Technical Efficiency of Smallholder Maize Producers in Ethiopia: The Case of Wolaita and Gamo Gofa Zones

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Abstract
Increasing population pressure and low levels of agricultural productivity have been critical problems of Ethiopia. These have aggravated the food insecurity situation by widening the gap between demand for and supply of food. Increasing efficiency in maize production could be taken an important step towards attaining food security. This study was undertaken to assess the technical efficiency of smallholder farmers and identify determinant factors. The mean technical efficiency was found to be 40 percent indicating that there was substantial level of technical inefficiency of smallholder farmers in maize production. Important factors that significantly affected the technical efficiency were agro-ecology, oxen holding, farm size and use of high yielding maize varieties. Thus, concerned authorities have to concentrate in lowlands, improve oxen holding farm households, consolidate the fragmented land holdings and promote high yielding maize varieties to enhance the technical efficiency of maize producers.
Keywords Data envelopment, Decision making unit, technical efficiency, Tobit

1. Introduction

Ethiopia, one of the world's centers of genetic diversity in crop germplasm (McCann, 2001), produces more of maize than any other crop (CSA, 2010). The area under maize cultivation in 2009/2010 was 1.69 million hectares from which 37.8 million quintals of maize were produced which was higher than that of any other cereal crop. From the country's total grain production, maize shares more than 27 percent (ibid). Maize is major food crop in Wolaita and Gofa areas of southern region of Ethiopia. Past extension programs had given the highest priority to maize over long periods of time because of its known ability to respond positively to improved inputs and the possibility of achieving dramatic growth in productivity (Samuel, 2006). However, the levels of productivity of the crop have remained to be low (Arega, 2003). Production inefficiency of smallholder farmers representing major supply of agricultural production in Ethiopia has been one of the key factors limiting agricultural productivity.

In order to improve maize production and productivity, an efficient use of production inputs has to be adopted by smallholder farmers. An understanding of the relationships between efficiency, policy indicators and farm-specific practices would provide policy makers with information to design programs that can contribute to increasing food production potential among smallholder farmers (Msuya et al., 2008). In Wolaita and Gofa areas of southern Ethiopia, information on the levels of productivity of maize and farm household technical efficiency in its production is lacking. Therefore, the present study was designed to determine the productivity of smallholder maize production and assess the technical efficiency of maize producer farmers and identify its determinant factors.

2. Research Methodology

2.1. The Study Areas and Sampling Technique

This study was carried out in Wolaita and Gamo Gofa zones of Southern Ethiopia. In order to select sample households, multistage sampling technique was followed. In the first stage, study districts were purposively selected based on the extent of maize production. The numbers of districts selected were two each from Wolaita and Gofa areas. In the second stage 2-3 villages where different soil fertility management practices have been promoted for maize production by extension agencies were selected from each district based on the discussion with district agricultural extension service officers. Finally 385 sample farmers were randomly selected from each village to administer the survey.

2.2. Methods of Data Analysis

Input-oriented analysis was applied to minimize inputs use of decision making units (DMUs) and still achieve the given current level of maize yields. If a DMU's actual productivity is equal to frontier productivity or lies on the frontier, it is perfectly technically efficient. On the contrary, if a DMU's actual productivity is less than frontier productivity or lies below the frontier, it is technical inefficient.

Estimation of technical efficiency follows non-parametric and parametric techniques. The non-parametric technique constructs frontiers and measures efficiency relative to the constructed frontier using linear programming techniques such as Data Envelopment Analysis (DEA). The parametric technique estimates frontiers and provides efficiency using econometric methods such as Stochastic Frontier Approach and distance functions. The conventional approach to the estimation of production functions consists of first specifying a parametric form for the function and then fitting it to observed data by minimizing some measure of their distance from the estimated function (Banker and Maindiratta, 1988). Statistical tests are performed by postulating again a parametric form for the distribution of the deviations of observed data from the fitted production function. The fundamental weakness of this approach lies in its inability to theoretically substantiate or statistically test the maintained hypotheses about the parametric form for the production function and the postulated distribution for the disturbance term. Furthermore, it is not immediately apparent what restrictions these hypotheses impose on the production correspondence (Javed et al., 2008).

DEA is a non-parametric approach based on utilizing the linear programming techniques to measure the efficiency and/or inefficiency. It constructs a linear piecewise frontier from the observed data, thus, it does not require any assumptions about the functional form and the distribution of error terms. Thus, DEA has main advantages in terms of not requiring the assumption of a functional form to specify the relationship between inputs and outputs, and the assumption about the distribution of the underlying data (Coelli, 1995 and Krasachat, 2003).

DEA efficiency measures are relative, as they refer to the sample they are calculated from. These relative rankings can be fragile if the number of firms in the sample is small relative to the number of outputs and inputs being considered (Andreu, 2008). In this study the number of farms was larger than the rule-of-thumb benchmark, M×N, where M is the number of outputs and N is the number of inputs. Overall, DEA's flexibility in accommodating multiple outputs and inputs in different units with no need to express a specific technical relationship among them has been seen as an advantage.

According to Coelli et al. (1998), it is necessary to select orientation from input oriented DEA model or output oriented DEA model according to which quantities the decision maker has more control over. Smallholder farmers in the study areas have more control over inputs than outputs. Accordingly, input oriented DEA model will be used in the study. Besides, it is pointed out that constant return to scale DEA model is only appropriated when all firms are operating at optimal scale. However, it is not possible to hold this assumption in agriculture in the study areas since smallholder farmers face constraints. As a result the variable returns to scale DEA model was applied for this study.

The outcomes of DEA of this study were efficiency scores which represent performance indicators as 1 = best performance and 0 = worst performance. The best of efficient DMUs lie on the frontier while the inefficient ones lie below the frontier. The efficient DMUs can be considered as benchmark of the inefficient DMUs. The inefficient DMUs can improve their performances to reach the efficient frontier by decreasing their current input levels (Cooper et al., 2006). The efficiency scores can be calculated by using a linear programming model as presented in Charner et al. (1978). Following the same authors, the linear programming model for this study is, therefore, constructed as follows.

$$\min_{\Delta,\lambda} \Delta_j$$

Subject to:

$$\sum_{j=1}^{n} y_j\lambda_j - y_j \geq 0, \lambda_j \geq 0 \text{ for } \forall j$$

$$x_{ij}\Delta - \sum_{i=1}^{m} x_{ij}\lambda \geq 0,$$

$$\sum_{j=1}^{n} \lambda_j = 1,$$

$$0 \leq \Delta \leq 1 \quad (1)$$

where Δ_j is a scalar which indicates technical efficiency scores of the j^{th} household; y_j is a 1xn vector of output produced by n households; x_{ij} is a m x n input matrix and λ_j is a n x 1 vector of weight value. The underlying assumptions of this model are that farm household j (1, 2, …, n) produces output y_j using a combinations of inputs x_{ij} (i = labor, seed, fertilizer, oxen power); and an input oriented production frontier of variable returns to scale (VRS). The objective function Δ_j is a scalar that represents the minimum level to which the use of inputs can be reduced without altering the output level. It is the global technical efficiency score (GTE) for the DMU ‘‘j’’. If this index is equal to one, the production unit is considered technically efficient. If it is less than one there is some degree of technical inefficiency. A Δ_j index equal to one ensures that the use of all inputs cannot be reduced at the same time, although a variation in the use of one of them may improve efficiency (Iraizoz et al., 2003).

The individual DEA efficiency score varies between 0.00 and 1.00. This means the efficiency scores are double-truncated at 0 and 1. Though other types of regression model such as multiple linear and one sided Tobit regression models can be applied only if the efficiency scores do not assume both or either of the upper and lower limits. Therefore, in this study, the two-limit tobit regression model was applied to identify the sources of efficiency since the dependent variable in this case assumed 0 as lower limit and 1 as upper limit (Maddala, 1999).

The two-limit Tobit model is defined as:

$$y_i^* = \beta_0 + \sum \beta_m X_{jm} + \mu_j \tag{2}$$

where y_i^* is latent variable representing the efficiency scores of farm j, β is a vector of unknown parameters, X_{jm} is a vector of explanatory variables m (m = 1, 2, ..., k) for farm j and μ_j is an error term that is independently and normally distributed with mean zero and variance σ^2. Denoting y_i as the observed variables,

$$y_i = \begin{cases} 1 & if \ y_i^* \geq 1 \\ y_j^* & if \ 0 < y_i^* < 1 \\ 0 & if \ y_i^* \leq 0 \end{cases} \tag{3}$$

The distribution of dependent variable in equation (3) is not normal distribution because its value varies between 0 and 1. The ordinary least square (OLS) estimation will give biased estimates (Maddala, 1999). Therefore, the alternative approach is using the maximum likelihood estimation which can yield the consistent estimates for unknown parameters vector. Following Maddala (1999), the likelihood function of this model is given by:

$$L(\beta,\sigma | y_j, X_j L_{1j}, L_{2j}) = \prod_{y_j = L_{1j}} \varphi\left(\frac{L_{1j} - \beta' X_j}{\sigma}\right) \prod_{y_j = y_j^*} \frac{1}{\sigma} \phi\left(\frac{y_j - \beta' X_j}{\sigma}\right) \prod_{y_j = L_{2j}} 1 - \varphi\left(\frac{L_{2j} - \beta' X_j}{\sigma}\right) \tag{4}$$

where L_{1j} = 0 (lower limit) and L_{2j} = 1 (upper limit) where $\varphi(.)$ and $\phi(.)$ 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).

The regression coefficients of the two-limit tobit regression model cannot be interpreted like traditional regression coefficients that give the magnitude of the marginal effects of change in the explanatory variables on the expected value of the dependent variable. In a tobit model, each marginal effect includes both the influence of explanatory variables on the probability of dependent variable to fall in the uncensored part of the distribution and on the expected value of the dependent variable conditional on it being larger than the lower bound. Thus, the total marginal effect takes into account that a change in explanatory variable will have a simultaneous effect on probability of being technically efficient and value of technical efficiency score. McDonald and Moffitt (1980) proposed a useful decomposition of marginal effects that was extended by Gould et al. (1989). From the likelihood function of this model stated in equation (4), Gould et al. (1989) showed the equations of three marginal effects as follows:

1) The unconditional expected value of the dependent variable

$$\frac{\partial E(y)}{\partial x_j} = [\varphi(Z_U) - \varphi(Z_L)] \cdot \frac{\partial E(y^*)}{\partial x_j} + \frac{\partial[\varphi(Z_U) - \varphi(Z_L)]}{\partial x_j} + \frac{\partial(1 - \varphi(Z_U)}{\partial x_j} \tag{5}$$

2) The expected value of the dependent variable conditional upon being between the limits

$$\frac{\partial E(y^*)}{\partial x_j} = \beta_m \cdot \left[1 + \frac{\{Z_L \phi(Z_L) - Z_U \phi(Z_U)\}}{\{\{\varphi(Z_U) - \varphi(Z_L)\}\}}\right] - \left[\frac{\{\phi(Z_L) - \phi(Z_U\}^2}{\{\varphi(Z_U) - \varphi(Z_L)\}^2}\right] \tag{6}$$

3) The probability of being between the limits

$$\frac{\partial[\varphi(Z_U) - \varphi(Z_L)]}{\partial x_j} = \frac{\beta_m}{\sigma} \cdot [\phi(Z_L) - \phi(Z_U)] \tag{7}$$

where $\varphi(.)$ = the cumulative normal distribution, $\phi(.)$ = the normal density function, $Z_1 = -\beta' X / \sigma$ and $Z_U = (1 - \beta X) / \sigma$ are standardized variables that came from the likelihood function given the limits of y^*, and σ = standard deviation of the model.

The marginal effects represented by the equations above were calculated by the STATA command mfx which was complemented by specific options that allowed the estimation of marginal effects of change in explanatory variables.

The theoretical model discussed above assumes that the dependent variable which is defined as the technical efficiency of smallholder maize producers depends on the following explanatory variables: agro-ecological location of household, rainfall distribution, sex of household head, age of household head, education of the household head in years of schooling, family size of household, oxen holding of household, farm size, use of hybrid seed, frequency of extension visit, distance to development centre, access to credit and consumption expenditure of household.

3. Results and Discussion

3.1. Technical Efficiency of Farmers in Maize Production

The results of DEA model indicate that the average technical efficiency was found to be about 0.40. This indicates that if the average farmer in the sample was to achieve the technical efficiency level of its most efficient counterpart, then the average farmer could realize 60 percent cost savings. This indicates that there was a substantial amount of technical inefficiency in maize production. However, about 7.26 percent of the DMUs operated at greater than 90 percent technical efficiency level in maize production (Table 1).

3.2. Determinants of Technical Efficiency

According to the results of tobit regression model, important variables affecting the technical efficiency were found to be agro-ecology, oxen holding, farm size, use of hybrid maize variety and consumption expenditure of farm households (Table 2). Farm size and use of hybrid maize variety were statistically significant at positively affecting the technical efficiency of smallholder maize producers at less than one percent level of significance. The use of hybrid maize variety also enhances maize productivity and technical efficiency in its production. Technical efficiency was also significantly influenced by agro-ecology, oxen holdings and consumption expenditure of households at 5 percent level of significance. The fact that technical efficiency was positively and significantly related to agro-ecology variable suggests that there is a room to increase maize productivity and efficiency in mid-altitude and even more in lowland areas.

The relationship between oxen holding and technical efficiency in maize production was positive and statistically significant. Thus, oxen availability is crucial to increase technical efficiency in maize production in the study areas. It can be observed that consumption expenditure was significantly and positively related to technical efficiency. This could be related to the efficiency-wage hypothesis in labor economics that improved consumption expenditure (or income) leads to better nutrition of laborers and hence the enhanced technical efficiency in production.

The marginal effects of changes in explanatory variables from Tobit regression analysis were computed following the procedure proposed by McDonald and Moffitt (1980) and Maddala (1999). The derived values for the statistically significant explanatory variables indicate the effects of a unit change in those variables on the unconditional expected value of technical efficiency, expected value of technical efficiency conditional upon being between 0 and 1, and probability of being between 0 and 1 (Table 3).

The result shows that a unit change in agro-ecological variable ordered from highland to lowland in an increasing order (i.e., with values 1 for highland, 2 for midland and 3 for lowland) increases the probability of a farmer being technically efficient by about 2.7 percent and the mean level of efficiency by about 3.7 percent with an overall increase in the probability and level of technical efficiency by 4.5 percent. That is a unit change in the agro-ecology brings about 4.5 percent increase in the expected value of unconditional technical efficiency. A unit change in the number of oxen owned by households would increase the probability of a farmer to be technically efficient by 1.2 percent and the expected value technical efficiency by 1.6 percent. A unit change in farm size would result in 4.2 percent change in the probability of a farmer under technically efficient category and about 6 percent change in the technical efficiency. A change in the dummy variable representing the use of hybrid maize variety from 0 to 1 would increase the probability of farmers to fall under efficient category by about 7 percent and the expected value of technical efficiency by about 8 percent.

4. Conclusion

This study was carried out in Wolaita and Gamo Gofa zones of southern Ethiopia to assess the technical efficiency of smallholder maize producers and factors determining its magnitude. The study was based on the cross-sectional data collected 385 randomly selected households. The DEA model was employed to determine the levels of technical efficiency of individual farm households in the sample. Moreover, a two-limit Tobit regression model was used to identify factors determining technical efficiency.

The mean technical efficiency was found to be 40 percent. This reveals that if the average farmer in the sample was to achieve the technical efficiency level of its most counterparts, then the average farmer could realize 60 percent cost saving without any reduction in the level of the output produced. The two-limit Tobit regression model results indicate that agro-ecology, oxen holding, farm size and use of high yielding varieties were significant determinants of technical efficiency.

The agro-ecological variable had a positive and significant influence on the technical efficiency in maize production. This implies that farmers in the higher altitude areas were less efficient in maize production than the farmers in the lower altitude areas. The result suggests that there has to be agro-ecology specific extension of maize technologies and concentrated efforts in the mid- and low-altitude areas to increase the level of technical efficiency in maize production. An oxen holding has significantly affected the technical efficiency of maize farmers. From this result, it can be recommended that there has to be increased availability of oxen for farm operation through targeted credit, improved health service and management practices.

The technical efficiency of the sample farmers was highly influenced by the use of hybrid maize variety. In other words, farmers who were users of hybrid maize variety were technically more efficient than non-users. As a result, increased endeavor should be applied to further improve the availability and affordability of hybrid maize seed through area specific multiplication and dissemination programs. Farm size was a highly significant variable in positively affecting the technical efficiency of the sample farmers in maize production. This requires policies that consolidate the fragmented farms and increase farm size per household for the case of this particular study by either strengthening the resettlement programs or absorbing the underutilized labor in these areas to off-farm opportunities.

Consumption expenditure was a significant determinant of the technical efficiency of farm households in maize production. Since higher consumption expenditure implies a better nutrition of farm households, it has a positive contribution to the technical efficiency. Therefore, rural income and expenditure enhancement programs such as employment generation schemes and paid social works would be of crucial importance in increasing the technical efficiency of smallholder maize producers in the study areas.

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Table 1. Frequency distribution of technical efficiency of maize producers

Technical efficiency range	Frequency	Percent
0.00-0.10	27	7.26
0.11-0.20	86	23.12
0.21-0.30	76	20.43
0.31-0.40	51	13.71
0.41-0.50	30	8.06
0.51-0.60	35	9.41
0.61-0.70	20	5.38
0.71-0.80	13	3.49
0.81-0.90	7	1.88
0.91-1.00	27	7.26
Total	372	100.00

Table 2. Tobit regression results of determinants of technical efficiency

Variable	Coefficient	t-ratio
AGROECO	0.048**	2.070
RAINDIST	0.024	0.780
SEX	0.041	0.590
AGE	-0.001	-0.850
EDU	0.000	-0.090
FAMISIZE	-0.007	-1.220
OXEN	0.021**	2.170
FARMSIZE	0.074***	5.500
HYV	0.107***	4.060
FRQEXT	0.003	1.590
DISTDC	-0.033	-0.690
CREDIT	-0.020	-0.710
EXPEND	0.001**	1.960
Constant	0.057	0.550

***, ** and * indicate the level of significance at 1, 5 and 10 percent, respectively.

Table 3. The marginal effects of change in explanatory variables

Variable	$\frac{\partial E(y)}{X_j}$	$\frac{\partial E(y^*)}{\partial X_j}$	$\frac{\partial[\varphi(Z_U)-\varphi(Z_L)]}{\partial X_j}$
AGROECO	0.04504	0.03686	0.02692
RAINDIST	0.02230	0.01836	0.01254
SEX	0.03763	0.03032	0.02621
AGE	-0.00084	-0.00069	-0.00050
EDU	-0.00029	-0.00024	-0.00018
FAMISIZE	-0.00660	-0.00540	-0.00394
OXEN	0.01952	0.01597	0.01166
FARMSIZE	0.06955	0.05692	0.04156
HYV	0.09837	0.07919	0.06989
FRQEXT	0.00277	0.00227	0.00166
DISTDC	-0.03065	-0.02508	-0.01832
CREDIT	-0.01845	-0.01504	-0.01145
EXPEND	0.00001	0.00001	0.00001