Economic Efficiency of Wheat Producers: The Case of Debra Libanos District, Oromia, Ethiopia

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A B S T R A C T
Ethiopia has enormous potential for wheat production, yet it remains a net wheat importer. This paper aims to examine the efficiency of wheat production in Debra Libanos district, Ethiopia. Two stages sampling technique was used to randomly select 150 farmers for the study. A stochastic production frontier and two-limit Tobit estimator was utilized in the study. The study reveals that technical (78.5 %), allocative (85.6%), and economic (66.7%) efficiencies. The yield gap was 5.13 quintal/ hectare showing a room to increase efficiencies. The study identified the determinants of wheat production efficiency in the area. Hence, to improve wheat production efficiencies strengthen extension services, improved technology utilization, and proper land ploughing. Besides, natural resource conservations that improve soil fertility should be the focus of the policymakers.

Introduction

In developing countries, agricultural production often falls short of its potential. Specifically, in sub-Saharan Africa, the majority of agricultural producers are poor, smallholder farmers with limited use of essential technologies such as sufficient improved seeds and fertilizers (Sheahan and Barrett, 2014).

In Ethiopia, the agricultural sector plays important roles in areas of food security, foreign exchange earnings, poverty alleviation, and employment creation. The sector accounts for about 35.8% of GDP, provides employment to more than 85% of the total population, generates about 79% of the foreign exchange earnings, and supplies raw materials for 70% of the industries in the country. Despite all these potentials, the sector failed to meet the food requirements of the growing population of the nation (UNDP, 2013). Consequently, Ethiopia is still a net importer of cereal crops mostly wheat. Yet, wheat is the most widely grown by smallholder farmers in the country. For example, about 1.7 million hectares (ha) of wheat was cultivated by about 4.2 million smallholder farmers. The average wheat yield, however, was about 27.4 qt per ha, during the 2017/18 cropping season (CSA, 2018). Wheat productivity in Ethiopia is far below the world average, which is 33.2 qt per ha (FAS, 2018). Oromia region, the largest regional state in Ethiopia, covers 53% of the total area and 58% of national wheat production. In the North Shoa zone of Oromia regional state, wheat accounts for 21% in terms of production. Furthermore, 52% of smallholder farmers in the zone were wheat producers with productivity of just 25 qt per ha. Wheat productivity was just 21 qt per ha in Debra Libanos district, which is located within the North Shoa zone of Oromia regional state. As observed from the data, the minimum output of wheat was 6.5 qt per ha while the maximum output was 38.5 qt per ha. These figures were far less than both regional and national levels. In areas where there are efficiency variations, introducing new technology may not bring the expected impact, unless factors associated with efficiency variation among farmers are identified and acted upon (Alemayehu et al., 2012).
Against this background, this study aims to analyze technical, allocative, economic efficiencies and their determinants of smallholder farmers in wheat production in Debra Libanos district, North Shoa zone, Oromia national regional state, Ethiopia.

Research Methodology

Data and Data Sources

The study primarily used a questionnaire to collect data that included institutional, socio-economic, farm characters, and demographic characteristics of the study area. A two-stage sampling technique was applied to select sample farmers. In the first stage, 3 kebeles (Kebeles are the smallest unit of administration in the Ethiopian government structure) were selected randomly from 7 wheat-producing kebeles. In the second stage, 150 sample farmers were selected using a simple random sampling technique based on probability proportional to the size of wheat producers in the 3 selected kebeles. The sample size was determined based on (Yamane, 1967) formula.

The simplified formula to calculate the sample size was:

\[-\frac{N}{1+Ne^2}\]

where: \(n = \) sample size, \(N = \) total number of wheat producers in the study area; \(e = \) level of precision which is 8% and 1 is for designates probability of the event occurring. The formula was preferred since the target population is homogenous and 8% of the precision level was applied to manage all samples to minimize cost and time. The distribution of the sample farmers across the three kebeles is as follows: Goro Wertu (58); Wakene (53) and Dire Jibbo (39).

Estimation Strategy

In the study area, wheat is a rain-fed cereal crop that may suffer from random shocks such as drought and irregular rainfall. A farmer may deviate from the frontier not only because of measurement error, statistical noise but also because of economic efficiency variations. For this purpose, the stochastic frontier model (SPF) was used in the analysis of the economic efficiency of wheat production. The stochastic frontier model is preferred because of its capability to capture measurement error and other statistical noises influencing the shape and position of the production frontier. A stochastic production frontier proposed by Coelli and Battese (1995) in accordance with the original models proposed by Meesuen and Broeck (1977) is applied to cross-sectional data to determine economic efficiency. Hence, most recent studies on economic efficiencies such as Mustafa et al., 2017; Nigusue, 2018; Milkessa et al. (2019) have applied stochastic production frontier model to account for random noise. The general stochastic production model is specified as:

\[y_m = f(X_m; \beta) + \varepsilon_m\] (1)

\(m = 1, 2, 3, ..., k,\) where \(y_m\) the production of the \(m^{th}\) sample farmer, \(f(X_m; \beta)\) was the convenient frontier production function e.g. Cobb-Douglas or Translog; \(X_m\) is a vector of inputs used by the \(m^{th}\) sample farmer, \(\beta\) is a vector of unknown parameters, \(\varepsilon_m\) is a composed disturbance term made up of two error elements \((v_m\) and \(u_m))\) and \(k\) represents the number of farmers who were involved in the survey.

Among the production function, Cobb-Douglas and translog production functions have been the most popularly used models in most empirical studies of agricultural production analysis. Some researcher argues that Cobb-Douglas functional form has advantages over the other functional forms in that it provides a comparison between the adequate fit of the data and computational feasibility. It is also convenient in interpreting the elasticity of production. In addition, it is very parsimonious with respect to degrees of freedom. According to Coelli (1995), Cobb-Douglas functional form has the most attractive feature such as its simplicity. Cobb-Douglas model assumes unitary elasticity of substitution, constant production elasticity, and constant factor demand. If the interest is to analyze the efficiency measurement and not analyzing the general structure of production function, it has an adequate representation of technology and insignificant impact on the measurement of efficiency (Coelli et al., 2005). When farmers operate in small farms, the technology is unlikely to be substantially affected by variable returns to scale (Coelli, 1995). Moreover, the Cobb-Douglas production function has been employed in many types of research dealing with efficiency such as (Musa et al., 2015; Kifle et al., 2017; Mustafa et al., 2017; Nigusu, 2018; Milkessa et al. 2019).

So, it was adopted for this study. Thus, the Cobb-Douglas frontier function was specified as follows:

\[Y_m = A X_1^{b_1} X_2^{b_2} \ldots X_n^{b_n}\] (2)

The linear form of Cobb-Douglas production function for this study was defined as:

\[\ln(Y_m) = \beta_0 + \beta_1 \ln SEED + \beta_2 \ln LND + \beta_3 \ln LAB + \beta_4 \ln CHEMFER + \beta_5 \ln OXEN + \varepsilon_m\] (3)

\[\ln(Y_m) = \beta_0 + \beta_1 \ln Y + \varepsilon_m\] (4)

\[\varepsilon_m = v_m \cdot u_m\]

Where, \(\ln\) denotes the natural logarithm, \(n\) represents the number of inputs used, \(m\) represents the \(m^{th}\) farmer in the sample, \(Y_m\) represents observed wheat production of the \(m^{th}\) farmer, \(X_{mn}\) denotes \(m^{th}\) farmer input variables was used in wheat production of the \(m^{th}\) farmer, \(\beta_0\) represents intercept, \(\beta_1; \beta_2; \ldots, \beta_5\) stand for the vector of unknown parameters, \(\varepsilon_m\) a composed disturbance term makes up of two elements \((v_m\) and \(u_m))\), \(v_m\) accounts for the stochastic effects beyond the farmer’s control, measurement errors and other statistical noises and, \(u_m\) captures the efficiency variation.

The dual cost function of the Cobb-Douglas production function was specified as:

\[\ln C_m = \alpha_0 + \sum_5 \alpha_i n w_{m} + \alpha_d Y + V_m + U_m\] (5)
Where m refers to the m\textsuperscript{th} sample farmers, n was a number of input, C\textsubscript{m} was the minimum cost of production, w\textsubscript{n} denotes input prices, Y\textsubscript{*} refers to wheat output which would be adjusted for noise, v\textsubscript{m} accounts for the stochastic effects beyond the farmer's control, measurement errors, as well as other statistical noises and u\textsubscript{m}, captures the technical efficiency variation. (Sharma et al., 1999) suggests that the corresponding dual cost frontier of the Cobb-Douglas production functional form in the equation could be rewritten as:

\[
C\textsubscript{m} = C(w\textsubscript{m}; Y\textsubscript{*}; a) + \varepsilon\textsubscript{m}
\]  

(6)

m=1, 2, 3... K

Economically efficient input vector of the m\textsuperscript{th} firm X\textsubscript{m}\textsuperscript{e} is substituting the firms input prices and adjusted output level, a system of minimum cost input demand equation was expressed as:

\[
\frac{\partial C}{\partial w\textsubscript{m}} = X\textsubscript{m}\textsuperscript{e}(w\textsubscript{m}; Y\textsubscript{*}; \beta)
\]  

(7)

Then the TE scores of the given farmer were calculated as followed:

\[
TE\textsubscript{m} = \frac{Y\textsubscript{*}}{Y} = \frac{f(X\textsubscript{m}, \beta)}{f(X\textsubscript{m}, \beta)} = exp(u\textsubscript{m})
\]  

(8)

Where, Y\textsubscript{*} = frontier output, Y\textsubscript{m} = actual output

The cost efficiency was defined in terms of the ratio of the observed cost to the corresponding minimum cost given the available technology. That was, cost efficiency (C\textsubscript{E})

\[
C\textsubscript{E} = \frac{C}{C\textsuperscript{*}} = exp(u\textsubscript{m})
\]  

(9)

Where, C = actual production cost and C\textsuperscript{*} = the frontier total production cost or the least total production cost level.

The AE was computed as the inverse of equation (10). Hence, farm-level AE would be obtained using the relationship:

\[
AE\textsubscript{m} = \frac{1}{CE} = \frac{C\textsuperscript{*}}{C}
\]  

(10)

Where, CE=cost efficiency, C\textsuperscript{*} = minimum (efficient) cost and C = actual cost. A measure of farm-specific EE was obtained from the product of TE and EE:

\[
EE\textsubscript{m} = AE\textsubscript{m} \times TE\textsubscript{m}
\]  

(11)

In this study, economic efficiency was estimated from stochastic production by using a censored two-limit Tobit regression estimator on farm-specific independent variables that explained efficiency variation across wheat producers. The rationale behind using a two-limit Tobit regression estimator was that there were a number of farm units for which efficiency was bounded between 0 and 1. Thus, the use of the Tobit estimator was intuitive because the parameter estimates were biased and inconsistent if OLS was utilized (Gujarati, 2004). This is because OLS underestimates the true effect of the parameters by reduced the slope as discussed in (Goetz, 1995). The degree of bias would also increase as the number of observations that take on the value of zero increases. This suggests that OLS regression was not appropriate and estimation with OLS would have led to biased parameter estimates. Therefore, the two-limit Tobit estimator offered the most preferred option and specified as follows:

\[
E\textsubscript{m}(TE, AE, ED) = \delta_0 + \sum_{l=1}^{12} \delta_l X\textsubscript{ml} + u\textsubscript{m}
\]  

(12)

Where m refers to the m\textsuperscript{th} farm in the sample farmers; L is the number of factors affecting economic efficiency (TE); E\textsubscript{m} is economic efficiency scores representing the (economic efficiency) TE of the m\textsuperscript{th} farm. E\textsubscript{m}* is the latent variable, \delta_0 is intercepting. \delta_l stands for unknown parameters to be estimated, u\textsubscript{m} is a random error term that is independently and normally distributed with mean zero and common variance. X\textsubscript{ml} represents demographic, institutional, socio-economic, and farm-related variables that were expected to affect economic efficiency. Denoting E\textsubscript{m} as the observed variables,

\[
E\textsubscript{m} = \begin{cases} 1 & \text{if } E\textsubscript{m}^* \geq 1 \\ E\textsubscript{m}^* & \text{if } 0 < E\textsubscript{m}^* < 1 \\ 0 & \text{if } E\textsubscript{m}^* \leq 0 \end{cases}
\]  

(13)

Results and Discussions

Before analyzing the econometric results, three hypothesis tests were tested using generalized Likelihood Ratio (LR). First, the null hypothesis that all coefficients of the interaction terms in Cobb-Douglas specification are equal to zero was accepted. Hence, the Cobb-Douglas functional form was used to estimate the efficiency of the sample farmers in the study area. The second hypothesis tested indicates that the stochastic production frontier was an adequate representation of the data, given the corresponding OLS production function. Hence, the stochastic frontier model best fits the data under consideration. The third hypothesis test shows that independent variables are simultaneously equal to zero were not accepted at 5% significance level. Hence, these variables simultaneously explain the sources of efficiency differences among the sample farmers.

Estimation of The Production Function

The result of the model showed that land, labor, chemical fertilizer and improved seed varieties utilizations have a positive and significant effect on wheat production. Hence, an increase in these inputs would increase the production of wheat significantly as expected. The coefficients of the production function are interpreted as elasticity since both the dependent and independent variables are in their natural logarithmic forms.

The value of sigma square (\sigma\textsuperscript{2}) for the frontier of wheat output was 0.128 which was significantly different from zero and significant at 1% level of significance. The significant value of the sigma square indicates the goodness of fit and correctness of the specified assumption of the composite error terms distribution (Idiong, 2005 and Okoye et al., 2007). The ratio of the standard error of u\textsuperscript{e} (\varepsilon\textsubscript{u}) to standard error \varepsilon\textsuperscript{2} (\varepsilon\textsubscript{v}), known as lambda (\lambda), is 2.488. Based on \lambda value, gamma (\gamma) which measures the
Yield Gap Analysis

Productivity can change due to differences in the production technology, efficiency of the production process, and environment in which production takes place. The yield gap always occurs due to TE variation among the farmers. So, analyzing the yield gap is important to estimate to what extent the production could be increased if all factors are controlled. It is computed as follows:

\[
\text{Yield gap (qt per ha)} = Y_m^* - Y_m
\]

Then, solving for \( Y_m^* \), the potential yield of each sample farmer was represented as:

\[
Y_m^* = \frac{Y_m}{\text{TE}_m}
\]

Where, \( \text{TE}_m \) the TE of the \( m^{th} \) sample farmer in wheat production; \( Y_m^* \) - the potential output of the \( m^{th} \) sample farmer in wheat production in qt per ha and \( Y_m \) - the actual output of the \( m^{th} \) sample farmer in wheat production in qt per ha. Therefore,

\[
Y_m^* = \frac{Y_m}{\text{TE}_m}
\]

Efficiency Scores of Sample Farmers

The mean TE of sample farmers was 78.5%. Other studies support this finding. For example, Desale (2017) found mean TE of 71.4% for sesame producers in the Tigray region of Ethiopia, and Nigusu (2018) found a mean TE of 79% for teff producers in the Northern Shoa zone of Ethiopia. On average, if sample farmers in the study area operated at full TE level, they could increase their output by 17.8% derived from

\[
\left[ \left( 1 - \frac{78.5}{95.5} \right) \times 100 \right]
\]

from using the existing resources and level of technology. In other words, it implies that on average sample farmers in the study area can decrease their inputs (land, labor, oxen, chemical fertilizer, and seed) by 17.8% to get the output they are currently getting. The most technically inefficient farmer would have an efficiency gain of 69.21% derived from

\[
\left[ \left( 1 - \frac{29.4}{95.5} \right) \times 100 \right]
\]

to attain the level of the most TE farmer (Table 3).

The mean score of AE was 85.6% which indicated that on average sample farmers in the study area could increase wheat output by 12.4% obtained from

\[
\left[ \left( 1 - \frac{85.6}{97.7} \right) \times 100 \right]
\]

\[
\text{AE} = \frac{\ln(\text{Y}_m) - \ln(\text{Y}_m^*)}{\ln(\text{Y}_m) - \ln(\text{Y}_m^{**})}
\]

Where, \( \text{AE} \) is the economic efficiency of sample farmers; \( \text{Y}_m \) - the actual output of the \( m^{th} \) sample farmer in wheat production in qt per ha; \( \text{Y}_m^* \) - the potential output of the \( m^{th} \) sample farmer in wheat production in qt per ha; and \( \text{Y}_m^{**} \) is the average total output of sample farmers in the study area in qt per ha.
if farmers used the right inputs and produced the right output relative to input costs and output price. The most allocatively inefficient farmer had an efficiency gain of 79.53% derived from

$$\left(1 - \frac{20}{97.7}\right) \times 100$$

to attain the level of the most AE farmers (Table 4). The mean EE 66.7% showed that there was a significant level of efficiency variation in the production process. The result also indicated that the farmer with an average level of EE would enjoy a cost saving of about 24.2% derived from

$$\left(1 - \frac{66.7}{88}\right) \times 100$$
to attain the level of the most efficient farmer. The most economically not efficient farmer would have an efficiency gain of 82.61% derived from

$$\left(1 - \frac{15.3}{88}\right) \times 100$$
to attain the level of the most efficient farmer (Table 5).

Having analyzed efficiencies wheat productions, determinants of these efficiencies are analyzed. Here, a two-limit Tobit estimator was utilized to identify the determinants of technical efficiency (TE); allocative efficiency (AE), and economic efficiency (EE) of smallholder farmers’ wheat production in the study area. Tobit is preferred to other estimators since TE, AE and EE are indices whose values are censored both from below and upper.

Table 1. Estimates of the Cobb-Douglas Frontier Production Function

<table>
<thead>
<tr>
<th>Variables</th>
<th>Parameters</th>
<th>MLE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Coefficient</td>
</tr>
<tr>
<td>Constant</td>
<td>$\beta_0$</td>
<td>2.454***</td>
</tr>
<tr>
<td>LnSEED</td>
<td>$\beta_1$</td>
<td>0.270***</td>
</tr>
<tr>
<td>LnLND</td>
<td>$\beta_2$</td>
<td>0.390***</td>
</tr>
<tr>
<td>LnLAB</td>
<td>$\beta_3$</td>
<td>0.120**</td>
</tr>
<tr>
<td>LnCHEMFER</td>
<td>$\beta_4$</td>
<td>0.305***</td>
</tr>
<tr>
<td>LnOXEN</td>
<td>$\beta_5$</td>
<td>0.062</td>
</tr>
<tr>
<td>Elasticity</td>
<td></td>
<td>1.147</td>
</tr>
<tr>
<td>Sigma square($\sigma^2$)</td>
<td></td>
<td>0.128</td>
</tr>
<tr>
<td>Lambda($\lambda$)</td>
<td></td>
<td>2.488</td>
</tr>
<tr>
<td>Gamma($\gamma$)</td>
<td></td>
<td>0.861</td>
</tr>
<tr>
<td>Likelihood</td>
<td></td>
<td>5.5</td>
</tr>
</tbody>
</table>

Note: *** and **, significant at 1% and 5% level of significance, respectively

Table 2. Yield gap analysis

<table>
<thead>
<tr>
<th>Variables</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual qt per ha</td>
<td>19.98</td>
<td>6.02</td>
<td>6.50</td>
<td>38.50</td>
</tr>
<tr>
<td>TE (%)</td>
<td>78.5</td>
<td>0.12</td>
<td>29.4</td>
<td>95.5</td>
</tr>
<tr>
<td>Potential (qt per ha)</td>
<td>25.12</td>
<td>5.22</td>
<td>16.21</td>
<td>42.17</td>
</tr>
<tr>
<td>Yield gap (qt per ha)</td>
<td>5.13</td>
<td>2.58</td>
<td>1.25</td>
<td>15.40</td>
</tr>
<tr>
<td>Money lost (birr per ha)</td>
<td>7183.69</td>
<td>3614.22</td>
<td>1750.05</td>
<td>21565.6</td>
</tr>
</tbody>
</table>

Source: Authors’ computation (2019)

Table 3. Tobit and marginal effect results of the TE determinants

<table>
<thead>
<tr>
<th>Variables</th>
<th>Parameters</th>
<th>Tobit Result</th>
<th>Computed marginal effect</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Coefficient</td>
<td>Std. Err.</td>
</tr>
<tr>
<td>Constant</td>
<td>$\delta_0$</td>
<td>0.3114***</td>
<td>0.0722</td>
</tr>
<tr>
<td>AGE</td>
<td>$\delta_1$</td>
<td>0.0031**</td>
<td>0.0012</td>
</tr>
<tr>
<td>EDUCLH</td>
<td>$\delta_2$</td>
<td>0.0020</td>
<td>0.0028</td>
</tr>
<tr>
<td>SEX</td>
<td>$\delta_3$</td>
<td>0.0133</td>
<td>0.0214</td>
</tr>
<tr>
<td>FAMSZE</td>
<td>$\delta_4$</td>
<td>0.0074**</td>
<td>0.0033</td>
</tr>
<tr>
<td>LIVESZE</td>
<td>$\delta_5$</td>
<td>0.0068***</td>
<td>0.0017</td>
</tr>
<tr>
<td>FARSZE</td>
<td>$\delta_6$</td>
<td>0.0044</td>
<td>0.0070</td>
</tr>
<tr>
<td>SOLFER</td>
<td>$\delta_7$</td>
<td>0.0104</td>
<td>0.0286</td>
</tr>
<tr>
<td>CREDIT</td>
<td>$\delta_8$</td>
<td>0.0128</td>
<td>0.0127</td>
</tr>
<tr>
<td>EXTERN</td>
<td>$\delta_9$</td>
<td>0.0221***</td>
<td>0.0073</td>
</tr>
<tr>
<td>FREQPLOU</td>
<td>$\delta_{10}$</td>
<td>0.0240**</td>
<td>0.0108</td>
</tr>
<tr>
<td>OFFARM</td>
<td>$\delta_{11}$</td>
<td>0.0137</td>
<td>0.0172</td>
</tr>
<tr>
<td>DTNMRKT</td>
<td>$\delta_{12}$</td>
<td>0.0002</td>
<td>0.0003</td>
</tr>
</tbody>
</table>

Note: *** and ** refers to 1% and 5% significance level respectively.
Sex of the smallholder farmer (SEX) was one of statistically significant association was AE at 10% and EE at 1%. The result indicated that male smallholder farmer was more efficient than female smallholder farmers. The possible reason is that male smallholder farmers carried out most of the activities on the farm and more frequent follow-up and supervision of the farm and they might accomplish the farming activities on time. Besides, male farmers are often willing to adopt new agricultural technologies. Specifically, a change in the dummy variable sex (0 to 1) would increase the probability being of the farmers allocatively efficient by about 9.87% and the expected value of AE and EE by about 4.11% and 3.99% with an overall increase in the probability and levels of AE and EE by 9.81% and 3.99%, respectively. This result is similar to the finding of (Milkessa et al., 2019). However, this result was contradictory to the finding of (Essa, 2011; Kifle et al., 2017).

Similarly, frequency of extension contact (EXTEN) enters the model of TE and EE with a positive coefficient at 1% significant level. A positive sign of this variable suggests that farmers have more frequency of extension contact could lead them to improvements in resource allocation, facilitates the practical use of modern techniques, adoption of improved agricultural production practices, and use inputs efficiently. More specifically, a unit increase in the number of extension contact would increase the probability of a farmer being technically efficient by 0.02% and the expected values of TE and EE by about 2.18% and 1.38% respectively, and the overall efficiency of TE and EE by about 2.21% and 1.38% respectively. This result was in line with the finding of (Kifle et al., 2017; Getachew et al., 2017). Other studies, however, found that extension contact negatively affects efficiency since extension workers are only concerned with increasing output and have not new skills and information to support the farmers (Musa, 2015; Mustafa et al., 2017). Pertaining to this study, the relative difference might be because of farmers who had high extension contact got new technology and correct management practices like timely sowing, weeding and can be used inputs as a proper way.

Likewise, livestock size (LIVESZE) entered the model pertaining to TE and EE with a positive coefficient at 1% of significant level supporting (Solomon, 2012; Mustafa et al., 2017; Getachew et al., 2017). This confirms the considerable contribution of livestock in reducing the cost of inputs in wheat production. In addition, given the importance of livestock in crop production as a source of draft power, income, and financing inputs the result seems intuitively appealing. More specifically, a unit increase in the size of livestock (TLU) would increase the probability

<table>
<thead>
<tr>
<th>Table 4: Tobit and marginal effect results of the AE determinants</th>
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<tbody>
<tr>
<td>Variables</td>
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<tr>
<td>-----------</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Constant</td>
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<tr>
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<td>SEX</td>
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<td>FAMSZE</td>
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<tr>
<td>LIVESZE</td>
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<td>FARSD</td>
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<td>SOLFER</td>
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<td>CREDIT</td>
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<tr>
<td>EXTEN</td>
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<tr>
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<tr>
<td>DTNMRKT</td>
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</tbody>
</table>

Note: *** and * refers to 1% and 5% significance level respectively.
being of technically efficient by about 0.05% and the expected values of technically and economically efficient by about 0.67% and 0.39% respectively. The overall increases in the probability and level of TE and EE by about 0.68% and 0.39% respectively. However, other researchers such as Desale (2017) argued that livestock size would negatively affect efficiency because livestock husbandry would compete for a resource with crop production and hence could not improve production efficiency. In the context of this study, the comparative disparity might be the effect of livestock size on efficiency was positive since the livestock in the crop production system was used as a source of income which in turn helps the farmers buy improved seed and fertilizers.

The tobit estimation result also shows that soil fertility (SOILFERT) entered the model corresponding to AE and EE at 10% and 1% level of significance respectively. This implies that farmers who have allocated fertile land for wheat production were more allocatively and economically efficient than their counterparts. Computed marginal effect result indicated that a change in the dummy variable, fertility status of the soil (0 to 1) would increase the probability of the farmer being allocatively efficient by about 11.12% and the expected values of AE and EE by about 6.65% and 6.76% with an overall increase in the probability and levels of AE and EE by 11.12% and 6.76% respectively. This result is consistent with findings by (Getachew et al., 2017; Milkessa et al., 2019).

The empirical result shows that farm size entered the model pertaining AE and EE with negative coefficients at 1%. This finding aligns with the popular law of diminishing returns in microeconomics. This could be because an increase in farm size diminishes the correctness of input use and hence inefficient utilization of farm inputs. The computed marginal effect result shows that a hectare increase in farm size would decrease the probability of a farmer being allocatively efficient by about 7.99% and the mean level of AE and EE by about 2.34% and 2.54% respectively with an overall decrease in the probability level of AE and EE by 7.99% and 2.54% respectively. This result is similar to the findings obtained by (Essa, 2011; Mustafa et al., 2017; Nigusu, 2018). In the context of the present study, relative disparity might be as increases farm size, decrease the timelines of inputs use making managing farm properly more difficult.

Interestingly, this study finds that frequency of ploughing (FREQPLOU) entered the model relating to TE and EE with statistically significant coefficients at 5%. This could be because timely and proper land ploughing would make the soil suitable for crop growth. The computed marginal effect result shows that a unit increase in the frequency of ploughing would increase the probability of a farmer being technically efficient by 0.18% and the expected values of TE and EE by about 2.37% and 1.89% and the overall increase with the level of TE and EE by about 2.39% and 1.894% respectively. The result supports a finding by (Bekabil, 2011).

Conclusions and Recommendations

This study finds that wheat producers in the study area are not operating at full TE, AE, and EE levels. This implies there are opportunities to increase efficiencies in wheat production in the area. Among others, frequent extension contact, livestock size, and frequency of ploughing are among important factors that affect the efficiency of smallholder wheat farmers. This implies that farmers who had more extension contact with extension workers, own large livestock size, and frequently plough their wheat farmland was more economically efficient than their counterparts. Therefore, to improve the economic efficiency of smallholder wheat producers, adopting new technologies such as the use of improved seed and improving natural resource conservation to improve soil fertility shall be the focus of policymakers.

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References


