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Impact of off-farm activities on technical efficiency: evidence from maize producers of eastern Ethiopia

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Abstract

This article analyzes the impact of participation in off-farm activities on technical efficiency of maize production in eastern Ethiopia. We combined propensity score matching with a stochastic production frontier model that corrects sample selection bias resulting from unobserved factors that potentially affect both households' decision to participate in off-farm activities and technical efficiency scores that most previous studies do not account for. The probit model results indicate that sex of the household head, literacy of the spouse, agricultural cooperative membership, family size, and access to market information had significant effect on farmers' participation in off-farm activities. In the meantime, it was found that farmers who participated in off-farm activities have a significant technical efficiency gain compared with their non-participant counterparts.

Keywords: Off-farm, Technical efficiency, Stochastic frontiers, PSM, Selection bias

Background

The vast majority of poor households living in the developing areas rely on agriculture for their food, income, and livelihood (Minten and Barrett 2008; Dethier and Effenberger 2012; Larsen and Lilleør 2014). Hence, the growth and development of the agriculture sector is considered to be the main pathway out of poverty and food insecurity and to have a pro-poor economic development in those areas (Diao et al. 2010; Kassie et al. 2013; Collier and Dercon 2014; Dawson et al. 2016).

The agriculture sector is the mainstay of the Ethiopian economy as it accounts for nearly 45% of GDP and employs about 85% of labor forces (Dercon et al. 2012). Despite its strategic role for the country's economy, the sector is dominated by subsistence and semi-subsistence farming system (Alemu et al. 2006; Anley et al. 2007; Francesconi and Heerink 2011; Teshome et al. 2016). Smallholders own on average less than 1 ha land per holder account for about 95% of land covered by crops on which they produce about 90% of agricultural outputs in the country (CSA, 2014). Moreover, the ever-increasing population of the country is reducing the farm sizes rapidly (Bezu and Holden 2014; Headey et al. 2014). This population growth coupled with a legal restriction on agricultural land market hindered farm expansion that made farms smaller and hiring labor superfluous, which created a significant level of unemployment in the rural part of the country (Bezu and Holden 2014). Hence, there has to be a mechanism to support the livelihood of the agricultural communities and absorb the excess labor in the rural economy. As emphasized by Lanjouw and Lanjouw (2001), the main options available for the unemployed rural community in this scenario are either migration to urban areas or engagement in off-farm activities in rural areas. Actually, smallholder farmers in developing countries rarely rely on a full-time agricultural work; rather, they often maintain a portfolio of activities in which off-farm activities are an important contributions to their well-being (Barrett et al. 2001; Foster and Rosenzweig 2004; Smith et al. 2005; Wouterse and Taylor 2008; Lanjouw and Murgai 2009; Zezza et al. 2009; Davis et al. 2010; Haggblade et al. 2010).

Empirical findings consistently show that incomes generated from off-farm activities ease the burden on agriculture as it enables households to have better incomes. Hence, they enhance food security as they manage food consumption fluctuations better than a household without such an activity (de Janvry and Sadoulet 2001; Ruben 2001; Barrett et al. 2001; Babatunde and Qaim 2010; Haggblade et al. 2010; Owusu et al. 2011; Bezu et al. 2012; Hoang et al. 2014; Mishra et al. 2015). Especially when the agricultural production fails due to climate change, pest, deceases, or other shocks, off-farm employment provides a risk management tool to reduce the income variability and will fill the gap that will be created between farm income and household consumption El-Osta et al (2008). By engaging in off-farm employment, farmers also become self-insured (Alasia et al. 2009) and they may invest in a risky but high-returning agricultural business.

Off-farm income can also enhance agricultural production by relaxing liquidity and credit constraints to purchase productivity enhancing agricultural technologies such as improved seed, fertilizer, machineries, and hiring labor (Ruben 2001; Lamb 2003; Matshe and Young 2004; Kilic et al. 2009; Oseni and Winter 2009; Anriquez and Daidone 2010). This is particularly true in developing countries where farmers are facing credit constraints (Stampini and Davis 2009).

Though there are ample empirical evidences on the impact of off-farm income on adoption of productivity-enhancing agricultural inputs, its impact on farm efficiency is mixed. For example, Mochebelele and Winter-Nelson (2000), Tijani (2006), Haji (2007), Pfeiffer et al. (2009), Bojnec and Ferto (2013), and Babatunde (2013) found a positive significant impact of off-farm income on farm efficiency. There are also cases (such as Goodwin and Mishra (2004), Chang and Wen (2011), and Kilic et al. (2009)) in which participation in off-farm activities has an adverse effect on the agriculture. They argued that if the income from the off-farm activities is more attractive than the agriculture, farmers might give less attention for the agriculture and they might devote more family labor and time for off-farm activities. There are also studies (such as Chavas et al. 2005, Bozoğlu and Ceyhan 2007; Lien et al. 2010, Feng et al. 2010; Chang and Wen 2011) that found no significant association between the two variables. Table 1 summarizes some of the empirical works that examined the role of off-farm activities on technical efficiency.

As it can be observed from Table 1, the findings are not consistent. This disagreement between empirical results could be due to the fact that the role of off-farm activities on farm productivity is different from context to context. The other important thing learnt from the above empirical works is that selectivity bias is not addressed in most of the cases; therefore, the reported impact and associated technical efficiency (TE) scores are likely to be biased (Bravo-Ureta et al. 2012; González-Flores et al.

Table 1 Summary of the studies which examined the relationship between off-farm income and technical efficiency

Authors	Country	Type of crop	Estimation technique	Relationship between TE and off-farm activities
Tijani 2006	Nigeria	Rice	SFA	+
Haji 2007	Ethiopia	Vegetable	DEA	+
Pfeiffer et al. 2009	Mexico	Agriculture	Combined SFA with instrumental variable	+
Kilic et al. 2009	Albania	Agriculture	Combined instrumental variables, Tobit, and SFA	No systematic relationship
Bozoğlu and Ceyhan 2007	Turkey	Vegetable	SFA	No systematic relationship
Lien et al. 2010	Norway	Agriculture	SFA	No systematic relationship
Feng et al. 2010	China	Rice	Instrumental variable	No systematic relationship
Bojnec and Fertő 2013	Slovenia	Agriculture	SFA	+
Chang and Wen 2011	Taiwan	Rice	SFA	–
Lien et al. 2010	Norwegian	Grain	SFA	No systematic relationship
Yang et al. 2016	China	Agriculture	SFA	No systematic relationship
Zhang et al. 2016	China	Agriculture	Combined SFA with instrumental variable	+
Abebe 2014	Ethiopia	Agriculture	Combined SFA with instrumental variable	+
Chavas et al. 2005	Gambia	Agriculture	Combined DEA with Tobit	No systematic relationship
Babatunde 2013	Nigeria	Agriculture	Combined SFA with instrumental variable	No systematic relationship
Larochelle and Alwang 2013	Bolivian	Potato	SFA	–
Goodwin and Mishra 2004	USA	Agriculture	Simultaneous equation	–

2014). Other studies like Abebe (2014) relied on a single frontier equation for both those who participated in off-farm activities and non-participants without giving due attention for potential differences between the two groups.

Hence, unlike previous works, this paper aims to estimate the impact of participation in off-farm activities on TE of smallholder maize producers of eastern Ethiopia by combining propensity score matching with the Greene (2010) model to control for both observed and unobserved heterogeneities.

Therefore, the results of this study adds to the existing literature (e.g., Abate et al. 2016; Barrett et al. 2001; Beyene 2008; Feng et al. 2010) through identifying the factors affecting the participation in off-farm activities. As the study evaluates the impact of participation in off-farm activities on the TE of maize producers, the study indicates the relationship between off-farm and on-farm activities and indicates whether there exists trade-off or complementarity between the two income-generating activities.

Methods

Econometric framework and estimation strategies

Estimation of technical efficiency

Technical efficiency (TE) refers to the ability of a decision-making unit (DMU) to produce the maximum feasible output from a given bundle of inputs (Farrell 1957; Xiaogang et al. 2005). Any deviation from this maximal output is considered as technical inefficiency (Coelli et al. 2005). TE can be measured by using either parametric or non-parametric approaches (Simar and Wilson 2015). The main difference between the two approaches is that the non-parametric approach assumes that the DMU has full control on the production process and all deviations from the frontier are associated with inefficiency. The parametric approach on the other hand distinguishes inefficiency from deviations that are caused by factors beyond the control of the DMU. Given the intrinsic variability of agricultural production due to factors like climatic change, plant pathology, and insect and pests, the assumption that all deviations from the frontier are associated with inefficiency, as assumed in the non-parametric approaches, is difficult to accept (Bauman et al. 2016). Hence, this study has adopted a parametric approach, specifically stochastic frontier analysis (SFA). Studies that utilized SFA to measure TE include Binam et al. 2004; Balcombe et al. 2007; Bozoğlu and Ceyhan 2007; Gedara et al. 2012; and Xu et al. 2015. The stochastic production frontier (SPF) function was independently proposed by Aigner et al. 1977 and Meeusen and Von den Broeck 1977). This model can be expressed in the following form.

$$Y_i = F(X_i;\beta)\ \exp(V_i - U_i) \quad I = 1, 2, 3 \ldots n \tag{1}$$

where Y_i is the observed maize production of the ith farmer, X_i is a vector of inputs used by the ith farmer, β is a vector of unknown parameters, V_i is the stochastic effect beyond the farmer's control, measurement errors, and other statistical noises which are assumed to be $N(0, \sigma_v^2)$and independent of the U_i which is a non-negative random variable assumed to account for technical inefficiency in production. As SFA requires prior specification of functional form of the production function, a log-likelihood ratio (LR) test was conducted to choose between the Cobb-Douglas and translog functional forms using the following formula given by (Coelli 1998).

$$LR = -2 \times (\ \ln L_{TL} - (\ \ln L_{CB})) \tag{2}$$

where $\ln L_{TL}$ and $\ln L_{CB}$ represent the log-likelihood function values obtained from the translog and the Cobb-Douglas production function, respectively. The LR[1] test result indicated that Cobb-Douglas production function is a more appropriate functional form for this study than the alternative translog production function. Several studies have utilized Cobb-Douglas production including Bozoğlu and Ceyhan 2007; Pfeiffer et al. 2009, and González-Flores et al. 2014.

Impact evaluation and efficiency estimation

Following the works of González-Flores et al. (2014) and Bravo-Ureta et al. (2012), we measured the impact of participating in off-farm activities on TE by combining propensity score matching (PSM) technique with the Greene (2010) model to correct biases from observed characteristics and for selectivity bias arising from unobserved variables, respectively. The first step in PSM is to predict the propensity score which is equal to the probability of receiving treatment, considering both treated and non-treated groups based on a given set of predetermined covariates, using a binary choice model (Cameron and Trivedi 2005). This step is followed by imposing the common support region, which is the area within the minimum and maximum propensity scores of treated and comparison groups, respectively (Caliendo and Kopeinig 2008). Several recent studies have applied PSM within the impact evaluation literature (e.g., Becerril and Abdulai 2010; Mishra et al. 2016; Abate et al. 2016; Chagwiza et al. 2016).

Nevertheless, PSM works only if selection is solely based on observable characteristics and potential outcomes are independent of treatment assignment. If unobservable characteristics affect the outcome variable, PSM is not the appropriate technique (Takahashi and Barrett 2013; Khonje et al. 2015). Hence, to handle biases from the unobserved characteristics, we used the model introduced by Greene (2010). According to this model, the sample selection and SPF models, along with their error structures, can be expressed as follows:

$$\begin{array}{ll} \text{Sample selection}: & F_i = 1[\alpha' \mathbf{z}_i + \omega_i > 0], \omega_i \sim N\,[0,1] \\ \text{SPF}: & y_i \ = \beta' \mathbf{x}_i + \varepsilon_i, \varepsilon_i \sim N\,\left[0, \sigma_\varepsilon^2\right] \\ & (y_i, \mathbf{x}_i) \text{ observed only when } F_\mathrm{i} = 1 \end{array} \tag{4}$$

$$\begin{array}{rl} \text{Error structure}: \varepsilon_i = & \nu_i - u_i \\ u_i = & |\sigma_u U_i| = \sigma_u |U_i|, \ \text{ where } \ U_i \sim N[0,1] \\ \nu_i = & \sigma_\nu V_i, \ \text{ where } \ V_i \sim N[0,1] \\ (\omega_i, \nu_i) \sim & N_2\,[0,1), \ \ \left(1, \rho\sigma_\nu, \sigma_\nu^2\right)] \end{array}$$

where F is a binary variable equal to one for participants on off-farm activities and zero for control, y is amount of maize produced, $\mathbf{z}$ is a vector of covariates included in the sample selection equation, and $\mathbf{x}$ is a vector of inputs in the production frontier; α and β are parameters to be estimated while ε_i denotes the characters in the error structure corresponding to the typical characterization of a stochastic frontier model and ρ captures the presence or absence of selectivity bias.

Study areas and sampling technique

This study is undertaken in the eastern part of Ethiopia specifically in the East Hararghe Zone of Oromia National Regional State. The Zone is classified into three major climatic categories namely, temperate tropical highlands, semi-temperate, and semi-arid. This wide range of agroecology allowed the area to produce different types of products including cereals, pulses, oilseed, vegetables, fruits, and cash crops such as coffee and *chat*. Among the cereal crops, maize is the dominant crop as both the size of land allocated to it and the number of households producing it was the highest compared to the other cereal crops cultivated in the zone (CSA 2014). From the selected zone, two districts namely Haramaya and Girawa were selected for this study based on their extent of maize production. Next, four rural *kebeles*[2] were randomly picked from both districts. Finally, 355 households (76 (which is equivalent to 21.41%) participants and 279 non-participants) were selected, proportional to the size of maize-producing farmers using simple random sampling technique with replacement.[3] Then, the primary data were collected using structured questionnaires administered by trained enumerators from February to March 2016.

Results and discussions

Descriptive statistics

Before embarking to the econometrics results, it is important to give brief information regarding the sample respondents and variables used in the econometrics model. Accordingly, Table 2 presents descriptive statistics of the variables[4] used for this study. As it is indicated in the table, 21% of the respondents have been participating in off-farm income-generating activities, which include selling firewood, renting assets, trading, and remittance. The mean age of the sample respondents is about 38 years. Nearly 90% of the sample households are headed by male. Concerning their educational status, 63.1% of the respondents and 24.2% of the spouses are literate. The mean family size of the respondents measured by adult equivalent (AE)[5] is 5.36. As far as the asset ownership is concerned, on average, they have 2.79 quxi[6] of land and 3.01 units of livestock measured by tropical livestock units (TLUs). The sample respondents, on average, travel about 35 min to reach the nearest market, and about 22% of respondents are members of agricultural cooperatives. The *t* test indicated that there is a statistical mean difference between off-farm participant and non-participant households in terms of educational status of the household head and the spouse, sex of the household head, and agricultural cooperative membership. Table 2 also indicated the input and output variables used to estimate the stochastic frontier production functions.

Table 2 Descriptive statistics

Variable	Pooled ($n = 355$)		Participants ($n = 76$)		Non-participants ($n = 279$)	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
District	1.437	0.497	1.487	0.503	1.423	0.495
Off_farm	0.214	0.411	1.00	0.00	–	–
Education_HH	0.631*	0.483	0.724	0.450	0.606	0.490
Education_spouse	0.242**	0.429	0.368	0.486	0.208	0.407
Age_HH	37.930	8.804	37.579	8.341	38.025	8.938
Sex_HH	0.896*	0.306	0.829	0.379	0.914	0.281
Coop	0.217***	0.413	0.382	0.489	0.172	0.378
Land owned	2.786	2.228	2.938	1.902	2.744	2.311
Distance_mkt	34.640	21.716	33.355	20.864	34.990	21.966
Social_role	0.31	0.463	0.368	0.486	0.294	0.456
Market_info	0.487***	0.027	0.711	0.052	0.427	0.03
Livestock	3.010	1.871	2.987	2.017	3.017	1.833
Family AE	5.361	1.802	5.586	1.940	5.300	1.762
Value_yield	5467.268***	3886.116	7091.053	4380.921	5024.946	3624.290
Value_fertilizer	468.069**	434.974	590.155	524.878	434.812	401.768
Value_seed	164.193***	116.374	207.586	133.923	152.373	108.404
Value_labor	1793.965****	1091.748	2266.322	1163.708	1665.295	1036.727
Land_maize	2.066***	1.447	2.618	1.697	1.916	1.335

*Significance at 10% level
**Significance at 5% level
***Significance at 1% level

Econometrics results

Determinants of participation in off-farm activities

This sub-section presents the result of the probit regression model, which was used to estimate the propensity score for matching the off-farm participants with non-participants. The model sufficiently fitted the data at one significant level (LR χ^2 (12) = 42.34; Prob > χ^2 = 0.00). The result, presented in Table 3, reveals that sex of the household head, literacy of the spouse, agricultural cooperative membership, family size, and access to market information have significant effect on farmers' participation in off-farm activities. Specifically, the result implies that being a female-headed household increases the probability of participation in off-farm activities.

Female-headed households are more likely to participate in off-farm activities than the male-headed counterparts because female-headed families engage in off-farm activities to offset their relative lower farm income compared to male-headed ones. However, this is against the result found by Beyene (2008).

Literacy of the spouse influences the participation in off-farm activities positively. Educated people have lower incentive to obtain income from own farming because educated people often have access to higher paying off-farm jobs (Lanjouw 2001; Satriawan and Swinton 2007) compared to uneducated ones. Therefore, the educated spouse would engage in higher earning off-farm activities so as to improve the livelihood of their family.

Agricultural cooperative membership has a positive influence on farmers' participation in off-farm activities. When a farmer becomes a cooperative member, he/she can get relatively more information from his/her fellows about the available off-farm works compared to non-members. Hence, his/her participation in off-farm activities would be more likely than the non-members.

Family size measured in terms of adult equivalent is an indicator of labor availability, and it has a positive influence to participate in off-farm activities. This is consistent with the results by Tassew et al. (2000) in such a way that large family size increases the households' participation in off-farm works since a larger family size requires

Table 3 Result of the Probit model of factors determining participation in off-farm activities

Off_farm	Coef.	Std. err.
Education _HH	0.055	0.295
Education_spouse	0.580*	0.326
District	0.208	0.342
Age_HH	– 0.014	0.018
Sex_HH	– 0.740*	0.424
coop	1.032***	0.327
Social_role	– 0.318	0.336
Landowned	0.003	0.061
Market_info	1.098***	0.301
Distance_mkt	– 0.001	0.007
Livestock	– 0.120	0.089
Family AE	0.192**	0.093
Cons	– 2.084**	0.836

*Significance at 10% level
**Significance at 5% level
***Significance at 1% level

relatively higher marginal income. This means that participation in off-farm activities can maintain the burden of large family size. Thus, households with large family size would have abundant labor and send some of the family members to off-farm activities.

Access to market information has a positive influence on farmers' participation in off-farm activities. Access to information about the availability of high-earning off-farm activities would give an opportunity to participate in those activities.

After estimating the probit model, we predicted the propensity scores and the common support region. The values of propensity scores of both treatment and comparison groups are found between 0.04806759 and 0.71167307. This leads to the total matched sample size of 344 respondents of whom 76 are participants and 268 are non-participants. Figure 1 shows the density estimates of the distribution of propensity scores for each group, along with the areas with and without common support.

Estimation of the SPF and measuring technical efficiency

Once the matched samples are constructed, the next step is to determine if the conventional SPF should be run for the whole sample or if separate frontiers are necessary for participant and non-participant farmers. To determine this, we conducted a LR test based on following specification:

$$LR = -2 \times (\ln L_P - (\ln L_d + \ln L_C)) \tag{5}$$

where $\ln L_P$, $\ln L_d$, and $\ln L_C$ represent the log-likelihood function values obtained from the pooled model, the participant, and the non-participant subsamples, respectively. Hence, we first estimated a SPF with pooled data by including a binary variable, *Off_farm*, as a regressor, which indicates whether the household participates or not in off-farm activities, and two separate SPF models, one for households participating in off-farm activities and the other for non- participants. The pooled SPF models indicated that there is no significant difference between the two groups of farmers in their TE score as the variable *Off_farm* are insignificant under both matched and unmatched SPF. However, this result is rejected by the LR test, which favors separate frontiers indicating the two groups have different production function. Then, to correct for the possible bias from observable heterogeneities, we re-estimated the above three frontiers (pooled, participants, and non-participants) using the matched data set.[7] However, results of LR test again supported separate frontiers for each groups. Finally, to correct for the possible bias from unobservables, two separate SPF models are re-estimated using Greene's (2010) selection

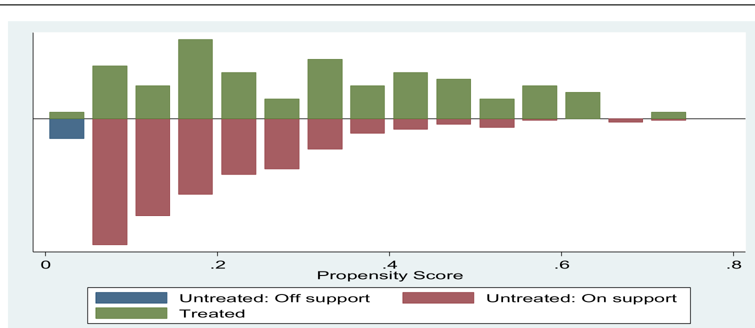

Fig. 1 The distribution of propensity scores for treated and untreated groups

Table 4 Conventional and selection SPF based on unmatched observation

	Conventional SPF						Selection			
	Pooled		Participant		Non-participant		Participant		Non-participant	
	Coef	se	Coef	se	Coef	se	Coef	se	Coef	se
Cons	5.568***	0.756	5.011***	0.000	5.615***	0.917	5.92418***	0.4524	4.96669***	0.667
Value_fertilizer	0.003***	0.001	0.003***	0.000	0.003***	0.001	.00267***	0.0003	.00406***	0.001
Value_seed	0.558***	0.173	0.579***	0.000	0.572***	0.212	.40810***	0.0964	.72837***	0.152
Value_labor	0.012	0.023	0.076***	0.000	− 0.003	0.030	.05214***	0.0098	− 0.00711	0.029
Land_maize	0.410**	0.174	0.315***	0.000	0.415*	0.212	.49672***	0.1002	.25527*	0.152
Off_farm	− 0.002	0.015								
Sigma	0.091***	0.007	0.033***	0.005	0.106***	0.010				
Sigma(u)							.21502***	0.0033	.42371***	0.014
Sigma(v)							.01373**	0.0059	.04182***	0.012
Rho(w,v)							.96882***	0.0905	− 0.40401	1.579

*Significance at 10% level
**Significance at 5% level
***Significance at 1% level

correction framework. The results of the SPF models are presented in Table 4 for the unmatched samples and in Table 5 for the matched samples.

The estimated value of sigma are significant at less than 1% probability level for all frontier functions indicating the conventional average production function is not an adequate representation of the data. The coefficients of rho, which indicate the presence of selection bias, are also significant in all selection frontiers except for the non-participants in the case of the unmatched data. This result suggests the presence of selection bias, thus lending support to the use of a sample selection framework to estimate separate SPFs for the beneficiaries and control groups.

As it is presented in the tables, the signs of all significant variables are positive as we expected. However, different input-output responses are found between these two groups of farmers. The result indicates that expenditure on inorganic fertilizer and seed are significant in all frontiers, while labor is found to be insignificant for non-participant respondents, which indicate that the amount of labor has no impact in

Table 5 Conventional and selection SPF based on matched observations

	Conventional SPF						Selection			
	Pooled		Participant		Non-participant		Participant		Non-participant	
	Coef	se	Coef	se	Coef	se	Coef	se	Coef	se
cons	4.407***	1.173	5.011***	0.000	3.459**	1.753	3.30277***	0.41786	4.59917***	1.44511
Value_fertilizer	0.003***	0.001	0.003***	0.000	0.003***	0.001	.00466***	0.00033	.00391***	0.00058
Value_seed	0.839***	0.275	0.579***	0.000	1.092***	0.414	1.00655***	0.09091	.78095**	0.33539
Value_labor	0.002	0.023	0.076***	0.000	−0.020	0.028	.05404***	0.01047	0.01089	0.02271
Land_maize	0.131	0.273	0.315***	0.000	−0.104	0.411	−0.08678	0.09178	0.17441	0.34022
Off_farm	0.002	0.015					.00169	.015266		
Sigma	.29978***	0.001	0.033***	0.005	0.105***	0.010				
Sigma(*u*)							.18861***	0.0029	.35989***	0.0098
Sigma(*v*)							.00973**	0.00449	.04921***	0.0093
Rho(*w*,*v*)							.76645**	0.39002	.89504***	0.33496

*Significance at 10% level
**Significance at 5% level
***Significance at 1% level

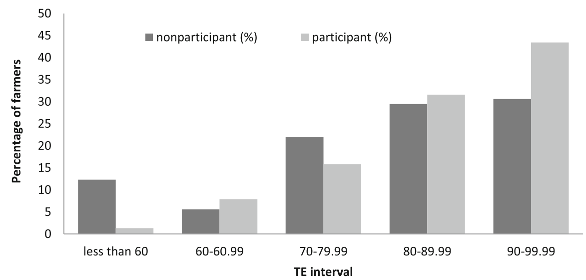

Fig. 2 The distribution of TE score for participant and non-participant farmers

determining the production level of maize in this subsample. Almost in all frontiers, the average production elasticity of seed and land allocated for maize are the highest.

Impact of participation in off-farm activities on technical efficiency

After estimating the SPF corrected for both observed and unobserved heterogeneities, we predicted the TE score of each sample respondent. Figure 2 presents the distribution of TE score for both participant and non-participant farmers. The TE scores range between 39.27 and 99.56 for the entire population. It indicates that the TE scores of 37.21% percent of the maize producers considered for this study were below the mean efficiency level. Considering only the participants, the TE score is ranged between 59.39 and 99.56 and the corresponding figure for the nonparticipants is found between 39.27 and 99.06.

Table 6 summarizes the TE mean difference between the two groups after correcting for bias from both observable and non-observable heterogeneities. The results indicate a significant mean difference between the two groups. Specifically, the result reveals farmers who are participating in off-farm income-generating activities have 6.23% of technical efficiency gain compared with their non-participant counterparts. The result is consistent with Pfeiffer et al. (2009).

As indicated in Table 5, the mean TE for pooled sample respondents was found to be 81.44% and the corresponding figure for households participating in off-farm activities and non-participants are 86.29 and 80.06%, respectively.

Finally, we examined which of the two groups (participants vs. nonparticipants) has higher output after controlling for biases from observed and unobserved variables. For this purpose, we compared the predicted frontier output of the two groups at three different input levels: (1) at the average for the smallest matched pair of farms, (2) at the average for the entire sample, and (3) at the average for the largest matched pair. The result is indicated along with a test of the mean difference in Table 7. As it is indicated in the table, households who are participating in off-farm activities are significantly more productive than the non-participant farmers. Thus, the analysis suggests that participants do not only exhibit higher TE but also higher total output.

Table 6 TE scores after bias correction

Variable	Combined		Participants		Non-participants		Difference
	Mean	Std. err.	Mean	Std. err.	Mean	Std. err.	Mean
TE	81.44	0.008	86.29	0.012	80.06%	0.009	6.23%***

*** significant at 1% probability level

Table 7 Predicted frontier output after bias correction

Predict frontier	Mean	Min	Max	Significance level
Participants	8225.957	2844.444	25,848.23	***
Non-participants	6187.10	2775.337	20,651.33	

*** significant at 1% probability level

Conclusion

This study analyzed the determinants of participation in off-farm activities and examined the impact of participation in off-farm activities on technical efficiency of maize production in eastern Ethiopia using data collected from 355 households. The probit model results indicate that literacy of the spouse, agricultural cooperative membership, family size, and access to market information had positively and significantly affected the participation in off-farm activities whereas male household head had negative and significant effect on participation in off-farm activities. The stochastic frontier production function was used to estimate technical efficiency scores, and propensity score matching was combined with Green (2010) to control sample selection bias. The result indicated that participation in off-farm activities have a positive influence on both production and productivity of maize. The result suggests that participants in off-farm activities are more technically efficient in maize production than the non-participants. The finding of this study indicated the existence of complementarity between on-farm and off-farm activities. This result challenges the perception that participation in off-farm activities may lead to a reduction in on-farm production due to competition between farm and off-farm works for family labor. The result indicates that livelihood diversification improves the agriculture sector in addition to creation of more employment opportunities as it provides a medium for family labor reallocation. This confirms the fact that off-farm income enhances agricultural production and productivity by providing cash to purchase agricultural technologies and efficiently utilize those resources.

Hence, given the complementarities between off-farm and farm activities, providing services like education and market information to the farmers and strengthening agricultural cooperatives should be facilitated to increase the participation of farmers in off-farm activities and in turn to improve their livelihoods.

Endnotes

[1]The critical value for a test of size α is equal to the value χ^2 (α), where this is the value, which is exceeded by the χ_1^2 random variable with probability equal to 2α (Coelli 1998).

[2]*Kebele* is the smallest administrative hierarchy in Ethiopia.

[3]Every *kebele* administration has a full list of households living in the area. We used this list as a sample frame. When the randomly selected farmer does not produce maize he/she will be replaced by a farmer next to him/her in the list.

[4]List and definition of variables used for this study is presented under Table 8 in the Appendix.

[5]Family size is calculated by converting difference in age and sex of members of the family members using conversion factor given in Table 9, and Table 10 in the Appendix indicates the conversion factor used to compute TLU.

[6]*quxi* is a local measurement unit equivalent with 1/8 of a hectare

[7]The sensitivity analysis is presented under Table 11 in the Appendix.

Appendix

Table 8 Definition of variables

Variable	Unit	Definition
District	Dummy	1 if the household is living in Girawa district; 0 otherwise.
Off_farm	Dummy	1 if the household participates in off-farm activities; 0 otherwise.
Education_HH	Dummy	1 if the household head is literate; 0 otherwise.
Education _spouse	Dummy	1 if the spouse of household head is literate; 0 otherwise.
Age_HH	Years	Number of years the household head lived
Sex_HH	Dummy	1 if the household head is male; 0 otherwise.
Coop	Dummy	1 if the household is a member of agricultural cooperatives; 0 otherwise.
Landowned	quxi	Size of land owned by the household
Distance_mkt	Minute	Distance between the nearest market
Social_role	Dummy	1 if the household head has social responsibility; 0 otherwise
Market_info	Dummy	1 if the household head has access to market information; 0 otherwise
Livestock	TLU	Size of livestock owned by the household
FamlyAE	AE	Family size measured by adult equivalent
Value_yield	Birr[1]	Value of maize produced by the household
Value_fertilizer	Birr	Value of inorganic fertilizer utilized for maize production
Value_seed	Birr	Value of seed used for maize production
Value_labor	Birr	Value of hired and family labor used for maize production
Land_maize	quxi	Size of land allocated for maize production

[1]Ethiopian currency; 1USD was equivalent with 21.21 ETB in the time of data collection

Table 9 Conversion factor for computation of adult equivalent

	Adult equivalent	
Age group (years)	Male	Female
< 10	0.6	0.6
11–13	0.9	0.8
14–16	1	0.75
17–50	1	0.75
> 50	1	0.7

Source: Storck et al. (1991)

Table 10 Conversion factors used to estimate tropical livestock unit (TLU) equivalents

Animal category	TLU
Calf	0.25
Donkey (young)	0.35
Weaned calf	0.34
Camel	1.25
Heifer	0.75
Sheep and goat (adult)	0.13
Cow and ox	1.00
Sheep and goat (young)	0.06
Horse	1.10
Chicken	0.013
Donkey (adult)	0.70

Source: Storck, et al. (1991)

Table 11 Sensitivity analyses

Gamma	sig+	sig−	t-hat+	t-hat−	CI+	CI−
1	0	0	0.837	0.837	0.823	0.847
1.25	0	0	0.822	0.847	0.81	0.867
1.5	0	0	0.812	0.865	0.793	0.881
1.75	0	0	0.798	0.877	0.78	0.891
1	0	0	0.837	0.837	0.823	0.847

Gamma log odds of differential assignment due to unobserved factors, *sig+* upper bound significance level, *sig−* lower bound significance level, *t-hat+* upper bound Hodges-Lehmann point estimate, *t-hat−* lower bound Hodges-Lehmann point estimate, *CI+* upper bound confidence interval ($a = .95$), *CI−* lower bound confidence interval ($a = .95$)

Abbreviations
CSA: Central Statistical Agency; DEA: Data envelopment analysis; DMU: Decision-making unit; PSM: Propensity score matching; SFA: Stochastic production approach; SPF: Stochastic production frontier; TE: Technical efficiency

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Availability of data and materials
The data that support the findings of this study can be obtained from the authors based on request.

Authors' contributions
MHA conceptualized the study and designed and performed the data analysis. KAM was responsible for the design of the questionnaire, interpretation of model results, and write-up of the manuscript. Both authors read and approved the final manuscript.

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Ethics approval and consent to participate
Ethical approval and consent to participate is not applicable for our study.

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