World Applied Sciences Journal 33 (10): 1631-1643, 2015
ISSN 1818-4952

DOI: 10.5829/idosi.wasj.2015.33.10.15612

Determinants of Household Level Poverty and its Impact on Farm Productive Efficiency: the Case of Eastern Ethiopia

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Abstract: Poverty alleviation has attracted a considerable degree of policy attention in recent years both at national and international levels. Poverty is no longer accepted as a way of life and coordinated attempts are being made to address the challenge. However, it takes a concerted and deliberate economic policy effort to generate robust and sustainable economic growth and its fair distribution to an increasing share of the population to address the problems of poverty in the long term perspective. This study evaluated the determinants of household level poverty status and its impact on farm households' technical efficiency of production in eastern, Oromia, Ethiopia. Both primary and secondary data were collected for the study. Primary data were collected from 180 sample respondents drawn from both poor and non-poor households in 2013/14 production year. Stochastic production frontier model was used for technical efficiency estimation and Propensity score matching method was applied to analyze the impact of poverty status on the technical efficiency. The logistic regression was employed to estimate propensity scores and the result showed that poverty was mainly determined by education of the household head, family size, Extension contact, participation to irrigation, farmers training, seed types used and sawing method. In matching processes, kernel matching with band width of 0.5 was found to be the best matching algorism. This method was also checked for covariate balancing with a standardized bias, t-test and joint significance level tests. The results revealed that non-poor households have got an improvement of 8.4% in technical efficiency than those of poor households. Results showed that household level poverty status has a significant, negative and robust impact on the outcome variables. The sensitivity analysis also showed that the impact estimates are insensitive to unobserved selection bias. All results obtained from different models revealed the negative impact of poverty on farm household technical efficiency. Therefore, policy makers should give due emphasis to the aforementioned variables to reduce household level poverty status and improve the livelihood of rural households.

Key words: Poverty · Impact · Farm Efficiency · Propensity score matching and Stochastic Frontier model

INTRODUCTION

In recent decades, mass poverty is recognized not only as ethically and politically unacceptable but also as a formidable hurdle for sustainable economic growth [1, 2]. Increasing awareness of the challenge and improvement in the economic capacity of nations to address the problems of chronic poverty has created the necessary environment for governments to undertake poverty alleviation policies. An increasing number of developing countries have adopted poverty reduction strategies and policies with the financial and technical assistance from international development partners and donors. Whereas a number of developed and some developing countries have achieved remarkable economic growth and poverty reduction, chronic poverty and economic stagnation have remained salient features of most developing countries.

Ethiopia's has a population of over 80 million and its economy is based mainly on agriculture, including crop and livestock production, which contributes 45 % of the national Gross Domestic Product (GDP), more than 80 % of employment opportunities and over 90 % of the foreign exchange earnings of the country.

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However, the Ethiopian economy, particularly agricultural development, is extremely vulnerable to external shocks like climate change, global price fluctuations of exports and imports and other external factors. According to the Humanitarian Requirements Document (HRD), 4.5 million people were in need of relief assistance and the humanitarian needs of Ethiopia were $454,356,911 for the July to December 2011 period. Out of this amount, $384,445,394 or 85 % is needed for food aid, while $69,911,517 or 15% for all other sectors/clusters. Food aid is needed in all regions of Ethiopia with Oromia and Somali regions requiring the highest amount.

According to [3] 39 percent of the population lives on less than US$1.25/day. On the United Nations Development Program's 2012 human development index, Ethiopia ranks 173 out of 187 countries. In the 2011 human development report, Ethiopia was ranked 174 out of 187 countries. Human development indicators are low, with exceptionally alarming statistics regarding food security and women's status and well-being.

As the result of this, extreme poverty is widespread in Ethiopia. The major causes of poverty and food insecurity in rural areas include land degradation, recurrent drought, population pressure, low input subsistence agricultural practices, lack of employment opportunities and limited access to services and technology. As a result more than 38 % of rural households fall below the food poverty line and 47% of children under five suffer from stunting [3, 4].

The root causes of poverty and chronic food insecurity in rural areas of the country are complex and various. One of the major contributing factors for the country's poverty and food insecurity is degradation of natural resources. Since there is rapid population growth in the country, especially, in rural area, the land size per household declines, as a result, people are forced to over use the land which leads to low productivity [5]. They also clear the forest for additional farm land, source of household energy, construction and means of income. This unwise use of the farming land and clearing trees degrades natural resources which result in recurrent drought. Risk adverse traditional farming system and rainfall dependant agriculture is also the other contributing factors for low productivity and food insecurity [6].

In addition, insufficient resources like capital and skills to invest in new technologies and shortage of supply in agricultural inputs have their own significant share for in subsistence agricultural and food insecurity. Besides, majority of the people in rural Ethiopia are stick to farming, they do not have access to off-farm income generating activities, improved technology and employment opportunities. As a result, more than 38 % of rural households fall below the food poverty line and 47 %t of children under five suffer from stunting hunger [5, 4].

Productivity level of the peasants remain near subsistence level and peasants work hard on their fragmented and ever dwindling plots and an emerging army of landless peasants has become a critical issue of concern. Capital investment, application of modern and improved agricultural production technology, secured landownership and effective financial services are some of the factors that could initiate and sustain improvement in productivity in agriculture. The main impediments to poverty reduction in Ethiopia emerge from a complex web of interaction of economic, political, demographic, social, geographic and institutional factors and hence poverty reduction policies should address these underlying forces to develop strategies with lasting effect [2].

The 2010 HDR introduced the Multidimensional Poverty Index (MPI), which identifies multiple deprivations in the same households in education, health and standard of living. The education and health dimensions are based on two indicators each while the standard of living dimension is based on six indicators. All of the indicators needed to construct the MPI for a household are taken from the same household survey. The indicators are weighted and the deprivation scores are computed for each household in the survey. A cut-off of 33.3 % t, which is the equivalent of one-third of the weighted indicators, is used to distinguish between the poor and non poor. The household deprivation score is 33.3% or greater, that household (and everyone in it) is multidimensional poor. Households with a deprivation score greater than or equal to 20% but less than 33.3% are vulnerable to or at risk of becoming multidimensional poor.

Income poverty, measured by the percentage of the population living below PPP US$1.25 per day and multidimensional deprivations in Ethiopia. It shows that income poverty only tells part of the story. The multidimensional poverty headcount is 48.3% points higher than income poverty. This implies that individuals living above the income poverty line may still suffer deprivations in education, health and other living conditions. The report showed that the percentage of Ethiopia's population that live in severe poverty (deprivation score is 50 % or more) and that are vulnerable to poverty (deprivation score between 20 and 30 %) [7].

Poverty in Ethiopia has economic, political, demographic, geographic, environmental and policy roots and causes. Ethiopia is one of the poorest countries in the world where low income and productivity, weak capital accumulation and investment, high levels of unemployment and underemployment are the main features of the economy. The agrarian based subsistence economy has been subject to the vagaries of natural forces and it could not achieve sustained economic growth or structural transformation. When an economy finds itself in such a situation, chronic poverty and vulnerability defines life for the majority of the population. It takes structural change and fundamental reforms to enable economic agents realize their economic potentials and improve their productivity and generate improvement in living standards. The Ethiopian economy could not achieve structural transformation and remains largely subsistence oriented mainly because of misguided economic policy and autocratic political regime.

This study therefore was designed to analyze the determinants of household level poverty and its impact on farm productivity in terms of their income, access to necessary enabling facilities and general well-being on the premise that there were a relationship between poverty and productivity.

MATERIALS AND METHODS

Back Ground of the Study Area: This study was conducted in Girawa district of Eastern Oromia National Regional State, Ethiopia. According to [8], the district has a total population of 263,924 of which 133,780 are male and 130,144 are female and total area of the district is about 1109.41 km^2 with density of 237.9. It is also characterized by different land scapes with the altitude ranging from 1215 to 3405 meter above sea level (m.a.s.l). The annual rainfall ranges from 550mm to 1100 mm with annual temperature ranging from 20°C - 27°C. The livelihood of the district basically originates from mixed farming. It comprises crop production and livestock rearing. Major types of crops grown in the area are sorghum, maize, common beans, highland pulses and many other vegetable crops like potatoes, onion, garlic and leafy vegetables. Livestock rearing is the secondary source of livelihood for the rural people in the area [9].

As sources of information both primary and secondary data sources were used. The primary data were collected in 2012 production year using semi-structured questionnaire that was administered by the trained enumerators. In addition to primary data, secondary data were also collected from relevant sources such as published and unpublished documents of the district and other relevant institutions for general description and to augment primary data.

The sampling procedure used was two stage random sampling. In the first stage out of the kebeles exist in the district two kebeles were randomly selected. In the second stage, sample respondents were selected randomly based on probability proportion to size. Finally, a total of 180 sample respondents were interviewed.

Data Analysis: To address the objectives of the study, poverty indexes, stochastic frontier approach and propensity score matching methods were employed. Poverty indexes used to construct poverty headcount, poverty gap and squared poverty gap based on the income poverty line of $1.25 per day as stated by human development index in 2012. Stochastic production frontier utilized to measure the farm households technical efficiency. Finally propensity score matching method employed to estimate propensity scores or determinants of household level poverty status and to measure its impact on farm efficiency.

Construction of Poverty Indexes: To examine the dimension of poverty, the FGT poverty measure was used. The first step taken was distinguishing the poor and non-poor. In order to classify into two groups, demarcation point or line is required to have single measuring yardstick in poverty analysis. These indices are Headcount index (HC), Poverty Gap index and Poverty Severity index.

Head Count Index (HC): It is insensitive to the depth or severity of poverty and hence, not good to assess the impact of a policy measures. Head Count Index (HC) is defined as the proportion of the population whose measured standard of living is less than the poverty line. The head count index does not tell us whether the poor are only slightly below the poverty line or whether their consumption falls substantially short of the poverty line. The head count measure also does not reveal whether all the poor are about equally poor, or whether some are very poor and others just below the poverty line. In other words, this index does not capture differences among the poor.

Poverty Gap (PG): This estimates the average distance separating the poor from the poverty line. The poverty gap is understood as the amount of income transfer needed to close up the gap. This is sensitive to the depth of poverty but not to its severity. The poverty gap index indicates the depth of poverty, which is, the difference between the poverty line and the mean income of the poor expressed as a percentage of the poverty line. Neither HC nor PG, or any combination of HC and PG adequately capture poverty adequately. Because, some transfer from the poor to the better one but both remaining below the poverty line will not change either HC or PG and combination of them. I fall the poor have exactly the same income, PG indicates the intensity of poverty. Therefore, PG can be used as an indicator of potential for eliminating poverty by targeting transfer to the poor, where the poverty gap yields the minimum possible cost. This as well, has a drawback of being insensitive to the distribution of income among the poor.

Severity of Poverty: This depicts the severity of poverty by assigning each individual a weight equal to his/her distance from the poverty line. Hence, this takes into account not only the distance separating the poor from the poverty line, but also the inequality among the poor. Therefore, as [10] stated to make PG sensitive to the income inequality among the poor, the severity poverty index is specified. This poverty index, FGT gives greater emphasis to the poorest of the poor by weighting each poor person by the square of his/her proportionate shortfall below the poverty line. FGT is more sensitive to redistribution among the poor in that a dollar gained by the poor would have more effect on poverty than that gained by the moderately poor people.

Based on poverty line, three poverty measures that are identified by [11] are employed. The headcount index indicates the proportion of population regarded as poor. If population size is n and P is the number of poor people then the headcount index is represented as:

$$Headcount\ Index\left(HC\right) = \frac{P}{n} \quad (1)$$

On the other hand, poverty gap index highlights how much are the poor below the poverty line on average. If Z is poverty line, Y_i is the per capita income of i, then the poverty gap is.

$$PovertyGrap(PG) = \frac{1}{n}\sum_{1=i}^{n}\left[\frac{Z_- y_i}{z}\right] \quad (2)$$

In the equation, z - y_i = 0 if y_i > z.

Squared poverty gap measures the severity of poverty giving more weight to the poor and is depicted as follows

$$Squared\ \ poverty\ gap\ (GP)^2 = \frac{1}{n}\sum_{1=i}^{n}\left(\frac{Z_- y_i}{Z}\right)^2 \quad (3)$$

The general formula for all these three measures, which depend on parameter, α is given below.

$$P(\alpha) = \frac{1}{n}\sum_{1=i}^{q}\left(\frac{z_- y_i}{z}\right)^{\alpha} \quad (4)$$

where α takes a value of zero for the headcount index, one for the poverty gap index and two for the squared poverty gap index.

Econometric Model

Stochastic Production Frontier Model: Besides allowing for technical inefficiency such stochastic production frontier models also acknowledge the fact that random shocks outside the control of the farm operator can affect output. Following [12] and [13] the SFP model is defined as.

$$\ln Y_i = \ln f(x_i, \beta) + \varepsilon_i \quad (5)$$

where: Y_i is total value of agricultural output and x_i are input variables, β is a vector parameter to be estimated and ε_i is the total error term.

The total error term in equation (5) could be decomposed into its respective two components as:

$$\varepsilon_i = V_i - U_i \quad (6)$$

where: V_i is the symmetric error term, accounts for factors outside the control of the farmer U_i is the technical inefficiency, accounting for random variations in output due to inefficiency and assumes positive values.

The empirical stochastic frontier production model that was applied to the analysis of data was specified as follows:

$$\ln VAO_i = \beta_0 + \beta_1 \ln LAB_i + \beta_2 \ln OXN_i + \beta_3 \ln CULA_i + \beta_4 + \ln FRT_i + \beta_5 \ln OFRT_i + \beta_6 \ln SEED_i + V_i - U_i \quad (7)$$

where subscripts i refer to the number of observation of the th farmer;

ln = logarithm to base e, VAO_i = represents the annual total agricultural output of household in monetary term (birr), OXN_i = total ox power utilized (oxen-days), $CULA_i$ = total area under cultivation (in hectares),

LAB_i = total human labor in man days utilized, $CFRT_i$ = material inputs of chemical fertilizer (kg), $SEED_c$ = costs of seeds (birr) and $OFRT$ = organic fertilizer. It is assumed that the inefficiency effects are independently distributed and U_i arises by truncation (at zero) of the normal distribution with mean U_i and variance σ^2. Where is U_i defined by the equation: The technical efficiency of production for the th farm is defined by:

$$Te_i = \exp(-U_i) \qquad (8)$$

The prediction of the technical efficiencies is based on its conditional expectation, given the observable value of (V_i - U_i). The technical efficiency index is equal to one if the farm has an inefficiency effect equal to zero and it is less than one otherwise.

The Logit Model: The logit and probit are the two most commonly used models for assessing the effects of various factors that affect the probability of adoption of a given technology. These models can also provide the predicted probability of adoption. Both models usually yield similar results. However, the logit model is simpler in estimation than probit model [14]. Hence, the logit model will be used in this study to analyze the determinant of household level poverty status. Following [15] and [14] the logistic distribution function for the household level poverty is specified as:

$$P_i = \frac{1}{1+e^{-zi}} = \frac{ez_i}{1+e^{z_i}} \qquad (9)$$

where, P_i = is the probability of being poor for the th farmer and it takes 0 or 1.

e^{zi} = stands for the irrational number e to the power of Z_i.
Z_i= a function of n-explanatory variables which is also expressed as:

$$Z_i = B_0+B_1X_1+B_2X_2+\ldots+B_nX_n \qquad (10)$$

where, X_1, X_2… X_n are explanatory variables.

B_0- is the intercept, B_1, B_2 … B_n are the logit parameters (slopes) of the equation in the model.

The slopes tell how the log-odds ratio in favor of being poor changes as an independent variable changes. The unobservable stimulus index *Zi* assumes any values and is actually a linear function of factors influencing household level poverty. It is easy to verify that Z_i ranges from -∞ to ∞, Pi takes 0 or 1 and that Pi is non-linear related to the explanatory variables, thus satisfying two requirements:

- As X_i increases P_i increases but never steps outside the 0 and 1 interval; and
- The relationship between P_i and *Xi* is non-linear, i.e., one which approaches zero at slower and slower rates as X_i gets small and approaches one at slower and slower rate as X_i gets very large. But it seems that in satisfying these requirements, an estimation problem has been created because P_i is not only non-linear in X_i but also in the B's as well, as can be seen clearly below.

$$P_i = \frac{1}{1+e^{-(B0+B_1X_1+B2X2+\ldots+B_n)}} \qquad (11)$$

This means the familiar OLS procedure cannot be used to estimate the parameters. But this problem is more apparent than real because this equation is intrinsically linear. If is the probability of being poor then (1-), the probability of being non-poor, can be written as:

$$i - P_i = \frac{1}{1+e^{z_i}} \qquad (12)$$

Therefore, the odds ratio can be written as:

$$\frac{P_i}{1-P_i} = \frac{1+e^{z_i}}{1+e^{-z_i}} = e^{z_i} \qquad (13)$$

Now $\frac{P_i}{1-P_i}$ is simply the odds ratio in favor of being poor. It is the ratio of the probability that of the poor farmers to the probability that he/she non-poor. Finally, taking the natural log of equation 15, the log of odds ratio can be written as:

$$Li = \ln\left(\frac{P_i}{1-P_i}\right) = \ln(e^{Bo} + \sum_{i=1}^{n} BiXi) = Z_i = Bo + \sum_{i=1}^{n} BiX_i \qquad (14)$$

where, Li is log of the odds ratio in favor of being poor, which is not only linear in X_i, but also linear in the parameters. Thus, if the stochastic disturbance term, (u_i), is introduced, the logit model becomes:

$$Z_i = B_0+B_1X_1+B_2X_2+\ldots+B_nX_n+ \qquad (15)$$

This model can be estimated using the iterative maximum likelihood (ML) estimation procedure. In reality, the significant explanatory variables do not have the same level of impact on the adoption decision of farmers. The relative effect of a given quantitative explanatory variable on the adoption decision is measured by examining adoption elasticity's, defined as the percentage change in probabilities that would result from a percentage change in the value of these variables. To calculate the elasticity, one needs to select a variable of interest, compute the associated P_i, vary the X_i of interest by some small amount and re-compute the P_i and then measure the rate of change $\frac{dX_i}{dP_i}$ as where d X_i and dPi stand for percentage changes in the continuous explanatory variable (X_i) and in the associated probability level (P_i), respectively.

When d is very small, this rate of change is simply the derivative of P_i with respect to Xi and is expressed as follows [14];

$$\frac{dX_i}{dP_i} = \frac{e^{z_i}}{(1+e^{z_i})^2} Bi = P_{i/(1-P_i)B_i} \tag{16}$$

The effect of each significant qualitative explanatory variable on the household level poverty is calculated by keeping the continuous variables at their mean values and the dummy variables at their most frequent values (zero or one).

Propensity Score Matching (PSM) Method: Propensity score matching (PSM) was used to estimate the impact of household level poverty status on farm productive or technical efficiency and is the difference in households' mean technical efficiency of the poor and non-poor households. A household can either be in the poor or non-poor. Thus, the fundamental problem of such an impact evaluation is a missing data problem. In other words, we are interested in answering the research question "what would have been the technical efficiency of poor households be if poverty was not in place?" Hence, this study applied PSM technique, which is a widely applied impact evaluation instrument in the absence of baseline survey data and randomization.

In the case of a binary treatment the treatment indicator equals one if individual i receives treatment and zero otherwise. The impact of a treatment for an individual, noted, is defined as the difference between the potential outcome in case of treatment and the potential outcome in absence of treatment:

$$T_i = Y_i(1) - Y_i(0) \tag{17}$$

The fundamental evaluation problem arises because only one of the potential outcomes is observed for each individual. The unobserved outcome is called counterfactual outcome. Hence, estimating the individual treatment effect is not possible and one has to concentrate on (population) average treatment effects.

ATT, which measures the impact of the program on those individuals who participated:

$$T^{ATT} = E[(T)D=1]=E[Y(1)|D=1]-E[Y(0)|D=1] \tag{18}$$

The second term - is not observed, we do observe E[Y(0)|D=0] thus we can calculate:

$$E[Y(1)|D=1]-E[Y(0)|D=0]=T^{ATT} + E[Y(0)|D=1]-E[Y(0)|D=0] \tag{19}$$

The difference between the left hand side of equation (17) and *ATT* is the so-called `self-selection bias'. The true parameter T^{ATT} is only identified, if:

$$E[Y(0)|D=1]–E[Y(0)|D = 0]=0 \tag{20}$$

Matching Quality and Testing: The primary purpose of the PSM is that it serves as a balancing method for covariates between the two groups of poor and non-poor households. Consequently, the idea behind balancing tests is to check whether the propensity score is adequately balanced. The success of propensity score estimation is therefore assessed by the resultant balance rather than by the fit of the models used to create the estimated propensity scores [16]. Finally, using predicted probabilities of poor household (i.e. propensity score) match pairs are constructed using alternative methods of matching estimators. The specific steps that would be followed are as follows:

- The relevant variables influencing the farm household's poverty status were selected and then the poverty association model estimated using logistic regression.
- The predicted probability of being poor (propensity scores) for poor and non-poor households are derived.

For any poor household, there is non-poor household with closest propensity score as the match. To accomplish the match, the researcher specifically used kernel matching estimators which compute an estimate of the poverty effect as the average difference in households' technical efficiency between each pair of matched households. Thus the mean impact of household's poverty on technical efficiency is given by:

$$\Delta_i = \frac{\sum_{j=1}^{p} Y_{ij1} - \sum_{i=1}^{NP} Y_{ijo}}{p} \tag{21}$$

where Y_{j1} is the technical efficiency of poor household j, Y_{ijo} is the technical efficiency of the th non-poor household will be matched to the j^{th} poor household, P is the total number of poor and NP is the total number of non-poor households.

RESULTS AND DISCUSION

Prevalence and Magnitude of Poverty: In this section, various estimates of poverty measures are presented. The estimates of the poverty headcount, poverty gap and squared poverty gap were evaluated in order to assess the present status, depth and severity of poverty in the study area based on the income poverty line of $1.25 per day as given by Human development index of 2012. Poverty prevalence in various categories of farming households with respect to their landholding, family size, education level and access to irrigation water is also presented.

Poverty Measures Based on Poverty Indices: The poverty estimates in the study area are presented in Appendix Table 2. The headcount index provides an estimate of the number of people living below the poverty line and measures the incidence of poverty. The headcount index showed that 42.78 % of the total sample households were living below the poverty line. This implies that 42.78 % of the sample households were unable to get minimum per capita income of $1.25 per day per adult for the requirement of food and non-food items expenditures. In other words, 42.78 percent of sample households were unable to get the minimum amount of income ($1.25 per adult per year). The overall poverty gap was 11.87 % indicating that poor households needed, on average, an additional 11.87 % of the present expenditure to attain their minimum basic needs. The squared poverty gap was 0.042 showing that there is an inequality among the lowest quartile sample households.

Efficiency Scores: The stochastic frontier output result indicated that the mean TE was 80 % with a minimum score of 48% and maximum of 95 %. The level of TE at which sample households operate is presented in Fig. 1. About 12.7 % of farmers in the study area were operating in the range of 91 % -100 % technical efficiency levels. Whereas about 38.9 % operate in the ranges of 81% -90 % and about 27.2 % operate in the range of 71 -80 %, about 14.4 % farmers operate in the range of 61%-70 % levels of technical efficiency and the remaining 6.1 % operating below 60 % but above 48 % technical efficiency levels.

The inefficiency component of the disturbance term (u) is significantly different from zero. Therefore, the null hypothesis of technical inefficiency (H_0: Sigma u=0) is rejected. This indicates that there is statistically significant inefficiency in the data. The lamda (λ) value is also greater than one in all the cases. This is a further indicator of the significance of inefficiency. It is evident from the results the estimate of gamma (γ) is large and significantly different from zero, indicating a good fit and the correctness of the specified distributional assumption. Moreover, the estimate of γ, which is the ratio of the variance output to variance of error term, was 0.74. This means that more than 74% of the variation in output among the farm households is due to differences in technical inefficiency.

Logit Model Results: The logistic regression model is used to estimate propensity scores for matching poor households with non-poor households. The model was estimated with STATA 11.2 computing software using the propensity scores matching algorithm developed by [17]. In the estimation data from the two groups; namely, poor and non-poor households were pooled such that the dependent variable takes a value 1 if the household was poor (treated) and 0 otherwise. Looking into the estimated coefficients, the results indicate that household level poverty status is significantly influenced by education level of the household head, family size, extension service, participation in irrigation, farmers training, seed types used and method of sawing

Level of Education (EDU): The model result reveals that this variable has the expected negative sign and significant at 1% probability level. The possible reasons are the literate farmers are better to manage their farm resources and agricultural activities and, willing to adopt improved production technologies. As a result, literacy reduces the probability of being poor among sample households. The odds ratio indicated that, other things remain constant; the probability of households to be poor is reduced by a factor of 0.23 as the household heads become literate. The finding that literacy is negatively related to poverty status of the house hold is consistent with the findings of [18].

Table 1: Variables definition and measurement

Variables name and code	Type, definition and Measurement
Variables of the model	
Dependent variable:	
Household level poverty (POVER)	Dummy, treated by poverty 1 if poor 0 if non-poor
Outcome variable:	
Technical efficiency (TE)	Technical efficiency of farm household measured as 1-inefficiency effect
Independent variables:	
Age (AGE)	Continuous, age of the household head in year
Sex (SEX)	Dummy, sex of household head 1 if male 0 if female
Education (EDU)	Continuous, education of household head in grade completed
Seed types used (SDT)	Dummy, seed types used for stable crops 1 if improved 0 if local
Family size (FAS)	Continuous, total size of the household members in numbers
Application of fertilizer (ACF)	Dummy, 1 if applied 0 if not
Cultivated land (CULA)	Continuous, cultivated land holding in hectares
Livestock holding (LSH)	Continuous, livestock holding in tropical livestock unit
Extension (NEXC)	Continuous, number of extension contact in the cropping year
Irrigation Participation (IRRP)	Dummy, 1 if household participated 0 if not
Farmers training (FTR)	Dummy, participation in farmers training 1 if yes 0 if no
Method of sawing (MSAW)	Dummy, sawing mode used 1 if line 0 broadcast
Soil Conservation (SCON)	Dummy, 1 if conserved 0 if not conserved
Soil fertility (SFS)	Dummy, soil fertility status of the farm 1 if fertile 0 otherwise
Weather road dist (WRD)	Continuous, distance from the weather road in minute

Table 2: Poverty indexes

Poverty indices	Index Values
poverty head count	42.78
Poverty gap	11.87
Squared Poverty gap	0. 042

Source: Survey result, (2015)

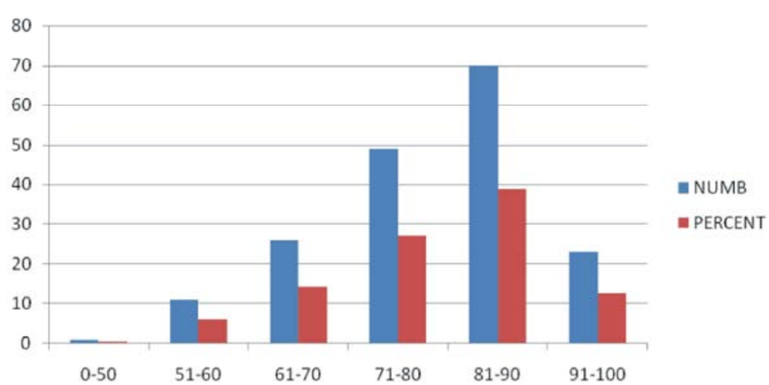

Fig. 1: Technical efficiency scores of farm households

Family Size (FSIZE): This variable was significant at 5 % probability level and positively related with the state of poverty. The positive relationship indicates that the odds ratio in favor of the probability of being poor increases with an increase in the family size measured in adult equivalent. The odds ratio 0.36 implies that, other things being constant, the odds ratio in favor of being poor increases by a factor of 0.36 as family size increase by one adult equivalent. The logistic model result revealed that households with large family size tend to be poor compared to household with small family size. The possible reason is that, given the limited family resources, large family size implies that family members share limited resources that leave the family to be poor. The result is agreed with the priori expectation and the findings of [19] and [20].

Extension (NEXC): The model result reveals that this variable has the expected negative sign and significant at 10 % probability level. The possible reasons are the farmers who receive the extension services are better to manage their farm resources and agricultural activities and, willing to adopt improved production technologies. As a result, extension service reduces the probability of being poor among sample households. The odds ratio indicated that, other things remain constant; the probability of households to be poor is reduced by a factor of 0.31 as the household heads have got the extension services. The finding that literacy is negatively related to poverty status of the house hold is consistent with the findings of [21].

Irrigation Participation (IRRP): It was hypothesized that the relationship between irrigation access and poverty status of the household is negative. As expected the binary logistic model result revealed that, use of irrigation is related negatively with poverty at 1 % significant level. The negative relationship indicates the use of irrigation reduces poverty among households. This can be justified by the fact that in rural area where agriculture depends mainly on rainfall which is highly variable spatially and temporally, sustainable moisture access through irrigation would improve the situation and help to boost agricultural output by allowing intensive agricultural growing two or more crops with in the year. This result is consistent with the findings of [18].

Method of Sawing (MS): Has a positive and significant relationship with probability of being poor at less than 5 % probability level. The possible justification is that those farmers that have used broad cast methods of sawing of the seed input might be due to over reliance by the farmers on old stocks for planting as well as incorrect spacing, which probably results in overcrowding thereby leading to competition for nutrients and consequently low yield. The odds ratio value indicated that other things remain constant; the odds ratio in favor of being poor increase by a factor of 1.06 as the farmers used broadcast method of sawing. This result is consistent with the findings of [22].

Farmers Training (FTR): This variable was hypothesized to influence poverty negatively. The result of the logit model indicated that sample households who had farmers training have less probability of being poor. This is confirmed by the negative coefficient of this variable and indicating that this variable is significantly influencing the poverty status of farmers at 1 % significant level. The possible reason is that training is the major source of information for rural farmers; farmers who have got training have better chance to increase and diversify their production and income and thereby improve their well-being. The odds ratio implies that, *ceteris paribus,* the probability of being poor decreases by a factor of 1.13 as the farmers have participated in training. The finding that farmers training are negatively related to poverty status of the households is consistent with the findings of [23].

Seed Types Used (SDT): This variable was hypothesized to influence poverty negatively. The result of the logit model indicated that sample households who used improved seed for stable food crops have less probability of being poor. This is confirmed by the negative coefficient of this variable and indicating that this variable is significantly influencing the poverty status of farmers at 10 % significant level. The possible reason is that improved seed is the major drivers of cropping technology that increase agricultural production of rural farmers; farmers who used improved seed have better chance to increase and diversify their production and crop and thereby improve their well-being. The odds ratio implies that, *ceteris paribus,* the probability of being poor decreases by a factor of 1.08 as the farmers have used improved seed for stable food crops. The finding that seed types are negatively related to poverty status of the households is consistent with the findings of [22].

Results presented in Table 3 show that the estimated model appears to perform well for the intended matching exercise. The pseudo-R^2 value is 0.3657. A low pseudo-R^2 value shows that poor households do not have many distinct characteristics overall and as such finding a good match between poor and non-poor households becomes simple. Fig. 2 portrays the distribution of the households with respect to the estimated propensity scores (appendix)

Matching Participant and Non-Participant Households: The common support region is the area which contains the minimum and maximum propensity scores of treatment and control group households, respectively. It requires deleting of all observations whose propensity scores is smaller than the minimum and larger than the maximum of treatment and control, respectively [24]. Accordingly, in this study the common support region would lie between 0.0017 and 0.987. In other words, households whose estimated propensity score was less than 0.0017 and larger than 0.987 are not considered for the matching exercise. As a result of this restriction, 44 households (37 non-poor and 7 poor households) were discarded.

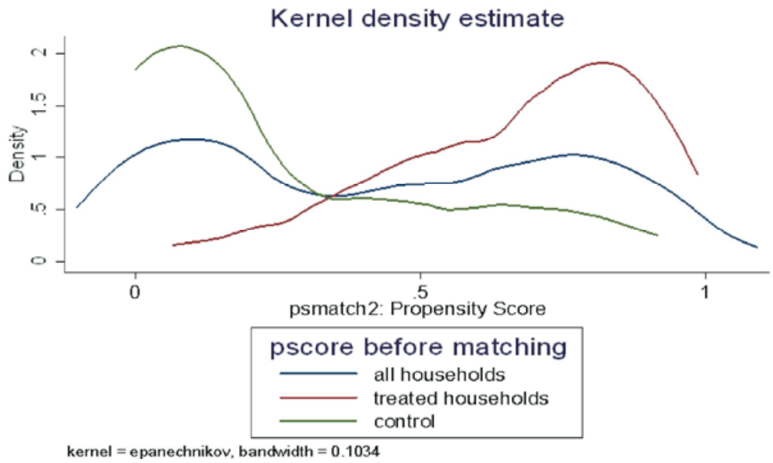

Fig. 2: Kernel density propensity score distribution

Table 3: Logistic regression results for determinants of household level poverty

Variables	Coefficient	SE	Z	P>z
Age of head	.0125194	.0194093	0.65	0.519
Sex of head	-.3162803	.6373435	-0.50	0.620
Education	-.2302698***	.0738973	-3.12	0.002
Seed types	-.8462717*	.4582183	-1.85	0.065
Application of fertilizer	-.9631039	.6959818	-1.38	0.166
Extension	-.0309219*	.0170828	-1.81	0.070
Soil conservation	-.4361939	.4936134	-0.88	0.377
Family size	.3631618**	.1459688	2.49	0.013
Cultivated land	.4741014	.9638235	0.49	0.623
Livestock holding	.1467526	.1061929	1.38	0.167
Irrigation participation	-1.29275***	.4891135	-2.64	0.008
Farmers training	-1.126175***	.4225274	-2.67	0.008
Method of sawing	-1.05824**	.4597823	-2.30	0.021
Soil fertility status	-.5145897	.4199557	-1.23	0.220
Weather road distance	.0013658	.006465	0.21	0.833
Constant	.6837619	1.670444	0.41	0.682
Log likelihood = -78.116635	Prob > chi2 =	0.0000	Number of obs =	180
Pseudo R2 = 0.3657 LR chi2(15) =	90.09			

Source: Own survey result. *, ** and *** mean significant at 10%, 5% and 1% probability levels, respectively.

Table 4: Distribution of estimated propensity scores

Groups	Obs	Mean	Std. Dev.	Min	Max
Total households	180	0.433	0.324	0.0017	0.987
Treatment households	78	0.671	0.221	0.0669	0.987
Control households	102	0.251	0.268	0.0017	0.915

Source: Own calculation result, 2015

Choice of Matching Algorithm: The choice of matching estimator is decided based on the balancing qualities of the estimators. According to [25], the final choice of a matching estimator was guided by different criteria such as equal means test referred to as the balancing test, pseudo-R^2 and matched sample size. Balancing test is a test conducted to know whether there is statistically significant difference in mean values of the two groups of the respondents and preferred when there is no significant difference after being matched. Accordingly, matching estimators were evaluated via matching the poor and non-poor households in common support region. Therefore, a matching estimator having balanced or insignificant mean differences in all explanatory variables, bears a low pseudo-R^2 value and also the one that results in large matched sample size is preferred. In line with the above indicators of matching quality, kernel matching with 0.5 band widths is resulted in a best fit matching estimator.

Table 5: Balancing test for covariates

		Mean		%reduct			
Variable	Sample	Treated	Control	%bias	Bias	t-test	t p>t
_pscore	Unmatched	.67147	.25123	170.9		11.22	0.000
	Matched	.64382	.54862	38.7	77.3	-1.10	0.273
AGEHH	Unmatched	43.141	39.961	28.9		1.93	0.055
	Matched	43.197	41.081	19.2	33.5	-0.30	0.763
SEXHH	Unmatched	.85897	.93137	-23.7		-1.61	0.110
	Matched	.84507	.90239	-18.7	20.8	0.07	0.945
EDU	Unmatched	1.0385	3.5294	-75.8		-4.85	0.000
	Matched	1.0563	1.341	-8.7	88.6	0.49	0.625
SDT	Unmatched	.23077	.4902	-55.8		-3.67	0.000
	Matched	.23944	.29396	-11.7	79.0	0.55	0.584
ACF	Unmatched	.80769	.93137	-37.1		-2.54	0.012
	Matched	.84507	.92261	-18.3	37.3	0.02	0.983
NEXC	Unmatched	12.5	20.549	-64.3		-4.20	0.000
	Matched	13.141	14.806	-13.3	79.3	0.42	0.676
SCON	Unmatched	.67949	.81373	-31.1		-2.09	0.038
	Matched	.69014	.75149	-14.2	54.3	-0.14	0.890
FSIZE	Unmatched	6.2949	5.598	44.0		2.92	0.004
	Matched	6.2254	5.9662	16.4	62.8	0.15	0.878
CULTAREA	Unmatched	.36538	.29596	31.2		2.13	0.034
	Matched	.33979	.33398	2.6	91.6	-0.12	0.901
LSHH	Unmatched	2.8993	3.7722	-37.9		-2.49	0.014
	Matched	2.8861	2.8659	0.9	97.7	-0.10	0.922
IRRP	Unmatched	.30769	.64706	-71.8		-4.76	0.000
	Matched	.33803	.35814	-4.3	94.1	0.57	0.572
FTR	Unmatched	.34615	.64706	-62.7		-4.17	0.000
	Matched	.38028	.37348	1.4	97.7	-0.14	0.889
MSAW	Unmatched	.20513	.53922	-73.2		-4.80	0.000
	Matched	.22535	.27265	-10.4	85.8	0.17	0.866
SFS	Unmatched	.32051	.53922	-45.0		-2.98	0.003
	Matched	.33803	.35179	-2.8	93.7	0.16	0.874
WRDIST	Unmatched	96.987	88.627	24.6		1.64	0.102
	Matched	96.408	95.422	2.9	88.2	-0.14	0.892

Source: survey result, 2015. Definition of the variables is given in the first table (Table 1).

Table 6: Chi-square test for the joint significance of variables

Sample	Pseudo R^2	LR chi^2	$p>chi^2$
Unmatched	0.375	92.44	0.000
Matched	0.017	3.19	1.000

Source: Own survey result, 2015.

Table 7: Average Treatment Effect on the treated (ATT)

Variable	Sample	Treated	Control	Difference	S.E[a].	T-stat
TE	ATT	0.754	0.817	-0.063	0.0179	-3.51***

Source: Own survey result. 2015. ***Mean significant at 1% probability level

Testing the Balance of Propensity Score and Covariates: After choosing the best performing matching algorithm the next step is to check the balancing of propensity score and covariate using different procedures by applying the selected matching algorithm(in our case kernel matching). As indicated earlier, the main purpose of the propensity score estimation is not to obtain a precise prediction of selection into treatment, but rather to balance the distributions of relevant variables in both groups. The mean standardized bias before and after matching are shown in the fifth columns of Appendix Table 5, while column six reports the total bias reduction obtained by the matching procedure.

In the present matching models, the standardized difference in covariate before matching is in the range of 123.7 % and 75.8 % in absolute value. After matching, the remaining standardized difference of covariate for almost all covariates lie between 0.9 % and 19.2 %, which is below the critical level of 20 % suggested by [26]. In all cases, it is evident that sample differences in the unmatched data significantly exceed those in the samples of matched cases. The process of matching thus creates a high degree of covariate balance between the poor and non-poor samples that are ready to use in the estimation procedure. Similarly, t-values in appendix Table 5 shows that before matching almost half of chosen variables exhibited statistically significant differences while after matching all of the covariates are balanced and become statistically significant.

The low pseudo-R^2 and the insignificant likelihood ratio tests support the hypothesis that both groups have the same distribution in covariates X after matching (Table 6). These results clearly show that the matching procedure is able to balance the characteristics in the poor and the matched non-poor groups. We, therefore, used these results to evaluate the impact of poverty status on outcome variable among groups of households having similar observed characteristics. This allows comparing observed outcomes for poor with those of a comparison groups sharing a common support.

Impact Estimate on Households' Technical Efficiency: The estimation result provides supportive evidence of statistically significant effect of the poverty status on farm household's technical efficiency measured in stochastic frontier. After controlling for differences in demographic, location and asset endowment characteristics of the poor and non-poor households, it has been found that, on average, the household poverty status has decreased rate of technical efficiency by 0.063. Stated in other words, the household level poverty has decreased farm household's technical efficiency nearly by 8.4 % (Table 7).

Rosenbaum bounds of sensitivity analysis results were calculated for household level poverty status impacts that are positive and significantly different from zero. Results show that the inference for the effect of the poverty is not changing though the poor and non-poor households have been allowed to differ in their odds of being poor up to 200% ($e^{\tilde{a}} = 3$) in terms of unobserved covariates. Thus, we can conclude that our impact estimates (ATT) are insensitive to unobserved selection bias and are a pure effect of household level poverty.

CONCLUSION AND RECOMMEDATIONS

This study was carried out to examine the impact of households level poverty status on farm productive efficiency and to identify its determinants in Girawa district of eastern parts of Ethiopia. For this study, both primary and secondary data were used. The primary data source was gathered from 180 sample households (78 poor and 102 non-poor) using semi-structured questionnaires. Secondary data were collected from different sources to support primary data. Stochastic production frontier model with Cobb-douglas functional form was used to estimate technical efficiency and propensity score matching was employed in impact evaluation.

The logistic regression result showed that Household level poverty status was significantly influenced by education of household head, family size, extension contact, participation in irrigation, farmers training, methods of sawing and seed types used. In doing so, propensity score matching has resulted in 71 poor households being matched with 65 non-poor households after discarding households whose values were out of common support region. In other words, matched comparisons of different outcome of interest were performed on these households who shared similar pre-participation characteristics except the treatment participation effect. The resulting matches passed on many process of matching quality tests such as t-test, reduction in standard bias and chi-square test.

The impact estimation results then indicate that there are significant differences in technical efficiency between treatment and comparison households, which could be attributable to the household level poverty status. The results revealed that non-poor households have got an improvement of 8.4 % in technical efficiency than poor households. The result of Rosenbaum bounding procedure to check the hidden bias due to unobservable selection shows that the estimated ATTs for significant outcome variable is insensitive which clearly indicate its robustness.

Therefore, it can be concluded that household level poverty is crucial in decreasing the farm households' technical efficiency of farmers which in turn could affect the welfare of the rural farm households. Therefore, government and non government and other stakeholders should encourage the current effort of poverty reduction and agricultural development program which assists to improve their household level efficiency and agricultural production of the country in general.

REFERENCES

1. Currie, J., 2011. Inequality at Birth: Some Causes and Consequences. American Econ. Review, 101(3): 1-22.
2. Moges, A.G., 2013. The Elusive War on Poverty: Public Policy Issues and Concerns, J. Intern. Public Policy, 31: 25-48.
3. United Nations Development Programme(UNDP), 2012. in Ethiopia. Annual Report 2012. Addis Ababa, Ethiopia.
4. MOARD (Ministry of Agriculture and Rural Development), 2009. Food Security Programme 2010-2014. Program Document. Addis Ababa, Ethiopia.
5. WFP (World Food Program) and FAO (Food and Agricultural Organization), 2010. The State of Food Insecurity in the World, Vialedelle Termedi Caracalla, 00153 Rome, Italy.
6. Seid Yimer, 2011. Determinants of food consumption expenditure in Ethiopia. Copenhagen, Denmark.
7. WFP (World Food Program), 2011. Ethiopia Food Security Outlook October, 2011.USAID, Ethiopia.
8. CSA (Central Statistical Agency of Ethiopia), 2010. Statistical Abstract of Ethiopia, Central Statistical Agency, Addis Ababa: Ethiopia.
9. BoARD (Buraeu of Agriculture and Rural Development), 2012. Annual report. Girawa district East Hararghe Zone.
10. Sen, A., 1976. Poverty: An Ordinal Approach to Measurement. Econometrica, 44(2): 219-231
11. Foster, G. and Thorbecke, 1984. A class of Decomposable Poverty Measures. Econometrica, pp: 52.
12. Aigner, D.J., C.A.K. Lovell and P. Schmidt, 1977. Formulation and estimation of stochastic frontier production models. J. Economet, 6: 21-37.
13. Meeusen, W. and J. Van Den Broeck, 1977. Efficiency estimation from cobb–douglas production function with composed error. International Economic Review, 18: 435-444.
14. Aldrich, J.H. and F.D. Nelson, 1984. Liner probability, logit and probit model: quantitative applications in the Social Science. Sera Miller Mc Cun, Sage Pub. Inc, University of Minnesota and Iola, London.
15. Gujarati, D.N., 2003. Basic Econometrics, Second Edition. McGraw Hill, Inc., New York.
16. Lee, W.S., 2006. Propensity score matching and variations on the balancing test: Melbourne Institute of Applied Economic and Social Research, the University of Melbourne.
17. Sianesi, B., 2004. An evaluation of the Swedish system of active labor market programs in Sweden. The r. Econ. and Stat, 86(1): 133-155.
18. Demeke, M., 2008. 'Impact of small scale irrigation schemes on poverty reduction": the case of Bahirdar zuria district in West Gojjam Adminstrative Zone. An MSC thesis presented to the School of Graduate studies of Haramaya University, pp: 121.
19. Bigsten, A. and S. Abebe, 2003. The Dynamics of Poverty in Ethiopia. WIDER Conference on Inequality, Poverty and Human Well-being. Gothenburg, Sweden, 30-31 May 2003.
20. Hilina, 2005. Dimensions and Determinants of Poverty in Pastoral Areas of Eastern Ethiopia: The Case of Shinile Zone Somli National Regional State. An MSC thesis presented to the school of Graduate studies of Alemaya University, pp: 125.
21. Ephraim, W.C. and M.M. Mirriam, 2013. Agricultural Growth and Poverty in Rural Malawi, University of Malawi. Annual Global Development Conference on Inequality, Social Protection and Inclusive Growth June 19- 21, 2013.
22. Dorward, A., E.W. Chirwa, T. Jayne, V. Kelly, D. Boughton and R. Slatter, 2008. Evaluation of the 2006/07 Agricultural Input Supply Programme, Malawi?. Final Report prepared for the Department for International Development and Ministry of Agriculture and Food Security, Malawi.
23. Omoregbee, F.E., A. Ighoro and S.A. Ejembi, 2013. Analysis of the effects of farmers' characteristics on poverty Status in Delta State. Intern. J. Humanities and Social Science Invention, 2(5): 11-16.
24. Caliendo, M. and S. Kopeinig, 2005. Some practical guidance for the implementation of propensity score matching, Discussion Paper No. 1588, University of Cologne.
25. Dehejia, R.H. and S. Wahba, 2002. Propensity score matching methods for non- experimental causal studies. The Review. Econ. and Stat, 84(1): 151-161.
26. Rosembaum, P.R. and D.B. Rubin, 1985. The central role of the propensity score in observational studies for causal effects. Biometrika, 70(1): 41-55.