) is assumed to be i.i.d with zero mean and constant variance which captures inefficiency as a result of factors beyond control of farmers and U_z proposed to capture inefficiency effects in the production of sorghum. Assuming that the production function in equation (4) is self- dual, the dual cost function of the Cobb-Douglas production function can be specified as:

$$lnC_z = \alpha_0 + \sum_{j=1}^{4} \alpha_j lnW_{jz} + \alpha_j lnY^* + V_z + U_z \quad (5)$$

Where z refers to the z^{th} sample farmer; j is the number of inputs; C_z is the minimum cost of production; W_{jz} denotes the input price of the z^{th} farm; Y* refers to sorghum output in kilogram(kg); α's are parameters estimated; V_z denotes random variables assumed to be independent and identically distributed random errors with zero mean and variance and U_z denotes non-negative random variables which are assumed to account for cost inefficiency and assumed to be with zero mean and variance. Sharma *et al.* (1999) suggested that the corresponding dual cost frontier of the Cobb-Douglas production functional form in equation (5) can be rewritten as:

$C_z = C(W_z, Y^*, \alpha) + \varepsilon_z \qquad z=1, 2, 3\ldots n$

The economically efficient input vector of the z^{th} farm X_z^e is derived by applying Shepard's Lemma and substituting the firm input prices and adjusted output level, a system of minimum cost input demand equation can be expressed as:

$$\frac{\partial C_z}{\partial W_z} = X_z^{e}(W_z, Y^*; \alpha) \tag{6}$$

We can define the farm-specific TE in terms of the observed output (Y_z) to the corresponding frontier output (Y^*) using the existing technology.

$$TE_z = \frac{Y_z}{Y^*} = \frac{f(X_z;\beta)exp\,(V_z - U_z)}{f(X_z;\beta)exp\,(V_z)} = exp\; exp\,(-U_z) \tag{7}$$

The cost efficiency of an individual farm is defined in terms of the ratio of the observed cost (C) to the corresponding minimum cost(C^*) given the available technology. That is, cost efficiency (C_E):

$$C_E = \frac{C}{C^*} = exp\; exp\,(U) \tag{8}$$

Where the observed cost (C) represents the actual production cost, whereas the minimum (efficient) cost (C^*) represents the frontier total production cost or the least total production cost level. The farm-specific allocative efficiency (AE) is defined as the ratio of the minimum total production cost (C*) to the actual observed total production cost (C).

$$AE_z = \frac{1}{C_E} = \frac{C^*}{C} \tag{9}$$

Following Ali *et al*. (2012), the EE index will be derived from equations (8) and (9) as follows: $EE_z = AE_z * TE_z$ (10)

Determinants of Efficiency: In this study, TE, AE, and EE estimates were derived from a stochastic production frontiers regressed using a censored Tobit model with farm-specific explanatory variables that explain the variation in efficiency across farm households. Tobit estimator was applied with efficiency censored between 0 and 1. OLS underestimates the true result of the parameters by reducing slope when the dependent variable is censored (Greene, 2003). Thus, two-limit tobit regression model was used, which was specified as:

$$y_z^* = \beta_0 + \sum_{k=1}^{12} \beta_k X_{kz} + U_z \tag{11}$$

Where: y_z^*, latent variable representing the efficiency scores of farm z (TE, AE and EE); β_o intercept; β_k unknown parameter; X_{kz} are demographic, institutional, socio-economic and farm-related variables which are expected to affect TE, AE and EE; k is the number of explanatory (independent) variables that affect TE, AE and EE and U_z is an error term that is independently and normally distributed with mean zero and variance σ^2. Denoting y_z as the observed variables:

$$y_z = \begin{cases} 1 \quad if \; y_z^* \geq 1 \\ y_z^* \; if \;\; 0 < y_z^* < 1 \\ 0 \text{ if } \; y_z^* \leq 0 \end{cases} \tag{12}$$

Likelihood Ratio Statistic: Aigner *et al.* (1977) proposed the log-likelihood function for the model in equation (4) assuming a normal distribution for the technical inefficiency effects (U_z). They expressed the likelihood function using λ parameterization, where λ is the ratio of the standard errors of the non-symmetric to symmetric error term (i.e. $\lambda = \sigma$ U/ σ v). However, there is an association between λ and γ the reason is that λ could be any non-negative value while γ ranges from zero to one and better measures the distance between the frontier output and the actual level of output resulting from technical inefficiency. According to Bravo and Pinheiro (1997) gamma (γ) can be formulated as:

$$\frac{\lambda^2}{1+\lambda^2} \tag{13}$$

The parameter γ measures the discrepancy between the frontier and observed levels of output and interpreted as the total variation in output from the frontier attributable to technical inefficiency. It has a value between zero and one. The value of zero indicates that the non-negative random variable, U_z is absent from the model while the value of one shows the absence of statistical noise or exogenous shocks from the model and hence a low level of farm's production compared to the best practice (maximum output) of the other farm that is totally a result of farm specific inefficiency. Likewise, the significance of σ^2 indicates whether the conventional average production function adequately represents the data or not.

In this study, the likelihood ratio was conducted to select the appropriate functional form that best fits the data. The value of the generalized likelihood ratio (LR) statistic to test the hypothesis that all interaction terms, including the square specification is equal to zero ($H_0 = 0 = \beta_{jz} = 0$) calculated as follows.

Following Greene (2003), the hypothesis tests were conducted using the LR statistics, λ which is defined in equation (13):

$$LR(\lambda) = -2 \, ln \, ln \left[\frac{L(H_0)}{L(H_1)}\right] = -2 \left[lnL(H_0) - lnL(H_1)\right] \tag{14}$$

Where: LR= Generalized log-likelihood ratio

L (H_o) = Denotes the likelihood function value under the null (H_o)

L (H_1) = Denotes the likelihood function value under alternative hypothesis (H_1)

This value compared with the upper 5% point for the χ^2distribution and the decision made based on the model result. If the calculated χ^2 value is less than the tabulated upper 5% point of the critical value, we accept the specified null hypothesis at the 5% level of significance.

Yield Gap Measurement: Yield gap is the difference between yield potential and actual farmers' yields over a given spatial or temporal scale (Ittersum *et al*., 2013). There are different types of potential yields, which give rise to three different types of yield gaps. The first type of yield gap is the difference between theoretical crop potential and experiment station yield. The second type of yield gap results from the difference between experiment station yield and potential farm yield due mainly to environmental conditions and the technologies available at research stations that are non replicable at the farm level. This form of yield gap is generally difficult to close and not economically viable. Finally, the third type of yield gap is the difference between potential farm yield and actual farm yield. This gap results mainly from management practices, such as low input usage and lack of improved seeds, and can be cost-effectively narrowed (FAO, 2015).

In this study, the third type of yield gap analysis was applied to determine how much sorghum yield is lost because of efficiency variation among farmers in the study area. From the stochastic model defined in equation (2), TE of the zth farmer was estimated as follows:

$$TE_z = \frac{Y_z}{Y_z{}^*} = \frac{f(Xz;\beta)exp\ (Vz-Uz)}{f(Xz;\beta)exp\ (Vz)} = exp\ (-U_z)$$

Then solving for Y_z^*, the potential yield (qt/ha) of each sample household was represented as:

$$Y_z^* = \frac{Y_z}{TE_z} = f(X_z;\beta)\ exp\ exp\ (V_z) \tag{15}$$

TE_z= technical efficiency of the zth sample household in sorghum production. Y_z^*= the frontier or potential output of the zth sample household in sorghum production in qt/ha. Y_z=the actual or observed output of the zth sample household farmer in sorghum production in qt/ha. Hence, yield gap (qt/ha) =potential yield (qt/ha)-actual yield (qt/ha).

Thus, Yield gap = $Y_z^* - Y_z$ (16)

3. Results and Discussions

3.1. Parameter Estimates of the SFPF Model And Cost Function

Given the specification of Translog, the Cobb-Douglas stochastic production was tested and found to best fit the data and was used to estimate the efficiency of farmers. The dependent variable of the estimated production function was sorghum output (qt) and the input variables used in the analysis were area under sorghum (ha), oxen (pair of oxen-days), labour (man-days in man-equivalent) and quantity of seed (kg).

The maximum likelihood estimate of the parameters of the SFPF for sorghum farm in Hidabu Abote district were presented in Table 1. The results of the model showed the input elasticity for each input in the SFPF. The parameters for labour and oxen power were found to be significant at 1%, as expected.

Table 1: MLE for the parameters of the SFPF

Variables	Parameter	Coef.	Std. Err.
Intercept	β_0	0.796	0.537
Log of seed	β_1	-0.003	0.145
Labour	β_2	0.444***	0.064
Log of OXEN	β_3	0.345***	0.084
Log of land	β_4	0.002	0.146
Variance parameter:			
$\sigma^2 = \sigma_V^2 + \sigma_U^2$		0.425	0.1028
$\lambda = \sigma_{u/}\sigma_v$		2.438	0.173
Gamma (γ)		0.856	
Log likelihood function	-87.31		

Note: *** refers to a significance level of 1%, respectively.

Source: Model output (2021)

The SFPF model results reveal that the estimated positive and large coefficient of labour (0.444) and oxen power (0.345) was found to be significant at 1% probability level. This suggests that a one percent increase in labour for sorghum production, all things being equal, would lead to an increase of 0.444% in the output of sorghum crops. In the same way, on average one percent increase in the amount of oxen power the output increases by 0.345%.

The diagnostic statistics of the inefficiency component reveals that sigma squared (σ^2) was statistically significant which indicates the goodness of fit and the correctness of the distributional form assumed for the composite error term. The ratio of the standard error of U (σ_u) to the standard error of V (σ_v), known as lambda (λ), is 2.438. Based on λ, gamma (γ) which measures the effect of technical inefficiency in the variation of observed output can be derived (i.e.$\gamma = \frac{\lambda^2}{[1+\lambda^2]}$) (Bravo and Pinheiro, 1997). The estimated value of gamma (γ) was 0.856 which indicates that 85.6% of the total variation in sorghum output from the frontier is due to technical inefficiency among sample farmers in the study area and 14.4% of the variation in output from the frontier is due to random noise or random error (beyond the control of the farmers like climate related factors). The result is approach to the finding of Haileselassie (2005) who found the value of gamma (γ) 82%.

The dual frontier cost function derived analytically from the stochastic production frontier shown in Table 6 is given by: $= 6.047 + 0.0002lnW_{1jz} + 0.0927lnW_{2jz} + 0.0099lnW_{3jz} + 0.0662lnW_{4jz} + 0.8002lnY^*$; Where C_z is the minimum cost of production of z^{th} sample farmers; W_{jz} denotes input prices of z^{th} farm; Y* refers to sorghum output in qt.

3.2. Efficiency Scores and Their Distribution

The MLE results of the stochastic frontier production functions estimated for the individual farm level TE, AE, and EE independently for sample smallholder farmers. The model output presented in Table 2 indicates that the mean values of TE, AE, and EE of the sample households were 65.2%, 79.8%, and 51.9%, respectively. This shows that the sample households were relatively better in AE than TE and EE. This result is close to the result of Ali *et al*. (2012) who studied EE of faba beans in Northern States of Sudan and found the mean TE, AE, and EE of 65%, 86% and 54%.

The mean TE of sample farmers was about 0.652 with a minimum level of 0.24 and the maximum level of 0.903. This means that if the average farmer in the sample was to achieve the technical efficient level of its most efficient counterpart, then the average farmer could realize 27.8% derived from (1-0.652/0.903)*100 increase sorghum output by improving TE with existing inputs and technology, using the resource at their disposal in an efficient manner without introducing other improved or external inputs and practice.

Table 2: Estimated TE, AE and EE scores

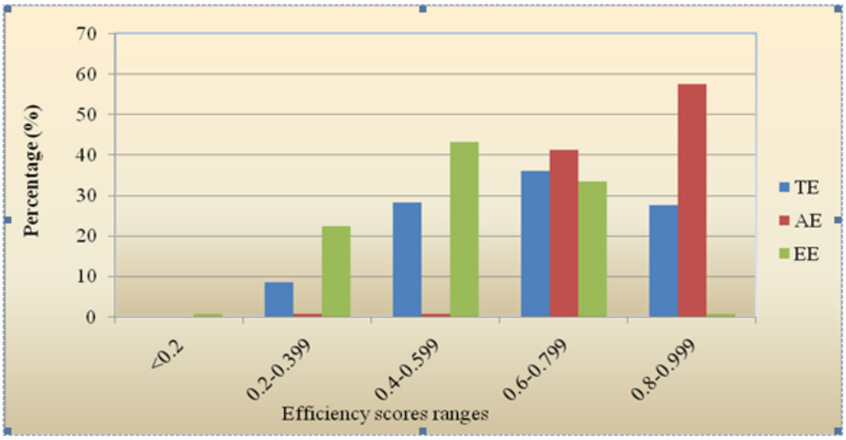
Types of efficiency	Mean	Std. Dev.	Min	Max
TE	0.652	0.167	0.240	0.903
AE	0.798	0.069	0.269	0.957
EE	0.519	0.135	0.155	0.845

Source: Own computation (2021)

Table 2 also shows that the average AE of the sample farmers was about 0.798 with a minimum of 0.269 and a maximum of 0.957. This shows that farmers are not allocatively efficient in producing sorghum and hence, a farmer with an average level of AE would enjoy a cost saving of about 16.61% derived from (1 – 0.798/0.957)*100 to attain the level of the most efficient farmer. Similarly, the mean EE of the sample farmers was 0.519 implying that there was a significant level of inefficiency in the production process. That is, the producer with an average EE level could reduce the current average cost of production by 38.58%, which derived from (1-0.519/0.845)*100 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 a substantial production cost savings of 38.58%. This low average level of EE was the total effect of both technical and allocative inefficiencies.

The distribution of the TE scores showed that about 35.95% of the sample households had TE scores of 0.6 to 0.799. But there were also some households whose TE score levels were limited to the range of 0.2 to 0.399, which is 8.5%. On average, households in this cluster have room to enhance their sorghum production at least by 40%. Out of the total sample households, only 27.45% had TE score of greater than 0.8. This implies that about 72.55% of the households can increase their production at least by 20%. The AE distribution scores indicated that about 57.2% of sorghum producers operated above 0.8 efficiency level. The distribution of EE scores also implies that 43.14% of the household heads have an EE score of 0.4-0.599. This also indicates the existence of substantial economic inefficiency than technical and allocative inefficiency in the production of sorghum during the study period in the study area (Figure 1).

Figure 1: Distribution of TE, AE and EE scores



Source: Own construction (2021)

3.3. Yield Gap Due to Technical Inefficiency Variation

Yield gap analysis is an important tool to estimate to what extent the production could be increased if all factors are controlled. The potential attainable level of crop yield (qt/ha), farmers used the available resources in an efficient manner was calculated using the actual observed individual level of sorghum output and the predicted individual TE from the frontier model. This enables us to determine the yield gap (yield lost) due to technical inefficiencies in the current production in the study area. From the relationship of TE in a given period of time as the ratio of the actual output to the potential output. The potential sorghum production of each individual farmer was calculated as follows:

$$TE_z = \frac{Y_z}{Y_z^*} = exp\ exp\ (-U_i)\ which\ gives\ Y_z^* = \frac{Y_z}{TE_z}$$

Where: TE_z = technical efficiency of the zth household in sorghum production.

Y_z^* = the frontier output of the zth household in sorghum production.

Y_z= the actual output of the zth household in sorghum production.

Hence, yield gap (qt/ha) =potential yield (qt/ha)-actual yield (qt/ha) = $Y_z^* - Y_z$

Using the values of the actual output obtained the predicted TE indices; the potential output was estimated for each household in sorghum production on the hectare base. Hence, the mean level of both the actual and potential sorghum yield in the cropping season was thus 17.19 qt/ha and 25.77 qt/ha, respectively. Using the t-test method, the mean difference of the actual and potential yield was found to be statistically significant at 1% level of significance. Therefore, the average yield gap that lost technical inefficiency, which was the mean difference between actual (17.19 qt/ha) and the potential output (25.77 qt/ha) was 8.58 qt/ha. This indicates that there is a room to increase the production level on average by 8.58 qt/ha with the existing level of input. On average, the money value of sorghum output that was lost due to technical inefficiency (yield gap) was 10725 birr/ha.

3.4. Determinants of Efficiencies

The results of two- limit Tobit model (Table 3) for each significant variable and its marginal effects of change in explanatory variables (Table 4, see page 16) on TE, AE, and EE were discussed as follows.

Table 3: A two- limit Tobit regression results of determinants of TE, AE and EE.

		TE		AE		EE	
Variables	Parameters	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Const	δ_0	0.5013***	0.0479	0.7336***	0.0337	0.3350***	0.0280
SEX	δ_1	0.0109	0.0210	0.0290**	0.0147	0.0300**	0.0122
EXPRNCE	δ_2	-0.0008	0.0009	0.0015**	0.0007	0.0003	0.0005
EDUC	δ_3	0.0092**	0.0046	0.0071**	0.0033	0.0141***	0.0027
TRCNDTN	δ_4	-0.0292	0.0250	0.0151	0.0175	-0.0078	0.0145
FAMSZE	δ_5	0.0007	0.0042	-0.0008	0.0030	0.0008	0.0025
SOILFERT	δ_6	0.0620**	0.0247	-0.0207	0.0173	0.0283*	0.0144
STRIGA	δ_7	-0.0864***	0.0233	0.0194	0.0164	-0.0532***	0.0136
DISTNCE	δ_8	0.0001	0.0002	-0.0003***	0.0001	-0.0001	0.0001
FEXTN	δ_9	0.0504***	0.0064	0.0044	0.0046	0.0482***	0.0039
NONFI	δ_{10}	-0.0112	0.0162	0.0113	0.0114	-0.0030	0.0094
TCLAND	δ_{11}	0.0101	0.0080	-0.0060	0.0056	0.0045	0.0046
LIVSTOK	δ_{12}	0.0036	0.0031	0.0000	0.0022	0.0032*	0.0018

Note: ***, ** and * sign represents significance at 1%, 5% and 10% levels, respectively.

Source: Model output (2021)

One of the variables which entered the model with positive coefficient is sex of the household head. It was found to have a positive effect on both AE and EE at 5%. Explicitly, a change in the dummy variable sex from (0 to 1) would increase the probability of the farmers being AE by about 0.54% and the expected value of AE and EE by about 2.81% and 3% with an overall increase in the probability and levels of AE and EE by 2.89% and 3%, respectively. Since male smallholder farmers carried out most of the activities on the farm, they might accomplish the farming activities on time and efficiently than female smallholder farmers. This result supports the finding of Awol (2014). However, the finding is contradictory with the findings of Chiona (2011) and Gosa and Jema (2018). Likewise, the educational level of the household was found to be positively associated with TE and AE of sorghum producers at 5% and EE at 1%, respectively. Specifically, a one-year increase in the educational level of the household head increases the probability of a farmer being technically efficient and allocative efficient by 0.08% and 0.18% and 1.41% with an overall increase in the probability and levels of technical, allocative and economic efficiency by 0.92%, 0.7% and 1.41%, respectively. These findings are consistent with results documented by Solomon Bizuayehu (2012), Chepng (2013), Sisay *et al.* (2015), Musa *et al.* (2015), Nigusu (2018) and Milkessa Asfaw *et al.* (2019). However, this finding of Getachew *et al*. (2018) contradicts with the result. The authors argue that farmers with higher education levels may give less attention to agricultural activities and as they may, invest their time and knowledge on non-agricultural activities.

Similarly, the frequency of extension contact enters the model with positive coefficient. Specifically, a one-time increase in the frequency of extension of the household head increases the probability of a farmer being technically efficient by 0.42% and the mean values of technical and economic efficiency by about 4.94% and 4.82% with an overall increase in the probability and levels of technical and economic efficiency by 5.03% and 4.82%, respectively. This supports studies by Haileselassie (2005), Musa *et al.* (2015); Wudineh and Endrias (2016), Getachew *et al*. (2018). However, the finding is conflicted with the empirical result of Gosa and Jema (2018) who found that frequency of extension contact has a negative and significant relationship with the efficiency of farmers.

The empirical results indicated that the perception of farmers on the fertility status of soil: associated positively with TE and EE as expected. Specifically, a change in the dummy variable, fertility status of the soil from (0 to 1), would increase the probability of the farmer being TE by about 0.6% and the expected values of TE and EE by about 6.05% and 2.83% with an overall increase in the probability and level of TE and EE by 6.18% and 2.83%, respectively. This may be associated with those fertile lands requiring less commercial fertilizer application which leads to reduction in cost and leads to increase in the efficiency of farmers. This result is similar to the empirical findings of Getachew *et al.* (2018) and Milkessa *et al*. (2019).

In a similar way, livestock ownership was found to be positively related to EE as expected. Precisely, a unit increase in TLU would increase the mean value of EE by about 0.32% with an overall increase in the probability and the level of EE by about 0.32%. This may be due to the considerable contribution of livestock in reducing the current cost of inputs in sorghum production. This finding is consistent with the research results by Solomon Bizuayehu (2012) and Kifle *et al* .(2017). However, the result conflicted with the finding of Bealu *et al*. (2016) who found that raising livestock affects efficiency negatively due to the fact that many livestock may compete for a resource with crop production.

In a quite similar manner, farm **e**xperience significantly and positively affected AE of the sampled households at 5% level of significance. Marginal effect result shows that a one-year increase of experience in sorghum farming would increase the probability of a farmer being AE by 0.04% and the mean value of EE by about 0.15% with an overall increase in the probability and level of EE by about 0.15%. As one gets skilful in the methods of production, he/she would be better in optimal allocation of resources in a cost minimizing way. The finding of this study agrees with the earlier research findings of Musemwa *et al.* (2013) and Gosa and Jema (2018). However, the result is contradictory with the findings of Getachew *et al.* (2018) who found that farming experiences may affect efficiency negatively due to the reason that those farmers having more experience of farming may not be responsive to modern input combinations that minimizes their costs.

However, variables distance from home to farm and Striga weed entered the model with negative coefficients at 1% significance level. Explicitly, a unit increase in the distance from home would decrease the probability of a farmer being AE by 0.009% and the mean value of allocative by about 0.03% with an overall decrease in the probability and the level of AE by about 0.03%. This is due to the fact that the farther the farmland or farm plot from the respondent's residence, the greater would be the cost of transport, management, supervision and opportunity costs. The result is consistent with the finding of Awol (2014). The result indicates that the sample farmer whose sorghum was exposed to striga infestation was less efficient than others. Specifically, a change in the dummy variable, striga weed infestation from (0 to 1), would decrease the probability of the farmer being technically efficient by about 0.56% and the expected values of TE and EE by about 8.5% and 5.32% with an overall decrease in the probability and levels of TE and EE by 8.63% and 5.32% respectively. There is also additional evidence by Gebisa (2007) that there was an estimated yield reduction of 65-70 % in major sorghum growing areas where heavy striga infestation losses often reach 100 %.

4. Conclusion and Recommendations

The stochastic frontier model results revealed that there was inefficiency in smallholder sorghum production in the district. The discrepancy ratio was about 85.6%. The study found that the average TE, AE, and EE was 65.2%, 79.8%, and 51.9%, respectively. This implies that farmers can increase sorghum production by 34.8% without increasing inputs if they were technically efficient, and reduce the current cost of input by 20.2% with cost minimization. There was room to improve EE by 48.1% if resources were efficiently used. An important conclusion coming out from the analysis is that sorghum producers in the study area are not operating at full TE, AE, and EE level, which implies that there is an opportunity for sorghum producers to increase output at existing levels of input and minimize cost without compromising the yield with the present technologies. The study also identified factors that positively and negatively affect efficiency.

The study suggested that extra efforts should be exerted to upgrade the skills and knowledge of farmers to improve sorghum management practices. Promoting improved technologies that reduce the domestic burden on female smallholder farmers could help promote efficiency in this farm household structure. Moreover, encouraging experience sharing via FTC to scale up best practices could also help promote efficiency. Improvement of soil status by applying compost and soil conservation techniques should have to be done by farmers through crop rotation, application of organic fertilizers, use of tied ridges on their farms, integrated soil fertility management and cultivation and assisting them in compost manure producing using local materials. Furthermore, the government should supply striga resistant sorghum. Farmers should be encouraged to apply climate smart agriculture to keep the fertility and moisture content of the soil, since striga infestation is less in moisture and fertile soil. Finally, particular attention shall be given to physical infrastructure development to increase efficiency in resource utilization and better connect farmers to local and central markets.

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Appendix - Table 4: Marginal effects of change in explanatory variables

	Marginal effect of TE			Marginal effect of AE			Marginal effect of EE		
Variables	$\partial E(y)$	$\partial E(y^*)$	$\partial[\varphi(Z_U) - \varphi(Z_L)]$	$\partial E(y)$	$\partial E(y^*)$	$\partial[\varphi(Z_U) - \varphi(Z_L)]$	$\partial E(y)$	$\partial E(y^*)$	$\partial[\varphi(Z_U) - \varphi(Z_L)]$
SEX	0.0109	0.0107	0.0008	0.0289**	0.0281**	0.0054**	0.0300**	0.0300**	0.0000**
EXPRNCE	-0.0008	-0.0008	-0.0001	0.0015**	0.0015**	0.0004**	0.0003	0.0003	0. 0000
EDUC	0.0092**	0.0090**	0.0008**	0.0070**	0.0068**	0.0018**	0.0141***	0.0141***	0.0000***
TRCNDTN	-0.0291	-0.0286	-0.0022	0.0150	0.0144	0.0042	-0.0078	-0.0078	0. 0000
FAMSZE	0.0007	0.0007	0.0001	-0.0008	-0.0008	-0.0002	0.0008	0.0008	0. 0000
SOILFERT	0.0618**	0.0605**	0.0060**	-0.0206	-0.0198	-0.0054	0.0283*	0.0283*	0. 0000*
STRIGA	-0.0863***	-0.0850***	-0.0056***	0.0193	0.0185	0.0058	-0.0532***	-0.0532***	0.0000***
DISTNCE	0.0001	0.0001	0.0000	-0.0003***	-0.0003***	-0.0009***	-0.0002	-0.0002	0. 0000
FEXTN	0.0503***	0.0494***	0.0042***	0.0044	0.0042	0.0011	0.0482***	0.0482***	0.0000***
NONFA	-0.0112	-0.011	-0.0009	0.0112	0.0108	0.0031	-0.0030	-0.0030	0.0000
TCLAND	0.0101	0.0099	0.0008	-0.006	-0.0057	-0.0015	0.0045	0.0045	0. 0000
LIVSTOK	0.0036	0.0035	0.0003	0.0000	0.0000	0.0000	0.0032*	0.0032*	0. 0000*

Source: Model output (2021)