

Determinants of Productivity and Efficiency of Resettled Farmers in Benishangul Gumuz Region, Ethiopia: A Comparative Analysis of Stochastic Frontier and Data Envelopment Approaches

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Abstract

The study measured the extents and principal determinants of productivity and technical efficiency of resettled farm households in Western Ethiopia using 2016 survey using stochastic frontier analysis (SFA) and data envelopment approach (DEA). Multi-stage sampling technique was used to collect data of 285 resettled farm households. Stochastic frontier approach showed that land, labor, local seed, oxen, improved seed and manure having enhanced effect on resettled farmers' productivity. The mean technical efficiency is found as 0.738 and hence forgone an income of 8,746.53 Birr due to their inefficiency. The mean scale efficiency was found to be 89 %. This reveals an increasing returns to scale nature of production technology. Spearman's correlation test revealed a significant agreement between SFA and DEA estimation. Tobit model revealed that livestock size, land fragmentation, crop diversification, technology adoption and sharecropping as having significant effect on TE. Therefore, the study recommends government and other concerned bodies to enhance local best farming practices, timely supply of improved inputs in fair price, strengthening mixed farming system, providing trainings and education, encouraging crop diversification, consolidating farm plots, encouraging soil management practices, strengthening tenancy security and providing appropriate health services that lead to boost their food security.

Keywords: DEA, Resettled Farm Households, Productivity, SFA, Technical Efficiency, Ethiopia

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1. INTRODUCTION

Two-thirds of the population of Sub-Saharan Africa live in rural areas and nearly half of this is smallholder farmers with the contribution of more than one-third of the GDP, employs more than two-thirds of the labor force, and generates major foreign exchange earnings. In spite of this, agricultural productivity has been disappointing in this region, unlike other developing countries (South Asia and Latin America), which has been resulted from low cereal yield, high reliance on traditional technology, and high land degradation resulted from population pressure (ECG, 2011 and Yu and Nin-Pratt, 2011).

Agriculture is the backbone of Ethiopian economy in its significant contribution in terms of GDP (43 percent), employment opportunity (80 percent), and foreign exchange earnings (83 percent). However, agricultural productivity in Ethiopia is still very low even compared to other SSA countries. This is outsourced from the limited usage of improved inputs, extreme dependence on traditional technology, weather risks, poor infrastructures, poor soil fertility, chronic crop and animal diseases, high land fragmentation and weak institutional services. Poverty in Ethiopia have been mainly related to poor productivity due to its structural rigidity and mainly managed by smallholder farmers who make non-separable production and consumption decisions (Devereux and Goethe, 2009). Currently, Ethiopian government has been giving much effort in enhancing productivity and efficiency of the farmers through introduction of modern technologies, institutional interventions, solving production constraints and a more efficient use of the existing technologies (Bamlaku et al., 2009; Megos, 2013; EGP, 2014).

Empirical studies on estimating farm specific level of productivity and efficiency in developing countries and Ethiopia in particular are scarce. Therefore, to fill the gaps and to add stock of knowledge in literature, this study undertook analysis of extent and determinants of productivity and technical efficiency of resettled farm households in Western Ethiopia using both SFA and DEA techniques as comparative analysis.

2. Review of Literature

Average traditional production function can be theoretically defined as the highest output attainable from a given bundle of factors of production and fixed technology. This definition assumes that technical inefficiency is absent from the production function. Following the independent works by Aigner et al. (1977) and Meeusen and van den Broeck (1977), serious attention has been given to the possibility of estimating the so-called frontier production functions, in an effort to bridge the gap between theory and empirical work. The Stochastic frontier production function is developed to bridge the above gap by including the concept of technical inefficiency which is defined as the amount by which the observed output falls short of the frontier output (Kumbhakar, 1988 and Ajibefun et al., 2006). Classical production theory assumes that producers in an economy always operate efficiently and any

observed output discrepancy from the frontier is due to external shocks which are entirely out of the control of farmers. Accordingly, performance of any firm may depend on differences in production technology, differences in the effectiveness of production process, and/or differences in the production environment. However, at particular period of time, even when production technology, environment and effectiveness of production process are given same, firms may exhibit different productivity levels due to differences in their efficiency (Korres, 2007).

Technical efficiency measures the relative ability of the farm households to obtain the maximum frontier output from given set of inputs or to minimize the cost of production at the given level of output and production technology. All feasible points below the production frontier are technically inefficient points. This concept involves assessing each farm household's actual production performance compared to a best-practice farmer. From time series point of view, the best practice frontier is the maximum potential output for the best practice year. Thus, the technical efficiency of farm household in this case is the ratio of his/her actual output for any particular year with his/her maximum potential output (Coelli et al, 2002 and Djokoto, 2012). Farrell (1957) described technical efficiency as a perspective of output expansion and input contraction, i.e., the ability of farmer to produce a maximum output from the given the bundles of inputs and technology (output-oriented approach) or to use minimum inputs to produce a given set of outputs at the prevailing technology (input-oriented approach). The technical inefficiency is occurred due to the presence of excessive input usage which is costly and since cost is not minimized then the profit is also not maximized (Vicente, 2004).

3. Methodology

Ethiopian, which is a sovereign state in the horn of Africa, is divided into nine regional states which are further divided into zones and woredas. The woreda as are further classified in to kebeles¹. Benishangul-Gumuz was established as regional state in 1994. Metekel zone is the study area that consists of seven woredas with an area of about 26,560 km² and altitude ranged from 600 masl to 2800 masl. About two-third of the zone is characterized by sub-humid and humid tropical low-land agro-climate. It has a total population of around 403,216 people with 81,919 farm household heads. The average family size of zone is around six. The population density of the zone is about 15.48 persons/km², i.e., the zone is relatively sparsely populated (CSA, 2013). This zone is located 550 km West of Addis Ababa, which is the Ethiopian capital city. This zone is dominated by the traditional mixed crop–livestock production system. Dominantly grown cereal crops in the study area are: maize, sorghum, rice and millet. Other oil crops produced are: sesame, niger seed, groundnuts, haricot beans, chickpeas, and soya beans (Solomon et al., 2014).

During 1984-1986, the government relocated about 600,000 people from severe drought affected and densely populated regions, majorly from Northern part of Ethiopia, to Metekel, Metema, Assosa, Gambella, and Kefa resettlement sites. Of the total figure, over 82,000 people moved to Benishangul-Gumuz, Metekel zone. In addition, the current regional government has undertaken intra-regional resettlement program from 2010 to 2013. This planned resettlement program was done voluntary based on public consensus for sake of having common public institutions in the form of villagization (Gebre, 2002; Asrat, 2009; and Kassa, 2015).

3.2. Sources and Methods of Data Collection

The study used multi-stage sampling technique to collect farm household data in 2016 production season. The study used pre-tested structured questionnaire and three extension workers (those experts who have been specialized in crop, livestock, and resources management) for each chosen kebele in the three districts. The study systematically selected 285 resettled rural households from 14 kebeles in 2016 production season.

3.3. Empirical Model Specification and Data Analysis

3.3.1. Parametric Stochastic Frontier Approach

Most empirical studies interchangeably used either Cobb-Douglas (C-D) or Translog function. Since Cobb-Douglas function has advantage of being self-dual, computational advantage in estimating and interpreting of output elasticity of inputs as well as less vulnerability to multicollinearity problem, the study preferred to use it over Translog frontier. Productive efficiency can be measured by using input-oriented or output-oriented approaches. Under constant returns to scale, unlike variable returns to scale, the input-oriented approach has the same result with output-oriented approach. Since the farmers in the study area have relatively more control on inputs and faced resource shortages, so the study gets input-oriented approach more appropriate than output-oriented. In fact, the selection of such orientation has only minor effect on efficiency measurement (Coelli, 1995; Coelli et al., 2005 and Begum et al., 2009).

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

$$\ln(\text{Output})_i = \beta_0 + \beta_1 \ln(\text{Land})_i + \beta_2 \ln(\text{Local Seed})_i + \beta_3 \ln(\text{Improved Seed})_i + \beta_4 \ln(\text{Labor})_i + \beta_5 \ln(\text{Herbicide})_i +$$

¹ It is the lowest administrative unit in the country.

$$\beta_6 \ln(\text{Pesticide})_i + \beta_7 \ln(\text{Ox})_i + \beta_8 \ln(\text{Urea})_i + \beta_9 \ln(\text{DAP})_i + \beta_{10} \ln(\text{Manure})_i + v_i - u_i \dots \dots \dots (1)$$

Where,

ln: it refers to the natural logarithm,

(Output)_i: it refers to the total value of crop outputs produced by the ith farm household in the study area for 2016 production season in Birr,

β₀: it refers to the constant term (intercept),

β_j: it refers to a vector of j unknown parameters to be estimated by MLE method,

X_j: it refers to the vector of inputs of ith the farm household, and

v_i – u_i: it refers to a two-component error term which captures the deviation of the observed crop output from its corresponding frontier output of ith farm household attributed to the effect of random shocks and technical inefficiency, respectively.

3.3.2. Non-Parametric Data Envelopment Approach

The DEA method constructs a non-parametric production frontier over the observed data. Charnes et al. (1978) proposed input-orientated CRS DEA to simultaneously construct production frontier with the aim of minimizing inputs with the given output level. The TE (θ_i) of ith the DMU is obtained by solving the following CRS DEA model (Coelli et al., 2005):

$$\begin{aligned} & \min_{\theta, \lambda} \theta_i \\ & \text{Subject to} \\ & -y_i + Y\lambda \geq 0 \dots \dots \dots (2) \\ & \theta x_i - X\lambda \geq 0 \\ & \lambda \geq 0 \end{aligned}$$

Where,

θ_i: it refers to a TE measure of the ith DMU under CRS DEA,

λ: it refers to an N x 1 vector of weights attached to each of the efficient DMUs,

y_i: it refers to total value of crop output produced by ith the DMU,

x_i: it refers to the vector of inputs, x₁, x₂, ..., x₁₀, used by the ith DMU

Y: it refers to the (1 x N) vector of outputs of all N DMUs in the sample, and

X: it refers to the (M x N) matrix of inputs of all N DMUs in the sample.

The CRS DEA assumption is only appropriate when all DMUs are operating at an optimal scale. Random shocks, imperfect competition, government regulation, asymmetric information, credit constraints, etc., may cause a DMU to be not operating at optimal scale. Banker et al. (1984) suggested an extension of the CRS DEA model to account for variable returns to scale (VRS) DEA. The use of VRS DEA model enables to calculate TE devoid of this SE effect. Note that the farm households in the study area have relatively direct control over inputs and faced resource shortages so the study gets input-oriented approach more important. In addition, VRS DEA is found to be more appropriate than its counterpart for measuring efficiency due to the above reason. The CRS linear programming problem can be easily relaxed to take in to account for VRS technology by adding the convexity constraint:

N1'λ = 1 to equation (3) as follow:

$$\begin{aligned} & \min_{\theta, \lambda} \theta_i \\ & \text{Subject to} \\ & -y_i + Y\lambda \geq 0 \dots \dots \dots (3) \\ & \theta x_i - X\lambda \geq 0 \\ & N1' \lambda = 1 \\ & \theta \geq 0, \lambda \geq 0 \end{aligned}$$

Where,

θ_i: it refers to the technical efficiency score of the ith DMU,

N1'λ = 1 : it refers to a convexity constraint which ensures that technically inefficient farm household is only benchmarked against farm household of a similar size,

N1: it refers to an N x 1 vector of ones,

Y: it refers to the output matrix for the farm households,

y_i: it refers to the total value of output of ith DMU in Birr,

X: it refers to the input matrix for the farm households,

x_i: it refers to the vector of convectional inputs, and

λ: it refers to a Nx1 constants.

VRS DEA forms a convex hull plane which envelops the data points more tightly than the CRS and thus provides

efficiency scores which are greater than or equal to CRS DEA. Estimating CRS DEA model gives the ‘overall TE’ scores, while VRS DEA model calculates only pure TE scores which capture the management practices of DMUs. The residual between overall TE and pure TE scores shows scale efficiency. The overall technical inefficiency can be decomposed into two components: one is due to scale inefficiency and the other due to pure technical inefficiency (Coelli et al., 2002). Mathematically it can be expressed as:

$$SE = \frac{TE_{CRS}}{TE_{VRS}} \dots \dots \dots (4)$$

3.3.3. The Two-Limit Censored Tobit Model

As vital inputs for policy formulation, reporting only estimated efficiency scores of farm households are intermediate results. So investigating principal factors that are supposed to be source of variation of TE scores among the farmers is vital. The main aim of this analysis is to answer whether this efficiency variability can be attributed to the principal internal factors which are under the control of farm households in the study area or not. Following the empirical works of Amemiya (1985) and Binam et al. (2005), the two limit-Tobit regression model is expressed as follow:

$$Y_i^* = \beta_0 + \beta_j Z_i + \mu_i \dots \dots \dots (5)$$

Where,

- Y_i^* : it refers to a latent value for the technical efficiency scores of the i^{th} farm household, separately,
- β_j : it refers to a vector of j parameters to be estimated using maximum likelihood estimation(MLE) method,
- Z_i : it refers to a vector of j demographic, socio-economic, environment and institutional related farm specific explanatory variables of the i^{th} farm household, and

μ_i : it refers to a random error term that is independently and normally distributed with mean zero and variance σ^2 of the i^{th} farm household.

The estimated values of technical efficiency scores of the i^{th} farm household is double censored from both lower and upper sides. The maximum likelihood estimation (MLE) is then used to obtain unbiased and consistent estimate of the unknown parameters of the two-limit censored Tobit model.

4. RESULTS AND DISCUSSIONS

4.1. Empirical Results of Stochastic Frontier Analysis (SFA)

4.1.1. Productivity of Farm Households

The MLE results of stochastic frontier Cobb-Douglas production function for the farm households are presented in the following table. To check the robustness of SFA, the results of OLS are also presented together.

Table 4.1: MLE and OLS Estimation of Cobb-Douglas Production Frontier

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

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

Source: Primary Survey Data of 2016 (Production Season)

Land was found to have highest significant and positive effect on the productivity of farm households at 1 percent significance level in line with the prior expectation. This shows that a 1 percent raise in size of land will lead to a 0.58 percent increment in value of crop output, holding other factors constant. As a result of alarmingly

rising population and declining in agricultural productivity, the country has faced challenges in balancing demand for and supply of foods. Therefore, the feasible solution to this serious problem is raising land productivity via intensive farming and applying environmentally friendly technology that can raise land fertility in subsistence farming.

Labor was found, in line with the prior expectation, to have positive and significant effect on farmers' productivity at 1 percent significance level. This implies that a 1 percent increase in labor usage will lead to a 0.36 percent increment in value of output, holding other factors constant. This reveals the fact that agriculture is labour intensive not only in the study area but also in the country in general.

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

Oxen drought power was also found to have significant and positive effect on farmers' productivity at 1 percent significance level. This implies that a 1 percent increase in the usage of oxen will lead to a 0.05 percent increment in output, holding other factors constant. In addition, herbicide (at 5 percent) and manure (at 1 percent) were found to have same significant and positive effect on farmers' productivity. This implies that, holding other factors constant, a 1 percent increase in the usage of herbicide and manure will lead to only 0.03 percent increment in value of crop output, respectively.

Importantly the value of gamma ($\gamma = 0.81$) was found as significantly different from zero at 1 percent level. This figure reveals that 81 percent of the variation of observed crop output from frontier level is due to farmers' inefficiency. However, the remaining 19 percent is due to stochastic noises. In addition, sigma square ($\sigma^2 = 1.10$) was found as significant at 1 percent which assures the goodness of fit of the model used and the validity of the distribution assumption used for the composite error terms.

4.1.2. Technical Efficiency Scores of Farm Households

The empirical model for technical efficiency was estimated by using MLE technique of Coelli's FRONTIER 4.1c computer program. The major interest of this section is to bring new estimates of TE scores of farmers so that it would be important for policy makers whether to invest in improved production technologies or to introduce efficiency-enhancing strategies with existing resources.

The average TE score of the resettled farmers equals to 73.84 percent which ranges from minimum of 14.43 percent and maximum of 91.30 percent. The mean actual value of crop output of a resettled farmer in the study area equals to 24,675.45 Birr while the average frontier crop output equals to 31,888.24 Birr. The actual yield of a resettled farmer equals to 5,765.29 Birr per hectare and the frontier yield equals to 7,450.52 Birr per hectare. This implies that he/she has forgone a total income of 7,212.79 Birr due to its considerable technical inefficiency. Using input-oriented approach, resettled farmers could decrease their input usages, on average, by 26.16 percent to get the same crop output at the existing technology if they use inputs fully technically efficiently.

4.2. Empirical Results of Data Envelopment Analysis (DEA)

4.2.1. Scale Efficiency Scores of DMUs

The mean scale efficiency (SE) score of the resettled decision making units (DMUs) was found to be 89 percent which shows that resettled DMUs were 11 percent scale inefficient. Regarding to the nature of returns to scale, 179 (62.80 percent) resettled DMUs had increasing returns to scale (IRS), 54 (18.95 percent) had decreasing returns to scale (DRS), and the remaining 52 (18.25 percent) had CRS. This reveals that the production technology of majority of the resettled DMUs were characterized by IRS consistent with the result of SFA technique.

4.3. Comparative Analysis of SFA and DEA

Since DEA fails to take in to account random shocks, unlike SFA where both random shocks and inefficiency effects are incorporated, it is expected to provide lower TE scores than SFA if external factors facing farm households are favorably attributed to efficiency. In addition, outliers in DEA lead to bring higher inefficiency than SFA. This shows that there is more production gain via efficiency improvement from DEA than SFA. Since VRS DEA approach is more flexible and hence encloses the data tighter than the CRS DEA approach, the estimated TE scores of DMUs under VRS DEA were found significantly higher than the TE scores estimated under CRS DEA at 5 percent level. In addition, less variability in TE scores was found in SFA than VRS DEA and CRS DEA. These results are consistent with Sharma et al. (1999), Wadud and White (2000), Minh and Long (2009), Theodoridis and Anwar (2011), and Odeck and Bråthen (2012). However, this result is found to be inconsistent with Wadud (2003) in which SFA resulted higher variability in TE scores than the DEA frontier.

SFA and DEA techniques brought different TE results mainly due to different returns to scale specifications. However, the Spearman's rank correlation test results reveal that the results of these methods are found to be strongly agreed at 1 percent level. This result is found to be consistent with studies like Wadud and White (2000),

Wadud (2003), Masterson (2007) and Theodoridis and Anwar (2011).

4.4. Empirical Results for the Determinants of Technical Efficiency

Table 4.3: MLE of Technical Efficiency Effects of Resettled Farm Households

Two-Limit Censored Tobit Regression Number of Obs.: 285
 LR $\chi^2(22) = 57.73$
 Prob > $\chi^2 = 0.000$

Variables	Coeff. (mfx)	St. Error	t _{cal}	p> t	95% C.I.	
					Lower	Upper
Constant	0.86	0.06	14.26***	0.000	0.74	0.96
Gender of Farmer	-0.04	0.03	-1.39	0.16	-0.11	0.02
Age of Farmer	-0.001	0.001	-1.38	0.17	-0.004	0.0006
Education of Farmer	0.024	0.021	1.14	0.26	-0.02	0.07
Family Size	-0.006	0.006	-1.04	0.30	-0.02	0.005
Family Literacy	0.001	0.008	0.12	0.90	-0.02	0.02
Dependency Ratio	-0.047	0.049	-0.94	0.35	-0.14	0.05
Health status of Farmer	-0.001	0.02	-0.04	0.97	-0.04	0.04
Farm Size	-0.01	0.01	-1.19	-0.23	-0.04	0.01
Farm Size Square	0.002	0.0015	1.03	0.30	-0.001	0.005
Off/non-farm Income	0.03	0.02	1.52	0.13	-0.008	0.06
Livestock Size	0.008	0.004	1.95**	0.05	-0.0001	0.016
Farmers' Association	0.01	0.02	0.62	0.54	-0.02	0.04
Share of Fertile Land	0.004	0.033	0.12	0.91	-0.06	0.07
Land Fragmentation	-0.01	0.007	-1.75*	0.08	-0.02	0.001
Pawe District	-0.10	0.03	-3.90***	0.000	-0.15	-0.05
Dangur District	-0.02	0.03	-0.63	0.53	-0.07	0.04
Crop Diversification	0.02	0.006	3.26***	0.001	0.009	0.034
Irrigation Participation	0.025	0.021	1.20	0.23	-0.02	0.07
Credit Access	0.002	0.02	0.11	0.92	-0.04	0.04
Extension Service	0.0001	0.0004	0.03	0.97	-0.001	0.001
Technology Adoption	-0.04	0.02	-1.85*	0.07	-0.07	0.002
Sharecropping Status	-0.05	0.02	-2.28**	0.02	-0.09	-0.007
Sigma (σ)	0.13	0.005	26***	0.000	0.12	0.14

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

Source: Primary Survey Data of 2016 (Production Season)

The results through the application of two-limit censored Tobit model in Table 4.5 shows that the TE effects of resettled farmers incorporated in the model are jointly significant as the p-value (0.000) of the log-likelihood ratio is significant at one percent level. This shows that not only the variables incorporated in the model are jointly responsible for the variation of technical efficiency among the resettled farmers, but also the existence of considerable technical inefficiency in the study area. Variables that were found to have significant effect on TE are explained follow:

Livestock Size: The MLE result of Tobit model showed that livestock size of resettled farmers, with coefficient of 0.008, was found to have significant effect on their TE at 5 percent level. The possible explanation is that farmers who possess more number of livestock invest the money what they generated from selling their livestock and livestock by-products on modern inputs. Besides threshing, pack animals are also used for timely transportation of inputs and crop outputs. It also serves as an alternative means to get compensation in time of crop failure and animal dung cakes as homemade fertilizer.

Land Fragmentation: The MLE result showed that land fragmentation was found to have significant and negative effect on TE of resettled farmers, with coefficient of -0.01, at 10 percent level. The possible reason might be that due to the difficulty of managing and applying modern technology on fragmented plots effectively and hence they are expected to lose more of their time by moving between plots.

Pawe District: The result of MLE showed that the coefficient of Pawe district was found as significant at 1 percent level with the coefficient of -0.1. The possible reason could be the fact that cultivated land in Mandura district is more fertile and the newly resettled farmers reside in this district have been given better support and follow up from regional government and NGOs in the form of better extension service via FTCs, timely distribution of inputs, and irrigation potential as compared to old resettled farmers reside in Pawe district.

Crop Diversification: The result of MLE showed that crop diversification was found to have significant and

positive effect, with coefficient of 0.02, at 1 percent level on the TE of resettled farmers. The possible explanation is that beside commercialization, planting diversified crops as risk minimization strategy during crop failure could enable the farmers to allocate their existing resources more efficiently and hence enhance soil fertility.

Technology Adoption: The result of MLE showed that technology adoption was found as significant at 10 percent level with coefficient of -0.04. The reason could be attributed to lower technical skills of farmers to properly exploit the full potential of existing technology. Farmers in the study area have lower experience with improved technology. This can be supported by the evidence that 48 percent of the resettled farmers totally relied on traditional technology and 45 percent of the resettled farmers are illiterate.

Sharecropping Status: The result of MLE showed that sharecropping was found as significant at 5 percent level with coefficient of -0.05. The possible reason is due to the possibility of cultivating large farm size with less managerial skills as well as tenancy insecurity as final output produced will be shared between tenant and land owner based on their contractual agreement. So the tenant has the tendency not to exert his/her full effort to produce the potential output because of his/her limited incentive make long-term investment on land fertility.

5. POLICY IMPLICATIONS

Since improving resource use efficiency of farmers will lead to boost their productivity and hence their food security there by achieving sustainable economic growth, the study forwarded the following policy suggestions for the government and other concerned bodies.

1. As important inputs like improved seed, fertilizer and agro-chemicals were found to have significant positive effect on crop production of farmers in the study area, policy makers should make further efforts in timely supply and intensified usage of productivity-enhancing improved and modern inputs in fair price as 91 percent of the respondents replied as they faced high input price and hence 63 percent of them did not have access to improved seeds.
2. Livestock ownership in general and oxen in particular have significant supplementary effect on both crop production and hence on TE scores of farmers via investing the money generated from selling their livestock and/or livestock by-products on modern inputs. Therefore, government officials should draw appropriate strategies that are vital for strengthening the integrated crop-livestock farming system, increasing and sustaining their productivity, investing on market infrastructures to easily find profitable markets for their products, and reducing crop and livestock related diseases.
3. As crop diversification was found to have significant positive effect on TE scores of farmers, then extension development agents should train and encourage farmers to diversify their crop varieties for sake of risk minimization during crop failure and surplus for market, to allocate their existing scarce resources more efficiently, and also to sustain and enhance soil fertility.
4. The farmers who cultivated sharecropped land were found to have significantly lower TE scores. Therefore, it is necessary to strengthen tenancy security for sharecroppers via strongly binding long-term contractual agreement for sake of most efficient land usages. In addition, consolidating fragmented plots and training farmers to use sound land management practices is vital as 61 percent of the farmers replied they faced farm land shortages.
5. The farmers with health problems during production season were found to have significantly lowered TE scores. Therefore, the concerned bodies should give top priority to expand health service coverage and provide appropriate health services to the farmers. This can be confirmed by the fact that the study area is sub-humid and humid tropical low-land with high incidence of malaria.
6. Last but not least, the concerned bodies should design district specific supportive strategies as they have farm-specific differences in production environment, institutions, and market infrastructures that brought considerable difference in their productivity and efficiency.

REFERENCES

- Amemiya, T. (1985). *Advanced Econometrics*, Cambridge, Massachusetts: Harvard University Press.
- Asrat, T. (2009). *The Dynamics of Resettlement with Reference to Ethiopian Experience*. Development Studies Centre, pp: 1-22, Dublin, Ireland.
- Banker, R.D., Charnes, A., and Cooper, W.W. (1984). Some Models for Estimating Technical and Allocative Efficiencies in Data Envelopment Analysis, *Management Science*, Vol. 30, pp: 1078-1092.
- Begum, I. A., Buysse, J., Alam, M. J., and Huylensbroeck, G. V. (2009). An application of Data Envelopment Analysis (DEA) to Evaluate Economic Efficiency of Poultry Farms in Bangladesh. Contributed Paper prepared for presentation at the International Association of Agricultural Economists Conference, Beijing, China, August 16-22, 2009.
- Binam, J. N., Tonye, N.W., Nyambi, G., and Akoa, M. (2005). Factors Affecting the Technical Efficiency among Smallholder Farmers in the Slash and Burn Agriculture Zone of Cameroon. *Food Policy*, Vol. 29, pp: 531-545.

- Bravo-Ureta, B.E. and Pinheiro, A.E. (1997). Technical, Economic and Allocative Efficiency in Peasant Farming: Evidence from Dominica Republic. *The Developing Economics*, Vol. xxxv-1, pp: 48-67. Cambridge University Press, Cambridge.
- Central Statistical Agency (CSA) (2013). Population Projection of Ethiopia for All Regions at Wereda Level from 2014 – 2017.
- Coelli, T.J, Rahman, S., and Thirtle, C. (2002). Technical, Allocative, Cost and Scale Efficiencies in Bangladesh Rice Cultivation: A Non-parametric Approach. *Journal of Agricultural Economics*, Vol. 53, No.3, pp: 607-626.
- Coelli, T.J, Rao, D.S.P., O'Donnell, C.J., and Battese G. (2005). *An Introduction to Efficiency and Productivity Analysis*. Centre for Efficiency and Productivity Analysis, Second Edition, pp.1-326, Springer, University of Queensland Brisbane, Australia.
- DeSilva, S. (2011). *Access to Markets and Farm Efficiency: A Study of Rice Farms in the Bicol Region, Philippines*. Levy Economics Institute of Bard College.
- Ethiopian Government Portal (EGP) (2014). Federal Democratic republic of Ethiopia. Accessed at <http://www.ethiopia.gov.et> on 26 December, 2014.
- Evaluation Cooperation Group (ECG) (2011). *Evaluative Lessons for Agriculture and Agribusiness*. Paper No. 3. World Bank, Washington, DC.
- Farrell, M. J. (1957). The Measurement of Productive Efficiency. *Journal of the Royal Statistical Society*, Vol .120, No.3, pp: 253-281.
- Gautam, M., Nagarajan, H. K., and Pradhan, K. C. (2012). Technical, Economic and Allocative Efficiency and Its Determinants of Indian Agricultural Farmers Using ARIS/REDS Panel Data. *National Council of Applied Economic Research*, No.16, pp: 1-35. NCAER Working Papers on Decentralization and Rural Governance in India.
- Gebre, Y. (2002). Differential Reestablishment of Voluntary and Involuntary Migrants: The Case of Metekel Settlers in Ethiopia. *African Study Monographs*, Vol.23, No.1, pp: 31-46. Graduate School of Asian and African Area Studies, Kyoto University.
- Kassa, T. A. (2015). *Resettlement and Sustainable Livelihoods in Ethiopia: A Comparative Analysis of Amhara and Southern Regions*. A PhD Thesis Submitted to the School of Graduate Studies of University of South Africa, South Africa.
- Meeusen, W. and Van Den Broeck, J. (1977). Efficiency Estimation from Cobb-Douglas Production Functions with Composed Error. *International Economic Review*, Vol.18, No.2, pp: 435- 444.
- Megos, A. (2013). *Environmental-Technology Gap and Technical Efficiency Estimates of Farm households in Northern Ethiopia (Metafrontier Analysis)*. A Thesis Submitted to the School of Graduate Studies of Mekelle University, Tigray, Ethiopia.
- Minh, N.K and Long, G.T. (2009). Efficiency Estimates for the Agricultural Production in Vietnam: A Comparison of Parametric and non-parametric Approaches. *Agricultural Economics Review*, Vol. 10, No. 2, pp: 62-78.
- Odeck, J and Bräthen, S. (2012). A meta-analysis of DEA and SFA studies of the Technical Efficiency of Seaports: A Comparison of Fixed and Random-Effects Regression Models. *Transportation Research Part A*, Vol. 46, pp: 1574–1585.
- Sharma, A. R., Leung, P., and Zaleski, H.M. (1999). Technical, allocative and economic efficiencies in swine production in Hawaii: A comparison of parametric & non-parametric approaches. *Agricultural Economics*, Vol. 20, pp: 23-35.
- Solomon, Z A., Binyam, K., Bilatu, A., Ferede, A., and Gadisa, M. (2014). Smallholder Cattle Production Systems in Metekel Zone, Northwest Ethiopia. *Research Journal of Agriculture and Environmental Management*, Vol.3, No.2, pp.151-157.
- Wadud, A. and White, B. (2000). Farm Household Efficiency in Bangladesh: A Comparison of Stochastic Frontier and DEA Methods. *Applied Economics*, Vo. 32, No.13, pp: 1665-1673.
- Wadud, M.A. (2003). Technical, Allocative and Economic Efficiency of Farmers in Bangladesh: A Stochastic Frontier and DEA Approach. *A Journal of Developing Areas*, Vol.37, No.1, pp: 109-126.
- Yu, B. and Nin-Pratt, A. (2011). *Agricultural Productivity and Policies in Sub-Saharan Africa*. Selected Paper prepared for presentation at the Agricultural and Applied Economics Association's 2011 AAEA and NAREA Joint Annual Meeting, July 24-26, 2011, Pittsburgh, Pennsylvania.