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The Impacts of Farmer Field School Training on Knowledge and Farm Technology Adoption: Evidence from Smallholder Maize Farmers in Oromia, Ethiopia

Admassu Tesso Huluka[1*] & Workneh Negatu[2]

[1] Wollega University, Department of Economics, Nekemte, Ethiopia

[2] Addis Ababa University, College of Development Studies, Addis Ababa, Ethiopia

[*] Admassu Tesso Huluka, E-mail: admassutesso@gmail.com

Abstract

This study examines the impact of Farmer Field School (FFS) training program on farmers' knowledge and farm technology adoption. The FFS program was sponsored by the Ethiopian government and launched in 2010. The study aims to compare the impact of the training on knowledge and agricultural technology adoption of those FFS graduate and non-FFS graduate maize farmers in Oromia, Ethiopia. For this, data was collected in 2013 from 446 randomly selected households of three districts consisting of 218 FFS graduate farmers and 228 non-FFS graduate farmers. The analytical procedure has involved two stages: in the first stage, descriptive analysis was used to detect existence of difference in the household and farm characteristics of the two groups of farmers. In the second stage, a semi-parametric impact evaluation method of propensity score matching with several matching algorithms was employed to estimate the program impacts. The result reveals that although FFS graduate farmers have relatively higher knowledge test score than the non-FFS gradate farmers, farm technology adoption index of the later farmer group exceeds the former groups. This finding suggests that there is no necessarily linear relationship between increased knowledge and increased technology adoption. This further implies that the mental attitude of the smallholder farmers in study area is not actually shaped by misconceptions of technology as claimed by the Ethiopian government, but rather because of their firm understanding of what works and does not work according to their own realities. The policy implication of this finding is that knowledge can be translated into practices if a set of enabling factors and conditions exist. These factors including farmers' positive perception of the technology benefits, access to complementary inputs, availability of crop insurance scheme, arrangement of credit facilities and favorable output markets as incentive for adopting full technologies.

Keywords

impact evaluation, knowledge, technology adoption, propensity score matching

1. Introduction

The Ethiopian government has issued agricultural Policy and Investment Frame work (PIF) which provides a clear statement of the goal and development objectives of the country spanning the over ten years of 2010 to 2020. This policy document aims to sustainably increase rural incomes and national food security through increased crop production (FDRE, 2010). Increased crop production, however, may be achieved in three different approaches: horizontal expansion approach, improvement approach and transformational approach. The first approach involves increased use of inputs while the second requires improvement of conditions or removal of some existing institutional constraints to increase output using the existing level of technology. The transformational approach requires a shift or improvement in the farm technology adoption such as use of technical packages (improved seeds, fertilizers, credits) and chemicals that shift the production function outwards.

Economic theory suggest that in order for producer to use the horizontal expansion approach, either input prices must fall or output prices must increase so as tom provide incentive to the users. In addition, there should be abundance of those critical inputs required for such production function, including farm sizes. However, given the already minimal farm size (Note 1) of smallholder farms in the study area, this source of output augmentation has very little applicability in the present economic and social context. The improvement approach involves estimation of the existing farmers' efficiency levels and its binding constraints. If the smallholder farmers are already reasonably efficient and hence there is little room for output augmentation through efficiency improvement, then, increasing output require the third alternative—transformation approach, which involves adoption of new farm technologies to shift the production frontier upward. In contrast, if there appears significant inefficiency among the smallholder farmers, then, the agricultural policy should gear towards training them how to increase their efficiency with the existing technology. This is because merely increasing adoption of more expensive agricultural technologies may result in liquidating the existing meager assets of the rural producers with very little gain in output augmentation. Thus, whether to recommend the improvement approach or transformation approach depends on empirical investigation of the existing situation.

Nonetheless, Ethiopian government seem to consider Farmer Field School (FFS) training program as panacea for increasing production and productivity of the smallholder farmers with little understanding of the existing situations of diverse groups of smallholder farmers. In effect, FFS training is merely considered as the best strategy to scale up the "best practices used by the model farmers whose productivity was more than two times higher than the average" (FDRE, 2010).

FFS aims to give special training to some purposively selected "model farmers", who, in turn, were supposed to transfer the knowledge to others through their farmers' networks that are administratively organized rather than using the existing social relationship. Accordingly, the selection of the "model farmers" into the training program was made by the district level government officials in collaboration with the Kebele (Note 2) level development agents. Although there is no as such transparent criterion guiding the selections of the model farmers, the past performance of the farmers with adoption of technological packages, increased agricultural production outputs, accessibility of the farmers in terms of geographical location and educational level are mainly considered as selection criteria. Ultimately, those who were administratively sampled have attended all the training sessions lasting for 15 days. There was a minimum of eight hours of training per day thereby making the total of 120 hours of training. After the completion of the model farmers' training, there were again series of meetings held with all farmers within each Kebele with the aim of briefing the essences of the training and how to organize all farmers into 1 to 5 network called "sub-development team" so as to facilitate the diffusion of knowledge and the best practices from the FFS participant farmers from now onwards, referred to as "FFS graduates" to non FFS participants. The desired outcome of FFS was to improve knowledge of the smallholder farmers as means to increase their agricultural technology adoption and hence their productivity. In effect, policymakers have assumed as if increased crop income is necessarily a linear function of increased knowledge, increased farm technology adoption, increased efficiency and increased productivity (Admassu et al., 2015).

However, studies reveal that although knowledge is important as predisposition in adopting farm technologies, there are other conditioning factors which influence the timing and amount of technology adoptions (Feder, Just, & Zilberman, 1985; Rola et al., 2002; Feder et al., 2004; Duflo et al., 2006; Todo & Takahashi, 2011). They suggest that lack of knowledge is just one of these factors hindering technology adoption, but not necessarily the only factor. Nonetheless, to the best of the authors' knowledge, there is no single empirical study examining the impact of FFS on the farmers' knowledge and farm technology adoption simultaneously. This paper aims to empirically examine the impact of FFS on the knowledge score and farm technology adoption index of the two farmer groups: FFS graduates vs. non FFS graduates. To this end, we have employed a semi-parametric impact evaluation method of propensity score matching with several matching algorithms to estimate the program impacts. This method helps to match program participating farmers and non-participating farmers based on their baseline similarities and clear out those factors to single out only program impacts. The result revealed that although FFS graduate farmers have relatively higher knowledge test score than their non FFS gradate counterparts, farm technology adoption index of the later farmer group exceeds the former groups. This implies that there is no necessarily linear relationship between increased knowledge and increased technology adoption.

2. Materials and Methods

Study area and sampling: this study was conducted in three purposively selected major maize producer districts in the Oromia region, East Wollega zone: Guto Gida district, Gida Ayana district and Boneya Boshe district. These three districts were purposively selected from the zone on the basis of their land under maize production and the role that maize crop plays in their socio-economic developments. In essence, maize crop is purposively selected because of the fact that it is Ethiopian's largest cereal commodity in terms of total production, productivity, and the number of its smallholder coverage (IFPRI, 2010).

Sample size: following the procedures employed by IDB (2010a) and World Bank (2007), we have employed power analysis for sample size determination and selected equal number of 246 smallholder farmers both from FFS graduates and non FFS graduates thereby making total sample size of 492.

Sampling strategy: first, we have selected three districts with good maize growing records. Second, from each district, we have purposively selected one kebele, from which households were randomly selected. Following the FFS program design, we have stratified our households from each Kebele into two excludable groups as: (i) FFS graduate farmers who were selected for the FFS training program, (ii) and non-FFS graduate farmers who were exposed to the FFS training via the FFS graduates and hence supposed to follow their best practices. Finally, we made six sampling frame for the three kebeles as we have two strata in each kebele. Stratified probability-proportional-to-size sampling offers the possibility of greater accuracy by ensuring that the groups that are created by a stratifying criterion are represented in the same proportions as in the population (Bryman, 1988). Accordingly, we have divided the total samples of 492 across the Kebeles as well as between the FFS graduates and non-FFS graduates following probability-proportional-to-size sampling technique. However, although 492 questionnaires were distributed to the sampled households, we have collected 446 properly filled questionnaires with distribution across the selected study districts as 142, 160 and 144 from Guto Gida, Gida Ayana and Boneya Boshe districts respectively.

Data sources and Collection techniques: data collection was classified into two stages. In the first stage, qualitative data were collected using key informant interviews and focus group discussions. In the second stage, detailed quantitative data were collected using structured questionnaires prepared with full understanding of the nature of the program. The questionnaires were pre-tested and ensured that all included items were relevant and the questionnaire contained the correct format for the data collection. The survey was conducted in June 2013 to July 2013.

Analytical Approach: the main challenge of this study, as it is the case for other impact evaluation studies, is to decide on the correct counterfactual: *what would have happened to the knowledge and farm technology adoption level of those farmers who participated in the training program if the program had not existed*? Given the non-random selection of farmers for the program participation, estimating the outcome variables by using the OLS would yield biased and inconsistent estimate of the program impact due to some confounding factors: purposive program placement, self-selection into the program, and diffusion of knowledge among the program participant and non-participant farmers. Thus, our impact evaluation design should enable us to control for such possible biases. For this, we have employed Propensity Score Matching (PSM) method to match program participating farmers and non-participating farmers based on their baseline similarities and clear out those factors to single out only program impacts.

Propensity Score Matching Model: in the absence of random selections, those farmers who participated in the FFS training and those excluded from it may differ not only in their participation status but also in other characteristics that affect both participation and knowledge and their agricultural technology adoption. The Propensity Score Matching (PSM) seeks to find non-participating farmers among farmers not receiving the training that are similar to the participating farmers, but did not participated in the training program. PSM does this by matching participating farmers to non-participated farmers using propensity scores. In other words, this approach tries to replicate the model farmer selection process as long as the selection is based on observable factors (Essama-Nssah, 2006; Ravallion, 2008; World Bank, 2010; IDB, 2010b). Thus, PSM searches a group of "control" farmers who are statistically "similar" in all observed characteristics to those who participated in the training program.

Under certain assumptions, matching on Propensity Score, *P*(*X*) is as good as matching on *X*. Therefore, rather than attempting to match on all values of the variables, cases can be compared on the basis of propensity scores alone, given that all observable variables which influences program participation and outcome of interest are properly identified and included (for further explanations on PSM, please see, Essama-Nssah, 2006; Heinrich et al., 2010; World Bank, 2010).

$$P(x) = pr(T = 1 | x) \quad (1)$$

PSM constructs a statistical comparison group that is based on a model of the probability of participating in the treatment *T* conditional on observed characteristics *X*, or the propensity score is given by:

The propensity score or conditional probability of participation may be calculated by using a probit or a logit model in which the dependent variable is a dummy variable T equal to one if the farmer participated in the FFS training and zero otherwise (Ravallion, 2008; World Bank, 2010; IDB, 2010). Although the results are similar to what would have been obtained by using probit, we have used logit model to estimate participation equation in this study. However, in order to determine if matching is likely to effectively reduce selection bias, it is essential to understand the two underlying assumptions under which the PSM is most likely to work: Conditional Independence Assumption and Common Support Assumption.

Conditional Independence Assumption: states that given a set of observable covariates *X* which are not affected by the program intervention, potential outcomes are independent of treatment assignment. If Y_1 represents outcomes for participants and Y_0 outcomes for non-participants, conditional independence imply:

$$(Y_1, Y_0) \perp T_i | X_i \quad (2)$$

This implies that selection is solely based on observable characteristics and that all variables that influence treatment assignment and potential outcomes are simultaneously observed by the researcher. Put in other words, it is to mean that after controlling for *X*, the participation assignment is "as good as random" and participation in the FFS training program is not affected by the outcomes of interest (Imbens, 2004; Ravallion, 2008; World Bank, 2010; IDB, 2010). This allows the non-participating households to be used to construct a counterfactual for the participating group. This assumption is sometimes called exogeneity or unconfoundedness assumption or ignorable treatment assignment (Imbens, 2004).

Clearly, this is a strong assumption since it implies that uptake of the program is based entirely on observed characteristics, and hence has to be justified by the nature of the program and data quality at hand. Although the nature of the program enabled us to justify that its uptake is based mainly on observable characteristics, we may relax such unconfoundedness assumption since we are interested in the mean impact of the program for the participants only (Imbens, 2004; Essama-Nssah, 2006; Ravallion, 2008; World Bank, 2010).

$$Y_0 \perp T_i | X_i \text{...}(3)$$

This equation states that, the outcome in the counterfactual state is independent of participation, given the observable characteristics. Thus, once controlled for the observables, outcomes for the non-participant represent what the participants would have experienced had they not participated in the program.

Common Support Assumption: states that for matching to be feasible, there must be individuals in the comparison group with the same value of covariates as the participants of interest. It requires an overlap in the distributions of the covariates between participants and non-participant comparison groups. This assumption is expressed as:

$$0 < \Pr(T = 1|x) < 1 \text{...}(4)$$

This equation implies that the probability of receiving FFS training for each value of *X* lies between 0 and 1. It ensures that persons with the same *X* values have a positive probability of being both participants and non-participants (Heckman, Ichimura, & Todd, 1998; Imbens, 2004; Ravallion, 2008). More strongly, it implies the necessity of existence of a non-participant analogue for each participant household and existence of a participant household for each non-participant household. However, since we are interested in estimating the mean effect of the intervention for the participants, as opposed to the mean effect for the entire population, we will use a weaker version of the overlap assumption which is expressed as:

$$P(x) = \Pr(T = 1|x) < 1 \text{...}(5)$$

This equation implies the possible existence of a non-participant analogue for each participant. It would be impossible to find matches for a fraction of program participants if this condition is not met. Thus, it is recommended to restrict matching and hence the estimation of the program effect on the region of common support. This implies using only non-participants whose propensity scores overlap with those of the participants. In sum, participating farmers will therefore have to be “similar” to non-participating farmers in terms of observed characteristics unaffected by participation; thus, some non-participating farmers may have to be dropped to ensure comparability (Heckman, Ichimura, & Todd, 1998; Ravallion, 2008).

The main purpose of the propensity sore estimation is to balance the observed distributions of covariates across two farmer groups (FFS graduates vs. non-FFS graduates) farmers. Hence, we need to ascertain that (1) there is sufficient common support region (overlapping of the estimated propensity scores) for the two groups of farmers, (2) and the differences in the covariates in the matched two groups have been eliminated. These two issues are the necessary conditions for the reliability of the subsequent estimate of the program impacts. Although there are many methods of covariate balancing tests, literatures show that the standardized tests of mean differences is the most commonly applied method. Hence, we have employed two methods for this study: standardized tests of mean differences and testing for the joint equality of covariate means between groups using the Hotelling test or *F*-test. The following equation shows the formula used to calculate standardized tests of mean differences (Imbens, 2004).

$$B_{before}(x) = 100.\frac{\overline{X}_T - \overline{X}_C}{\sqrt{\frac{[V_T(X) - V_C(X)]}{2}}}, B_{after}(x) = 100.\frac{\overline{X}_{TM} - \overline{X}_{CM}}{\sqrt{\frac{[V_T(X) - V_C(X)]}{2}}} \ldots(6)$$

Where for each covariate, $\overline{X}_T$ and $\overline{X}_C$ are the sample means for the full treatment and comparison groups, $\overline{X}_{TM}$ and $\overline{X}_{CM}$ are the sample means for the matched treatment and comparison groups, and $VT_{(X)}$ and $Vc_{(x)}$ are the corresponding sample variances. Rosenbaum and Rubin (1985) suggest that a standardized mean difference of greater than 20 percent should be considered as "large" and a suggestion that the matching process has failed. In addition to test of covariate balancing, we have also checked that there is sufficient overlap in the estimated propensity scores of the two groups of farmers after matching.

Given that the above specified assumptions holds, and there is a sizable overlap in *P*(*X)* across participants and non-participants, the PSM estimator for the average program effect on the treated (ATT) can be specified as the mean difference in *Y* over the common support, weighting the comparison units by the propensity score distribution of participants (Caliendo & Kopeinig, 2005; World Bank, 2010). A typical cross-section estimator can be specified as follows:

$$ATT_{PSM} = E_{p(x)|T=1,}\left\{E\left[Y_1|\mathrm{T}=1, \mathrm{p(x)}\right] - E\left[Y_0|\mathrm{T}=0, \mathrm{p(x)}\right]\right\}\ldots\ldots\ldots\ldots(7)$$

This equation shows that, PSM estimator is simply the mean difference in outcomes over the common support, appropriately weighted by the propensity score distribution of participants.

2.1 Definitions and Measurement of Variables

2.1.1 Variables to Estimate the Propensity Score

Participation in the training program (dependent variable) is a dichotomous variable taking the value 1 if the household head has participated and considered as treatment group, and takes a value 0 if he or she did not directly participate in the training program but could be exposed to the information conveyed in the training program through interactions with the FFS graduates and hence considered as a control unit. The independent variables include those characteristics that determined project placement in order to replicate the selection process.

2.1.2 Impact Indicator Variables

Knowledge Score: the first and the immediate channel through which the FFS training program is supposed to impact was through enhancing the knowledge of the smallholder farmers. Although the training program includes many complex thematic areas, we have focused only on knowledge of the smallholder farmers in relation to maize production technology as the study considers only the impact of FFS on maize farmers. Following Rola et al. (2002) and Godtland et al. (2004) we have prepared knowledge test scores index from a series of 12 questions each related to improved maize seed varieties, and the related technologies. The appropriateness of the questions were also checked by the respective development agents of each woreda to make sure that the FFS training program has covered the important issues. Then, marks were assigned to each of these questions: if their responses were correct for each question, a score of maximum mark of 1 point was given for each; different marks for different level of correct answers were provided and a score of 0 if no correct answer was given. The simple sum of these scores ranging 0 to 12 provides the observed score of knowledge about the technologies. This knowledge test score captures just the knowledge of some agricultural technologies introduced at different times. The combined knowledge test scores were divided by maximum point of 12 so as to get knowledge test index. Accordingly, the knowledge test index falls between 0 and 1. Finally, the observed knowledge test index was used as the dependent variable in the equations 7 above to estimate the knowledge difference between the two groups using PSM.

Agricultural technology adoption index: to measure farm technology adoption difference between the participants and non-FFS graduate farmers, we have prepared farm technology adoption index following Bereket and Zizzo (2011). Farm technology adoption index is prepared as the aggregate result of adopting various technologies such as row planting, improved seeds, herbicide, pesticide, chemical fertilizers, green manures, good agronomic practices, crop rotation, intercropping, and soil conservation practices. Accordingly, questionnaires consisting of 10 items were prepared in such that "1" representing that the household adopting the technology and "0" otherwise. The sum of the results for each technology category provides the technology adoption result of the household where the maximum point is 10 and the minimum point to be 0. Division of the technology adoption result of each respondent by the maximum achievable point of 10 gives their respective technology adoption index in which case 1 representing full technology adoption and index 0 means, failure to adopt any of the technologies specified in the questionnaire. Then, the observed agricultural technology adoption index was used as the dependent variable in the equations 7 above to estimate the agricultural technology adoption difference between the two farmer groups.

3. Results and Discussion

This section presents the survey results and discussions by dividing it into sections. In the first section, comparison of some selected household characteristics was made by farmer groups so as to verify the similarities of the samples. Section two presents comparison of major input and output performance indicators between the FFS graduates and non-FFS graduate farmers followed by section three presenting impact evaluation using PSM method.

3.1 Household and Farm Characteristics by Farmer Groups

Table 1 presents the descriptive statistics for both FFS graduates and non-FFS graduate farmers. Almost in all the cases, FFS graduates were identified with the highest scores in terms of educational levels, non-farm income, family sizes, estimates of asset values, total land size as well as farm size covered by maize. Significant differences were also observed in the proportions of household head owning mobile cell phone, radio ownership, participation in farmers' cooperatives, as well as in the number of contacts with the Kebele level development agent. Those FFS graduate farmers had the highest scores than those non-FFS graduate farmers in all cases.

Table 1. Household and Farm Characteristics by Farmer Groups

	Mean		t-test	
Variables	FFS Graduate	Non FFS	t	p>|t|
Household head age	39.642	40.785	-1.240	0.215
Household head sex	0.927	0.877	1.750	0.081
Education level of head	3.202	1.355	7.000	0.000
Household head literate	0.720	0.368	7.950	0.000
Farm Experience	22.4	23.3	-0.980	0.327
None farm income	1242.7	885.5	1.280	0.202
Firmly size	6.1	5.6	2.170	0.031
Dist. Techno	0.708	0.751	-0.650	0.514
Dist. Town	6.798	7.195	-0.880	0.380
Pair of Oxen (yes=1)	0.812	0.640	4.120	0.000
Mobile cell (yes=1)	0.564	0.421	3.050	0.002
Radio (yes=1)	0.541	0.469	1.520	0.129
Total Asset (Birr)	26887.0	19194.0	5.350	0.000
Land certificate (yes=1)	0.857	0.798	1.640	0.101
Coop member	0.867	0.702	4.310	0.000
Number of DA contact/year	9.569	6.627	2.340	0.020
Total land (Ha)	2.750	2.177	3.500	0.001
Maize land (Ha)	1.557	1.133	4.170	0.000

This significant difference between the farmers groups could be explained by the intended principles of model farmer selection criteria adopted by the government. Although there was no as such transparent criterion guiding the selections of the model farmers, the educational level of the farmers, the past performance of the farmers with adoption of technological packages, agricultural production outputs, accessibility of farmers in terms of geographical location and history of participation in farmers training centers were some of the factors considered in selecting the participant farmers.

3.2 Maize Production Parameters by Farmer Groups

Table 2 presents maize production parameters by farmers' groups. Comparison of maize production parameters between the two farmer groups shows that FFS graduate farmers were significantly different from the non-FFS graduate farmers specifically in terms of oxen labour, knowledge test score, family labour use as well as labour cost. In all these cases, FFS graduate farmers were identified with statistically significant mean score than the non FFS graduate farmers. However, the difference between the two farmer groups diminishes as we compare in terms of labour per hectare, DAP and Urea application per hectare.

Table 2. Comparisons of Performance Indicators by Farmer Groups

	Mean		t-test	
Variables	FFS Graduate	Non FFS	t	p>|t|
Total land (Ha)	2.750	2.177	3.500	0.001
Oxen labor	15.0	10.7	4.750	0.000
Family labor	57.1	47.5	2.860	0.004
Hired labour	23.6	13.8	2.450	0.015
knowledge test	8.434	7.980	4.260	0.000
Adoption index	6.256	6.111	1.000	0.317
Labour cost (Birr)	3596.0	2721.0	3.070	0.002
Non cash Cost (Birr)	3207.500	2567.400	3.160	0.002
Cash cost (Birr)	7541.200	5336.900	2.880	0.004
Total labor/ha (man-day)	56.7	59.4	-1.110	0.267
Cash cost/ha (Birr)	4250.9	4050.6	1.080	0.281
Non cash cost/ha (Birr)	2388.2	2570.3	-1.390	0.164
Family labor/ha (Birr)	46.301	50.979	-1.840	0.066
DAP/ha (kg)	83.419	83.144	0.090	0.929
UREA/ha (kg)	85.2	83.0	0.660	0.512

This implies that although FFS graduates seem to have applied more agricultural inputs than non FFS graduates, their input use per hectare declines owing to their possession of relatively large farm sizes.

Thus, there was no as such apparent difference between the two farmer groups in terms of fertilizer use per hectare, total labor application per hectare and total cost per hectare.

3.3 Assessment of Farmer Field School Impacts

3.3.1 Propensity Score Estimates

In estimating propensity score matching, the samples of program participants and non-participants were pooled, and then participation equation was estimated on all the observed covariates *X* in the data that are likely to determine participation (World Bank, 2010). Accordingly, we first fitted all data collected on the covariates into logit model and gradually reduced the number of the covariates until we get the desired good match. Finally, we have maintained those influential covariates determining the program participation. These covariates included comprise of different forms of assets such as natural resource (land), financial resource (access to credit), physical asset (infrastructure such as access to roads), social capital (social networks), and human forms of capital (experience and education levels). Table 3 presents the logit estimates of the FFS program participation equation.

Table 3. Estimation of Propensity Score: Dependent Variable (HH Participation in FFS)

					Number of obs=445	
					Wald chi2(20)=74.71	
					Prob>chi2=0.0000	
Log pseudolikelihood=-190.04376					Pseudo R^2=0.1549	
Variables	Coef.	Robust St.Err.	z	P>|z|	[95%Conf.interval]	
Household head age	-.0108551	.026434	-0.41	0.681	-.0626648	.0409546
Household head sex (1 male)	.0938002	.3921801	0.24	0.811	-.6748586	.862459
Household education	.0955047	.0697257	1.37	0.171	-.0411551	.2321646
Household literacy (1 yes)	1.139841	.3750863	3.04	0.002	.4046854	1.874997
Farming Experience	.0138987	.025946	0.54	0.592	-.0369545	.064752
None farm income (Birr)	.0000365	.0000438	0.83	0.404	-.0000492	.0001223
Family Size	-.0275738	.0631437	-0.44	0.662	-.1513332	.0961857
Distance from techno centre	-.0086456	.1285851	-0.07	0.946	-.2606677	.2433766
Distance from district town	-.0675697	.0393377	-1.72	0.086	-.1446702	.0095308
Has a pair of oxen	.6056229	.2973728	2.04	0.042	.0227828	1.188463
Has mobile phone	.2386495	.286769	0.83	0.405	-.3234074	.8007064
Estimated asset value	7.35e-06	.0000104	0.71	0.479	-.000013	.0000277
Has land use certificate	.0971948	.3450007	0.28	0.778	-.5789941	.7733838
Head is member of coop.	.453459	.3240438	1.40	0.162	-.1816549	1.088573
Number of DA visit/year	.017125	.0101495	1.69	0.092	-.0027674	.0370178
Head has access to credit	-.524440	.3757721	-1.40	0.163	-1.260941	.2120588

Household land size (ha)	.042385	.1042641	0.41	0.684	-.1619685	.2467394
Maize farm land (ha)	.198122	.1925527	1.03	0.304	-.1792743	.5755184
Constant	-2.9335	.7304996	-4.02	0.000	-4.365277	-1.501771

It shows that some covariates are significantly associated with FFS program participation. Educational level of the household head measured in terms of years of schooling, household head literacy measured as ability to read and write; possession of household assets such as one or more pair of farming oxen, are strongly related with FFS program participation. Furthermore, possession of mobile phone, total asset values, as well as social network such as participation in farmers cooperative, number of development agents' contact with the household per year, possession of land use certificate, possession of larger farm size were positively associated with FFS program participation. In the contrary, such covariates as age of the household head, family size, distance from centers where farm technologies were distributed and distance from the district town were negatively associated with the FFS program participation. The younger the household head, the more likely she/he is better educated and hence has more chance of being selected into the training program. These findings are consistent with the stated criteria of selecting household heads for FFS program participation as it was designed to train few affluent households, who are supposed to be easily trained and train others. This result also indicates that participation in the FFS program was mainly influenced by observable covariates and hence hidden covariates played very little role which, in turn, implies that the results of program assessment using PSM approach were unbiased and consistent.

As the main purpose of the propensity score estimation was to balance the observed distributions of covariates across two farmer groups, we need to establish that there is sufficient common support region for the two groups of farmers. We also need to be sure of that the differences in the covariates in the matched two groups have been eliminated. These two requirements are the necessary preconditions for the reliability of the subsequent estimations of the program impacts.

The predicted propensity scores range from 0.0365417 to 0.8797614 with mean value of 0.3310722 for the FFS graduates farmers, while it ranges from 0.0185319 to 0.9011666 with mean value of 0.1716005 for those non-FFS graduate farmers. Accordingly, the common support region was satisfied in the range of 0.03654173 to 0.8797614 with only 17 losses of observations (one from those FFS graduates and 16 from those non-FFS graduates farmers). Figure 1 below shows the regions of common support for the two groups of farmers.

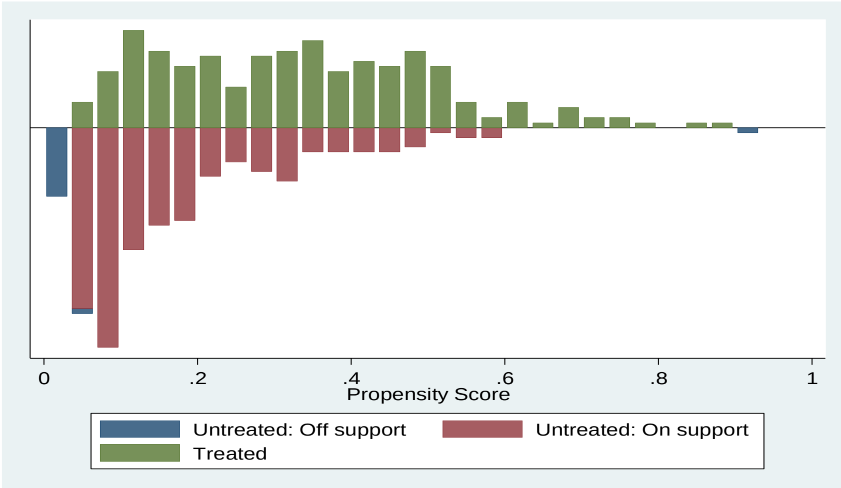

Figure 1. Propensity Score Distributions and Common Support for the Propensity Score Estimation

Note that "untreated off support" indicates those observations in the non-FFS graduates that do not have suitable comparison from the FFS graduates and hence excluded from the analysis while "untreated on support" indicates those observations in the non-FFS graduate that do have suitable comparison from the FFS graduates and used in the analysis. Thus, the graph clearly reveals that there is considerable overlap in the predicted propensity scores of the two groups. To verify whether the differences in the covariates in the matched two groups have been eliminated, we need to test covariate balancing. Accordingly, Table 4 presents results from covariate balancing test before and after matching. Mean standardized bias between the two groups after matching is significantly reduced for all matching algorithms suggesting that there is no systematic difference between the two groups after matching. The standardized mean difference which was around 26 percent for all covariates used in the propensity score before matching is significantly reduced to about five to seven percent after matching (Note 3), which has substantially reduced total bias to between 73.3 to 82.4 percent depending on which matching algorithm is used.

Table 4. Quality of Matching before and after Matching

Algorithms	Before Matching			After Matching			Total bias reduction (%)
	Pseudo R^2	LR X2 (P-value)	Mean std Bias	Pseudo R^2	LR X2 (P-value)	Mean std Bias	
NNM	0.179	110.28 (p=0.000)	26.2	0.042	23.82 (p=0.250)	5.4	79.4
RBM (0.01)	0.179	110.28 (p=0.000)	26.2	0.037	19.58 (p=0.484)	7	73.3
RBM (0.005)	0.179	110.28 (p=0.000)	26.2	0.029	12.08 (p=0.913)	5.3	79.8
KBM	0.179	110.28 (p=0.000)	26.2	0.01	5.93 (p=0.999)	4.6	82.4

Note: NNM=Nearest Neighbor Matching with replacements;

RBM (0.01)=Radius Based Matching with replacement using caliper of 0.01;

RBM (0.005)=Radius Based Matching with replacement using caliper of 0.005;

KBM=Kernel Based Matching.

In addition, comparisons of the pseudo R^2 and p-values of likelihood ratio test of the joint insignificance of all regressors obtained from the logit estimations before and after matching (Sianesi, 2001) shows that the pseudo R^2 is substantially reduced from about 18 percent before matching to about one percent in the case of kernel matching and to four percent with nearest neighbor matching. The joint significance of covariates was rejected since the p-values of likelihood ratio test are insignificant in all matching cases. In sum, the high total bias reduction, lower pseudo $R^{2,}$ low mean standardized bias and insignificant p-values of the likelihood ratio test after matching suggests that the propensity score equation specification is successful in terms of balancing the distributions of covariates between the two groups of farmers.

Although there are a number of methods to match the sample FFS program participants with the sampled non-FFS program households, the methods used in this analysis are the nearest neighbor matching (attnd), radius matching with two different calipers (attr 0.01 and attr 0.005) and kernel matching (attk), each with two different commands-*Psmatch2* (Note 4) and *Pscore* (Note 5). Asymptotically, all the four matching methods with two different command types are supposed to lead to the same conclusion although the specific results may not be necessarily the same. This is to mean that, if the FFS impact on any of the impact indicator is robust, the results from most matching algorithms must lead to the same conclusion. Thus, such use of different matching algorithms with two different command types is used as effective method of checking the robustness of the estimation of program impact.

3.3.2 Impact of FFS on Knowledge

As enhancing farmers' knowledge is supposed to be the first and the immediate channel through which the FFS program intervention impacts on the intended outcome indicators, it is logical to assess the intervention impact at this level. Accordingly, Table 5 below shows the estimated program impact on the knowledge test score index of the farmers.

Table 5. Agricultural Knowledge Test Index across Farmer Groups

Command	Algorithms	FFS Graduate (N)	Non FFS (N)	ATT	Std.Err	t
Psmatch2	attnd	217	228	0.0203	0.0084	2.4100
	attr 0.01	202	228	0.0145	0.0073	1.9800
	attr 0.005	177	228	0.0144	0.0077	1.8700
	attk	217	228	0.0174	0.0066	2.6300
	attnd	217	194	0.0240	0.0090	2.7810

Pscore	attr 0.01	191	212	0.0190	0.0060	3.1480
	attr 0.005	174	199	0.0170	0.0060	2.7660
	attk	217	212	0.0190	0.0080	2.3430

Note: *attnd* stands for nearest neighbor matching; *attr* for radius matching, and attk for kernel matching algorithms.

The result reported in Table 5 under column ATT shows that estimated average program effect on the knowledge test index of those FFS graduate farmers is between 1.4 to 2.4 percent higher than the non-FFS graduate farmers and this finding is statistically significant. Furthermore, the fact that the estimated program effects using different matching algorithms with two different stata commands implying similar interpretation further confirms the robustness of the finding. The result is also consistent with others previous studies (Godtland et al., 2004; Praneetvatakul & Waibel, 2006; Todo & Takahashi, 2011). Thus, it can be safely concluded that participation in the FFS training significantly enhances agricultural knowledge of the participants.

However, the long term empowerment goals of FFS training program depends on enabling graduates to continue to expand their knowledge and to help others to learn and to organize activities within their communities to institutionalize different practices (Douthwaite et al., 2003; Anderson & Feder, 2007; Braun & Duveskog, 2008; Soniia & Christopher, 2011). In this case, however, we did not find any evidence of FFS graduate farmers helping other farmers to gain more agriculture skills and build their self confidence. When asked about their main source of the agricultural skills they have been exercising, most farmers (54 percent), including those FFS graduate farmers stated that they depend largely on development agents' advice while to some extent (23 percent of the farmers), confirmed that they depended on existing traditional practices. Merely about 19 percent of the respondents stated that they share experiences of FFS graduate farmers while others stating that they depended on different sources (the statistical table is not reported here for brevity but can be provided upon request).

Moreover, during our focus group discussions with the farmers, it was revealed that some farmers lack confidence in the agricultural skills of some FFS graduates and hence have reservations to share their experiences. It was further revealed that some of the so called model farmers were not actually models in terms of their agricultural technical capabilities but merely selected as models because of their devotion to the ruling party political view. Besides, the focus group discussions unveiled that even some farmers who were actually models in their agricultural practices are not willing to genuinely share their experiences with other farmers either because of personal envy and or because they lack skills in how to approach and transfer their skills to others. This finding is consistent with the earlier study by Bereket and Zizzo (2011) who argued that smallholder farmers in Ethiopia have low tendency to learn from each other regarding agricultural practices.

3.3.3 Impact on Agricultural Technology Adoption

Agricultural technology adoption index is prepared as the aggregate result of adopting various technologies such as row planting, improved seeds, herbicide, pesticide, chemical fertilizers, compost, crop rotation, intercropping, and soil conservation practices as explained above. Accordingly, Table 6 presents technology adoption index comparisons across the farmer groups.

Table 6. Comparison of Technology Adoption Index across Farmer Groups

Command	Algorithms	FFS Graduate (N)	Non FFS (N)	ATT	Std.Err	t
	attnd	214	226	0.0042	0.0143	0.2900
Psmatch2	attr 0.01	190	226	0.0163	0.0131	1.2400
	attr 0.005	170	226	0.0210	0.0131	1.6000
	attk	214	226	0.0149	0.0123	1.2200
	attnd	217	194	0.0130	0.0090	1.3690
Pscore	attr 0.01	191	212	0.0040	0.0070	0.6060
	attr 0.005	174	199	0.0090	0.0070	1.1930
	attk	217	212	0.0090	0.0070	1.2460

Table 6 shows that none of the eight coefficients are statistically significant. The result shows that despite statistically significant higher knowledge test index they have registered, the FFS graduate farmers are similar to those non FFS graduates in terms of technology adoption.

As explained above, the technology adoption index shows the aggregate result of adopting various technologies. However, since not all types of technologies are equally important in enhancing production and productivity, it is reasonable to see the impact of FFS training program on the chemical fertilizers adoption separately. This is because most farmers consider chemical fertilizers as fundamental inputs for maize production. Accordingly, Table 7 below shows comparisons of fertilizer cost per hectare across the farmer groups.

Table 7. Comparison of Cost of Chemical Fertilizers across Farmer Groups

Command	Algorithms	FFS Graduate (N)	Non FFS (N)	ATT	Std.Err	t
	attnd	217	228	0.0684	0.3289	0.2100
Psmatch2	attr 0.01	202	228	-0.0540	0.2366	-0.2300
	attr 0.005	177	228	-0.1060	0.2358	-0.4500
	attk	217	228	-0.0510	0.2141	-0.2400
	attnd	217	94	-0.0500	0.3060	-0.1650
Pscore	attr 0.01	191	212	0.220	0.163	1.348
	attr 0.005	174	199	0.205	0.168	1.217

attk	217	212	-0.027	0.147	-0.182

The result shows that none of the eight coefficients are statistically significant. Furthermore, the sign of the coefficients are mixed. Five out of the eight matching algorithms implied that per hectare cost of chemical fertilizers are lower for the FFS graduates than other farmers indicating that they apply lower fertilizer per hectare. This is also confirmed by simple statistical mean comparison of their level of DAP and UREA fertilizer application per hectare. In all the cases, the non-FFS graduate farmers applied more fertilizers per hectare although the FFS graduate farmers seem to have used more quintals of fertilizers per year. Given the fact that FFS graduate farmers have larger maize farm size (1.55 ha) than the non FFS graduates (1.13 ha), the former group fertilizer use per hectare declines although their total fertilizer use may exceed the later farmer groups with relatively smaller maize land. Thus, although the FFS graduate farmers have experienced significantly higher knowledge test index, they couldn't automatically translate their knowledge into practices. This confirms that there is no necessarily linear relationship between having more knowledge and adopting more technologies. Evidence shows that although knowledge is important as predisposition in adopting technologies, there are other conditioning factors which influence the timing and amount of technology adoptions. The result confirms the conclusions of previous studies (Feder, Just, & Zilberman, 1985; Duflo et al., 2006) suggesting that lack of knowledge is just one of the factors hindering technology adoption, but not necessarily the only factor.

Thus, some farmers could be more reluctant to adopt new technologies than others not necessarily because of lack of knowledge but because of their cost benefit analysis of the technologies. Studies show that modern technologies such as High Yielding Varieties (HYV) are less stable and riskier strategy compared to the traditional varieties and hence poorer farmers are exposed to greater dangers of crop failure and hunger with HYVs than with local technology (Timer, 1998; Duflo et al., 2006). Consequently, some farmers tend to limit their level of technology adoption to their risk absorbing capacity, which is, in turn, the function of their existing assets. In addition, most farmers have expressed their concern over the inappropriate timing of technology supply, poor quality of the technologies, supply of inappropriate technology for their agro ecology, as well as the increasing trend of the prices of technologies. Thus, it could be safely concluded that smallholder farmers in the study area are not adopting full technology packages not because of demand side problems, but rather mainly because of the supply side problems. The policy implication of this finding is that knowledge can be translated into practices if a set of enabling factors and conditions exist, including farmers' positive perception of the technology benefits, access to complementary inputs, availability of crop insurance scheme, arrangement of credit facilities and favorable output markets as incentive for adopting full technologies.

4. Summary and Conclusions

The paper assesses the impacts of Farmer Field School (FFS) on farmers' knowledge and agricultural technology adoption two years after the launch of the program. FFS training program was sponsored by the Ethiopian government in 2010. To see the impact of the program on these two impact indicators, we have employed a semi-parametric impact evaluation method of propensity score matching with several matching algorithms. This method helps to match program participating farmers and non-participating farmers based on their baseline similarities and clear out those factors to single out only program impacts. The result reveals that although FFS graduate farmers have relatively higher knowledge test score than their non-FFS gradate counterparts, farm technology adoption index of the later farmer group exceeds the former groups. This finding suggests that there is no necessarily linear relationship between increased knowledge and increased technology adoption. This further implies that the mental attitude of the farmers are not actually shaped by misconceptions of technology as claimed by the government, but rather because of their firm understanding of what is good and what is bad according to their own realities. It is really a temptation to try to convince the farmers by FFS training to adopt full technology package in the absence reliable supplies of the technologies where to the contrary, outdated technologies are supplied at very later than the right time in the face of escalating prices and nonexistent crop insurance scheme. The policy implication of this finding is that knowledge can be translated into practices if a set of enabling factors and conditions exist including farmers' positive perception of the technology benefits, access to complementary inputs, availability of crop insurance scheme, arrangement of credit facilities and favorable output markets as incentive for adopting full technologies.

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Notes

Note 1. In Ethiopia, land holding share of 83 percent by smallholders farming setup less than 2 hectares and the average size of the small farms is about 1.25 hectare (EEA, 2002; Admassu et al., 2015).

Note 2. Kebele is the lowest administrative unit in Ethiopia.

Note 3. Rosenbaum and Rubin (1985) suggested that a standardized mean difference greater than 20 percent should be considered too large and an indicator that the matching process has failed.

Note 4. Psmatch2 is Stata module to perform full Mahalanobis and propensity score matching, common support graphing, and Covariate imbalance testing developed by Leuven and Sianesi (2003).

Note 5. Pscore was developed by Becker and Ichino (2002) for the estimation of average treatment effect based on propensity score. Although the estimated effects under both commands may differ, both estimates are expected to lead to the same conclusion if the detected impact estimation results are robust enough.