IMPACT OF SMALL-SCALE IRRIGATION ON FARM HOUSEHOLDS' TECHNICAL EFFICIENCY: THE CASE OF EASTERN OROMIA, ETHIOPIA

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ABSTRACT

This study evaluated the impact of small-scale irrigation 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 200 sample respondents drawn from both participant and non-participant households in 2012 production year. Stochastic production frontier model was used for technical efficiency estimation and Propensity score matching method was applied to analyze the impact of small-scale irrigation on the farm household's technical efficiency with the help of logistic regression function to estimate propensity scores. In matching processes, kernel matching with band width of 0.5 was found to be the best matching algorism. Households that participate in irrigation practice have got an improvement of 8.92% in technical efficiency than those households that were not participating in irrigation practice. Participation in irrigation has a significant, positive 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 positive impact of irrigation on farm household technical efficiency. Therefore, policy makers should give due emphasis to the aforementioned variables to increase participation in irrigation farming and improve the livelihood of rural households.
Keywords: Irrigation, technical efficiency, propensity score matching and stochastic frontier.

INTRODUCTION

Ethiopia is an agrarian country where around 95% of the country's agricultural output is produced by smallholder farmers (MoARD, 2010). The contribution of agriculture to national GDP (43%), employment (85%), export earnings (85%), and supply of industrial raw materials (70%) has remained high (World Bank, 2011). Although the country is endowed with three main resources namely land, water and labor for production, agriculture in the country is mostly small-scale, rainfall dependent, traditional and of subsistent nature with limited access to technology and institutional support services. Yet achieving higher and sustained agricultural productivity growth remains one of the greatest challenges faced by the nation (Belay and Degnet, 2004; Spielman et al., 2010).

Irrigation contributes to livelihood improvement through its direct and indirect benefits. The direct benefits of irrigations are; increased income, food security, and poverty reduction. Irrigation also benefits the poor through higher production, productivity, lower risk of crop failure, and higher and year-round farm and non-farm employment. Irrigation enables smallholders to adopt more diversified cropping patterns, and to switch from low-value staple production to high-value market-oriented production to diversify income base sources. Indirectly, irrigation areas have potential to become 'nuclei of growth' which are attractive for inward investments in other infrastructure and services such as banking to facilitate this growth. This upward growth spiral has taken place in Asia (Hussien and Hanjira , 2004; Asayehegn et al., 2011), with a positive effect on poverty levels. However it is not evident that this is happening at a significant scale in Ethiopia. In this direction the government of Ethiopia is making serious efforts by allocating a fairly large amount of budget for the development of irrigation structures. The manufacturing and or importation of simple and manually operated water lifting devices are being encouraged. However, in economic terms, the incentive for the farmer to use a given technology would ultimately depend on the return or the income he generates from the technology (Baley et al., *2010).*

The total irrigable land potential in Ethiopia is 5,300,000 hectares assuming use of existing

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technologies, including 1,600,000hectares through rain water harvesting and ground water. There are 12 river basins that provide an estimated annual run-off of ~125 billion m^3 water per year, with the potential of irrigating a total of 3,731,222 hectares from surface water. The distribution of the surface water potential breakdown by size is; five percent small scale irrigation, nine percent medium scale irrigation and 86 percent large scale irrigation. The potential available estimates for rain water harvesting range from 40,000 to 800,000 hectares. The area under irrigation development to-date is estimated to be 640,000 hectares for the entire country which is 5% of the potential irrigable (Awulachew et al., 2010).

Agriculture in Ethiopia is heavily dependent on rainfall, which is highly varies both spatially and temporally. Despite Ethiopia's agricultural dominance, a high and growing human population, recurrent droughts and periodic floods, complicated by climate change that has been accompanied by severe soil and landscape degradation in some regions contributed to a situation of national food insecurity (FAO, 2011). This, therefore, calls for different interventions, irrigation being one of the options, which could help with adoptive strategies to cope up with the challenging drought. The dependence of most of the farmers on rain-fed agriculture has made the country's agricultural economy extremely fragile and vulnerable to the impacts of weather and climatic variability often leading to partial or total crop failure, which in turn resulted in food shortages (MoWE, 2011). Therefore, this study was initiated to evaluate the impact of small-scale irrigation in farm households' technical efficiency of Girawa district.

MATERIALS AND METHODS

The study was conducted in Girawa district of Eastern Oromia, Ethiopia. According to CSA (2010), Girawa district has a total population of 263,924 of which 133,780 are male and 130,144 are female and the total area of the district is about 1,109.41 km^2. The district has three agro-ecological zones, as kola, woina dega and dega, of which about 48.9%, 31.1% and 20% are kola, woina dega and dega climate conditions respectively. The district also characterized by different land scapes with the altitude ranging from 1,215 to 3,405 meter above sea level (m.a.s.l). The annual rainfall ranges from 550mm to 1,100 mm with annual temperature ranging from 20 ºC - 27ºC (BoARD, 2012).

Girawa district has a range of water resources suitable for irrigation activities. Traditional irrigation has a long history in the district whereas modern irrigation schemes are not as much. The total irrigable land potential in the district is 6,113 hectares, out of which 4,014ha has surface water potential and the remaining 2,100 hectares estimated to be ground water potential. However the estimated area under irrigation to-date is 3,025.5 of which traditional irrigation accounts for 1,842 hectares, modern irrigation covers 690.5 hectares and the area underground water(in the form of well) is 493 hectares that benefits about 29,332 households.

Both primary and secondary data sources were used. The primary data were collected using semi-structured a questionnaire administered by trained enumerators. Secondary data were collected from relevant sources such as published and unpublished documents from the agricultural and rural development and water resource development offices of the district and other relevant institutions (Care Gara Muleta) for general description to augment primary data.

Methods of Data Analysis

Stochastic frontier has been used to estimate the efficiency levels from the production function and propensity score matching was employed to measure the impact of small scale irrigation on farm households' technical efficiency. The critical assumption behind the model is that the deviation of output from the frontier is due to inefficiency and random shocks. Then following Aigner et al. (1977) the stochastic production frontier (SPF) model is defined as:

$$\ln Y_i = \ln f(x_i, \beta) + \varepsilon_i \quad (1)$$

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 (1) could be decomposed into its respective two components as:

$$\varepsilon_i = V_i - U_i \qquad (2)$$

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

The inefficiency effect U_i is defined as

$$U_i = f(z_i, \delta) \qquad (3)$$

Where: U_i is technical inefficiency Z_i are farm specific factors δ is a vector of parameters
The technical efficiency (TE) of production of i^{th} farm is defined as

$$TE = \exp(-U_i) \qquad (4)$$

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.

Propensity Score Matching Method (PSM)

Propensity score matching (PSM) was used to estimate the impact of small-scale irrigation on farm productive or technical efficiency and is the difference in households' mean technical efficiency with the participation and non-participation in the irrigation farming. A household can either be in the program or outside the program. 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 participating households be if small-scale irrigation 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 D_i equals one if individual i receives treatment and zero otherwise. The impact of a treatment for an individual i, noted Ti, is defined as the difference between the potential outcome in case of treatment and the potential outcome in absence of treatment:

$$T_i = Y_i(1) - Y_i(0) \qquad (5)$$

The fundamental evaluation problem arises because only one of the potential outcomes is observed for each individual i. The unobserved outcome is called counterfactual outcome. Hence, estimating the individual treatment effect i 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:

$$\mathrm{T}^{ATT} = \mathrm{E}[(\mathrm{T})\mathrm{D} = 1] = \mathrm{E}[\mathrm{Y}(1)|\mathrm{D} = 1] - \mathrm{E}[\mathrm{Y}(0)|\mathrm{D} = 1] \qquad (6)$$

The second term - $\mathrm{E}[\mathrm{Y}(0)|\mathrm{D} = 1]$ is not observed, we do observe $\mathrm{E}[\mathrm{Y}(0)|\mathrm{D} = 0]$ thus we can calculate:

$$\mathrm{E}[\mathrm{Y}(1)|\mathrm{D} = 1] - \mathrm{E}[\mathrm{Y}(0)|\mathrm{D} = 0] = \mathrm{T}^{ATT} + \mathrm{E}[\mathrm{Y}(0)|\mathrm{D} = 1] - \mathrm{E}[\mathrm{Y}(0)|\mathrm{D} = 0] \qquad (7)$$

The difference between the left hand side of equation (7) and ATT is the so-called `self-selection bias'. The true parameter T^{ATT} is only identified, if:

$$\mathrm{E}[\mathrm{Y}(0)|\mathrm{D} = 1] - \mathrm{E}[\mathrm{Y}(0)|\mathrm{D} = 0] = 0 \qquad (8)$$

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 participants and non-participants. 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 (Lee, 2006). Finally, using predicted probabilities of participation in the program (i.e. propensity score) match pairs are constructed using alternative methods of matching estimators. The specific steps that would be followed are as follows:

(1) The relevant variables influencing the participation of farm households in irrigation were selected and then the irrigation participation model estimated using logistic regression.

(2) The predicted probability of participation in an irrigation (propensity scores) for irrigating and non-irrigating households are derived.

For any irrigating household, there is non-irrigating 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 irrigation effect as the average difference in households' technical efficiency between each pair of matched households. Thus the mean impact of small-scale irrigation on technical efficiency is given by:

$$\Delta_i = \frac{\sum_{j=1}^{P} Y_{ij1} - \sum_{i=1}^{NP} Y_{ij0}}{P} \qquad (9)$$

Where Y_{j1} is the technical efficiency of irrigating household j, Y_{ijo} is the technical efficiency of the i^{th} non-irrigating household will be matched to the j^{th} irrigating household, P is the total number of irrigators and NP is the total number of non-irrigators.

Table 1. Variables definition and measurement

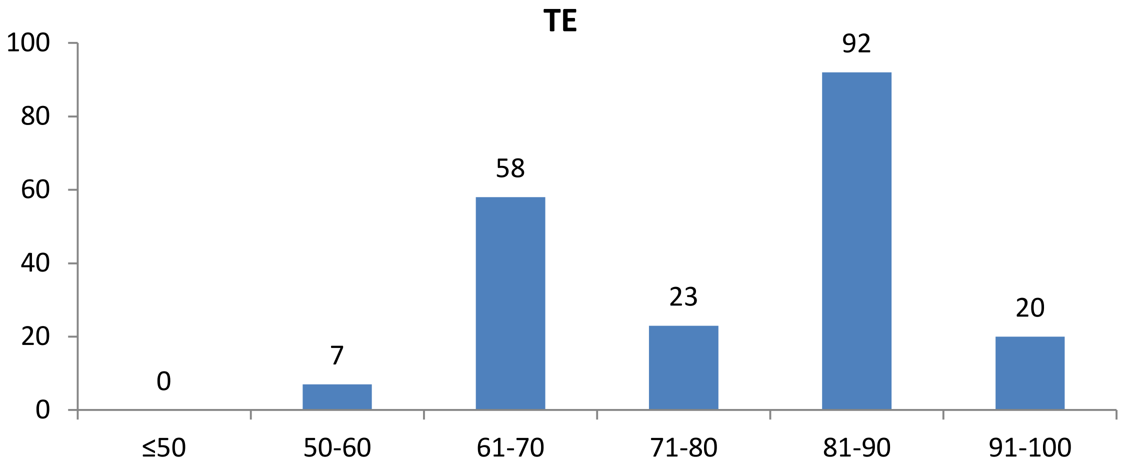
Variables name and code	Type, definition and Measurement
Variables of the model	
Dependent variable:	
Irrigation participation (IRP)	Dummy, participation in irrigation farming 1 if yes 0 if no
Outcome variable:	
Technical efficiency (TE)	Technical efficiency of farm household measured as 1-inefficiency 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
N/off-farm income (NFI)	Continuous, non/off-farm income in birr
Family size (FAS)	Continuous , total size of the household members in numbers
Economic active (EAM)	Continuous , economically active force of the family in male equivalent
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 distance (IRSD)	Continuous , farm distance from irrigation source in minute
Farmers training (FTR)	Dummy, participation in farmers training 1 if yes 0 if no
Transportation (TRM)	Dummy, transportation mode used 1 if animal pack 0 otherwise
Social status (SOS)	Dummy, participation in social status 1 if yes 0 if no
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

RESULTS AND DISCUSSION

Efficiency Scores

The stochastic frontier output indicates that the mean TE was 81.5% with a minimum efficiency score of 53% and a maximum of 95%. The level of TE at which sample households operate is presented in figure (1) in which technical efficiency level is on the y-axis whereas the numbers of sample farmers are on the x-axis. About 10% of farmers in the study area were operating in the range of 91%-100% technical efficiency levels. Whereas about 46% operate in the ranges of 81%-90% and about 29% operate in the range of 71%-80%, about 11.5% farmers operate in the range of 61%-70% levels of technical efficiency and the remaining 3.5% operating below 60% but above 53% technical efficiency levels.

Figure 1. Technical efficiency scores of farm households



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 (ɣ) is large and significantly different from zero, indicating a good fit and the correctness of the specified distributional assumption. Moreover, the estimate of ɣ, which is the ratio of the variance output to variance of error term, was 0.75. This means that more than 75% 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 participant households with non-participant households. The model was estimated with STATA 11.2 computing software using the propensity scores matching algorithm developed by Leuven and Sianesi (2003). In the estimation data from the two groups; namely, participants and non-participants households were pooled such that the dependent variable takes a value 1 if the household was irrigation user (treated) and 0 otherwise. Looking into the estimated coefficients, the results indicate that participation is significantly influenced by age of household head, means of transportation, participation in social organization, non-farm income, and cultivated land area and distance from weather road and distance from irrigation schemes.

Age of the household head: This variable was negatively and significantly related with probability of participation at 5% probability level. The odds ratio of 0.96 implies that, other things being constant, the odds ratio in favor of using irrigation decreases by a factor of 0.96 as age increase by one year. The possible reason was that older farmers are less likely to adopt innovations and thought to be more conservative in implementing modern technologies. This result is consistent with the findings of Hilina (2005).

Distance from irrigation source: this variable has a negative sign and significant at less than 5 % probability level. The odds ratio of 0.96 for irrigation distance implies that, other things being constant, the odds ratio in favor of using irrigation water increases by a factor of 0.96 as irrigation distance decreases by one unit (in minutes). Within the same topography, this could be households who are situated in nearby places do not incur much cost to access the irrigation scheme; therefore, they quickly decide to participate in the scheme. This result is consistent with the findings of Yenetila (2007) and Asayehegn *et al.* (2011).

Means of transportation: it has been found to be negatively related to the probability of being participated at 1 % significant level. The possible justification is that most of the sample households use pack animals as a means of transportation due to lack of transportation facilities and unavailability of good roads. The odds ratio value indicated that other things remain constant; the odds ratio in favor of using irrigation would decrease by a factor of 0.316 if this means of transportation become pack animals. Tracey-White (2005) puts idea of lack of transportation facilities and unavailability of good road hampered the farmers' decision and in turn agricultural productivity

Non/off-farm income: had a Positive and statistically significant relation with probability of participation at less than 10 % probability level. Its odds ratio effect shows that, participation of family members in non/off-farm income increase probability of participation in irrigation farming by 1.001, other variables being constant. The implication of this result is that, irrigation farming like any other business requires financial capital. It also needs chemicals, seeds, fertilizers and in certain instances irrigation pipes and sprinklers. This result is consistent with the findings of Asayehegn *et al.* (2011) and Yenetila (2007)

Cultivated land area: It was found to be positive and statistically significant at 10% probability level with probability of participation. The reason for this could be that fragmentation of cultivated land is a problem of crop diversification for most of the farmers in the study area and they are normally poor so they might employ to off/non-farm activities. The odds ratio implies that if other factors are held constant, the odds ratio in favor of using irrigation water increases by a factor of 7.83 as farm size increase by one unit (ha). This result is consistent to the findings of Hirko (2009) and Baley *et al.* (2010).

Distance to all Weather roads: was found to be negative and statistically significant at 5% probability level with probability of participation. The reason for this could be that, transport operators are in most cases reluctant to reach such areas and some of the farmers fail to get their produce to the market in time. The values of odds ratio also implies that if other factors are held constant, the odds ratio in favor of using irrigation water decreases by a factor of 0.983 as weather road distance increase by one unit (minute). This result is consistent with the findings of Takele (2008).

Social organization: has a positive and significant relationship with probability of participation at less than 1 % probability level. The possible justification is that those farmers that have position in social organization are parts that responsible in managing and resolving irrigation related conflicts, and therefore, it might be due to influential power over others. The odds ratio value indicated that other things remain constant; the odds ratio in favor of using irrigation increase by a factor of 3.836 as the farmers being participated in social organization. This result is consistent with the findings of Yenetila (2007).

Table 2. Logistic regression results for determinants of participation in irrigation farming

Variables	**Coefficient**	**Odds Ratio**	**SE**	**Z**
Constant	4.119**		1.894	2.17
Age	-0.039**	0.962	0.017	-2.32
Sex	1.018	2.766	0.657	1.55
Education	0.03	1.031	0.075	0.4
N/off-farm income	0.00012*	1	0.0001	1.74
Family size	-0.094	0.91	0.122	-0.77
Economic active force	0.031	1.031	0.222	0.14
Cultivated land	2.058*	7.832	1.084	1.9
Livestock holding	0.03	1.03	0.092	0.33
Irrigation distance	-0.042**	0.959	0.021	-2.02
Farmers training	0.144	1.155	0.454	0.32
Extension	0.005	1.005	0.02	0.26
Transportation	-1.151***	0.316	0.452	-2.55
Social status	1.344***	3.836	0.402	3.35
Soil fertility	0.175	1.192	0.496	0.35
Weather road distance	-0.017**	0.983	0.008	-2.18

Number of obs	=	200	Pseudo R2	=	0.278
Prob > chi2	=	0.0001	Log likelihood	=	-100.12
LR chi2 (15)	=	77.01			

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

Results presented in Table 2 show that the estimated model appears to perform well for the intended matching exercise. The pseudo-R^2 value is 0.28. A low pseudo-R^2 value shows that participant households do not have much distinct characteristics overall and as such finding a good match between treated and non-treated households becomes simple. Figure 2 below portrays the distribution of the households with respect to the estimated propensity scores

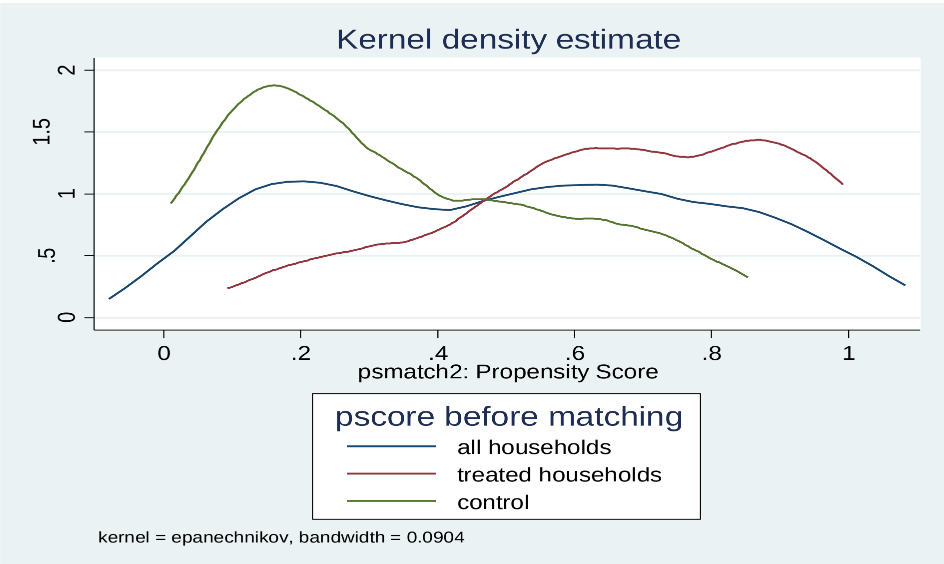


Figure 2. Kernel density of propensity score distribution of sample household

Choice of Matching Algorithm

The choice of matching estimator is decided based on the balancing qualities of the estimators. According to Dehejia and Wahba (2002), 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 participant and nonparticipant 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 3. Performance measures of matching estimators

Matching Estimator	Performance Criteria		
	Balancing test*	Pseudo-R^2	Matched sample size
Nearest Neighbor			
1 neighbor	10	0.232	158
2 neighbor	6	0.169	158
3 neighbor	8	0.132	158
4 neighbor	9	0.128	148
Kernel Matching			
With no band width	9	0.115	158
Band width of 0.1	11	0.104	158
Band width of 0.25	14	0.062	158
Band width of 0.5	15	0.006	158
Caliper			
0.01	12	0.134	125
0.1	10	0.232	158
0.25	10	0.232	158
0.5	10	0.232	158

Source: own calculation result

* Number of explanatory variables with no statistically significant mean differences between the matched groups of program and non-program households.

Matching Participant and non-Participant Households

Accordingly, in this study the common support region would lie between 0.093 and 0.853. In other words, households whose estimated propensity score was less than 0.093 and larger than 0.853 are not considered for the matching exercise. As a result of this restriction, 42 households (30 participant and 12 non-participant households) were discarded following Caliendo and Kopeinig, (2005). Statement of common support region requires deleting of all observations whose propensity scores is smaller than the minimum and larger than the maximum of treatment and control, respectively

Table 4. Distribution of estimated propensity scores of sample household

Groups	Obs	Mean	Std. Dev.	Min	Max
Total households	200	0.500	0.290	0.010	0.992
Treatment households	100	0.664	0.246	0.093	0.992
Control households	100	0.336	0.232	0.010	0.853

Source: Own calculation result, 2013.

Testing the Balance of Propensity Score and Covariates

In the present matching models, the standardized difference in covariate before matching is in the range of 4.7% and 79.3% in absolute value. After matching, the remaining standardized difference of covariate for almost all covariates lie between 1.8% and 19.2%, which is below the critical level of 20% suggested by Rosenbaum and Rubin (1985). 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 participant and non-participant samples that are ready to use in the estimation procedure. Similarly, t-values in 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.

Table 5. Balancing test for covariates for the sample household

Variables	Sample	Mean		%reduction		t-test	
		Treated	Control	%bias	Bias	T	p>t
_pscore	Unmatched	0.664	0.336	137.6		9.73	0.001
	Matched	0.547	0.459	36.8	73.3	0.42	0.675
AGE	Unmatched	39.210	43.97	-41.9		-2.96	0.003
	Matched	40.257	42.168	-16.8	59.9	-0.33	0.743
SEX	Unmatched	0.940	0.860	26.8		1.89	0.060
	Matched	0.914	0.933	-6.4	76.2	-0.37	0.713
EDU	Unmatched	3.360	1.510	53.1		3.75	0.001
	Matched	2.800	2.130	19.2	63.8	0.48	0.634
NFI	Unmatched	1694	404	34.2		2.42	0.017
	Matched	781	504.830	7.3	78.6	-0.27	0.786
FAS	Unmatched	5.770	5.880	-6.6		-0.47	0.639
	Matched	5.971	5.857	6.9	-4.4	0.14	0.892
EAM	Unmatched	3.164	2.667	50.8		3.59	0.001
	Matched	3.006	2.843	16.7	67.2	0.25	0.806
CULA	Unmatched	0.324	0.334	-4.7		-0.33	0.741
	Matched	0.304	0.313	-4.3	8.5	0.04	0.965
LSH	Unmatched	4.296	2.987	55.8		3.95	0.001
	Matched	3.793	3.445	14.9	73.4	0.32	0.746
IRSD	Unmatched	20.970	29.780	-79.3		-5.60	0.001
	Matched	24.657	26.591	-17.4	78	0.12	0.908
FTR	Unmatched	0.740	0.500	50.8		3.59	0.001
	Matched	0.657	0.592	13.8	72.8	0.21	0.832
NEXC	Unmatched	20.490	13.670	54.2		3.83	0.001
	Matched	17.214	15.267	15.5	71.4	0.27	0.788
TRM	Unmatched	1.710	1.830	-28.7		-2.03	0.044
	Matched	1.771	1.779	-1.8	93.6	-0.11	0.915
SOS	Unmatched	0.490	0.200	63.7		4.51	0.001
	Matched	0.357	0.286	15.7	75.3	0.14	0.889
SFS	Unmatched	0.750	0.520	49		3.46	0.001
	Matched	0.700	0.671	6.5	86.7	0.26	0.796
WRD	Unmatched	80.100	104.550	-78.3		-5.54	0.001
	Matched	87	92.680	-18.2	76.8	-0.37	0.711

Source: Own survey result, 2013.The definition of the above variables are given in the first table (Table 1).

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 participant and the matched non-participant groups. We, therefore, used these results to evaluate the impact of small-scale irrigation scheme on outcome variable among groups of households having similar observed characteristics. This allows comparing observed outcomes for participants with those of a comparison groups sharing a common support.

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

Sample	Pseudo R^2	LR chi^2	p>chi^2
Unmatched	0.286	79.290	0.001
Matched	0.006	1.290	1.000

Source: Own survey result, 2013.

Impact Estimate on Households' Technical Efficiency

The estimation result provides supportive evidence of statistically significant effect of the small-scale irrigation on household technical efficiency measured in stochastic frontier. After controlling for pre-participation differences in demographic, location and asset endowment characteristics of the irrigation user and non-user households, it has been found that, on average, the participant household has increased rate of technical efficiency by 0.0694. Stated in other words, the irrigation has increased farm households technical efficiency nearly by 8.92 %(Table 7).

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

variable	Sample	Treated	Control	Difference	S.E[a].	T-stat
TE	ATT	0.854	0.784	0.069	0.013	5.180***

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

Rosenbaum bounds of sensitivity analysis results were calculated for small-scale irrigation impacts that are positive and significantly different from zero. Results show that the inference for the effect of the irrigation is not changing though the participants and non-participant households have been allowed to differ in their odds of being treated up to 200% (e^{γ} = 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 irrigation.

CONCLUSION AND RECOMMEDATION

The impact estimation results indicated that there are significant differences in technical efficiency between treatment and comparison households, which could be attributable to the participation in small-scale irrigation. The results revealed that households that participate in irrigation practice have got an improvement of 8.92% in technical efficiency than those households that were not participated in irrigation practice. 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 participation in irrigation is crucial in increasing the farm households' technical efficiency of farmers which in turn could improve the welfare of the rural farm households. Therefore, government and non-government and other stakeholders should encourage the current effort of irrigation development program which assists to improve their household level efficiency and agricultural production of the country in general.

REFERENCES

Aigner DJ, Lovell CAK, Schmidt P, 1977. Formulation and estimation of stochastic frontier production models. *Journal of Econometrics*, 6: 21 – 37.

Asayehegn K, Yirga C, Rajan S, 2011. Effect of small-scale irrigation on the income of rural farm households: The case of Laelay Maichew district, Central Tigray, Ethiopia. *Journal of Stored Products and Postharvest Research*, 2(10): 208 – 215.

Awulachew SB, Lambisso R, Asfaw G, Yilma AD, Moges SA, 2010. Characterizing, assessment of performance and causes of underperformance of irrigation in Ethiopia. *Ethiopian Journal of Development Research*, (In press).

Belay K, and Abebaw D, 2004. Challenges facing agricultural extension agents: A case study from South-western Ethiopia. African Development Bank, Blackwell Publishing Ltd, Oxford, UK. Research Working Paper 3494. The World Bank: Washington DC.

Belay K, Samson E, Belayneh B, Degeye G, Demeksa T, Estifanos W, Zelalem L, Addisu D, Tucker J and Zemede A. 2010. Income diversification through improved irrigation in Ethiopia: impacts, constraints and prospects for poverty reduction evidence from East Harerghe Zone, Oromia Region, Ethiopia

BoARD (Buraeu of Agriculture and Rural Development), 2012. Annual report. Girawa district East Hararghe Zone.

Caliendo M, Kopeinig S, 2005. Some practical guidance for the implementation of propensity score matching, Discussion Paper No. 1588, University of Cologne

CSA (Central Statistical Agency of Ethiopia), 2010. Statistical Abstract of Ethiopia, Central Statistical Agency, Addis Ababa: Ethiopia.

Dehejia R H, Wahba S, 2002. Propensity score matching methods for non- experimental causal studies. *The Review of Economics and Statistics*, 84(1): 151–161.

FAO (Food and Agriculture Organization), 2011. Independent evaluation of the programmes and cooperation of the food and agriculture organization of the united nations in Ethiopia

Hirko W, 2009. Agricultural extension and technology adoption in Bako Tibe district of Oromia Region. An M.Sc. Thesis Presented to the School of Graduate Studies of Addis Ababa University.99p.

Hilina M, 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. 125p.

Hussein I, Hanjira MA, 2004. Irrigation and poverty alleviation: Review of the Empirical Evidence. *Irrigation and Drainage*, 53: 1-15.

Lee WS, 2006. Propensity score matching and variations on the balancing test: Melbourne Institute of Applied Economic and Social Research, the University of Melbourne.

Meeusen W, van den Broeck J, 1977. Efficiency estimation from cobb–douglas production function with composed error. *International Economic Review*, 18:435–444.

MoWE, (Ministry of Water and Energy), 2011. Water and development quarterly bulletin 5. MWR: Addis Ababa.

MoARD (Ministry of Agriculture and Rural Development), 2010. Ethiopia's agriculture sector policy and investment framework: Ten Year Road Map (2010-2020).

Rosenbaum PR, Rubin DB, 1985. The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70(1): 41–55.

Sianesi B, 2003. An evaluation of the Swedish system of active labor market programs in Sweden. *The Review of Economics and Statistics*, 86(1):133-155.

Spielman D, Byerlee D, Avid J, Alemu D, Kelemework D, 2010. Policies to promote cereal intensification in Ethiopia: The search for appropriate public and private roles. *Food Policy*, 35: 185-194.

Takele M, 2008. Small-scale irrigation scheme utilization and farmers' willingness to pay for irrigation water: The case of Bosha-01 irrigation scheme in Central Oromia. An M.Sc. Thesis Presented to the School of Graduate Studies of Haramaya University.154p.

Tracey-White J, 2005. Rural – Urban linkages: An infrastructure identification and survey guide. Agricultural services Bulletin 161. FAO, Rome, Italy.

World Bank, 2011. Ethiopian agricultural growth project. Project appraisal document. Addis Ababa: Ethiopia.

Yenetila A, 2007. Factors influencing the use of irrigation water at Gedeb irrigation scheme, Machakel Woreda, East Gojam Zone. M.Sc. Thesis Presented to the School of Graduate Studies of Haramaya University.114p.