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Impact assessment of agricultural technologies on household food consumption and dietary diversity in eastern Ethiopia

Chanyalew S. Aweke [a], Jemal Y. Hassen [b], Muluken G. Wordofa [c,*], Dereje K. Moges [d], Getachew S. Endris [e], Debbebe T. Rorisa [f]

[a] Research, Extension and Publication Director of Haramaya University, Ethiopia
[b] Senior Agricultural Extension Scientist, Haramaya University, Ethiopia
[c] Research Theme Leader for Institutions, Innovation Systems and Economic Development, Haramaya University, Ethiopia
[d] Sociology and Social Anthropology, Haramaya University, Ethiopia
[e] Agricultural and Rural Innovation Systems, Haramaya University, Ethiopia
[f] BENEFIT-REALIZE Project, Arsi University, Ethiopia

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ABSTRACT

Food insecurity remains a major challenge to rural households in Eastern Ethiopia. To improve food and nutrition security of vulnerable households in eastern Ethiopia, several agricultural technologies have been scaled-up by Haramaya University for more than six decades. However, the impact of these technologies on household nutritional outcomes was not systematically studied. This study examined the impact of selected agricultural technologies on household food and nutrition security. Cross-sectional data were generated from 248 randomly selected rural households. Of these, 52% were non-users of improved agricultural technologies disseminated by the university while the remaining 48% sample respondents were users. The data generated from the field were analyzed using Propensity Score Matching (PSM) procedure and descriptive statistics. Results from the econometric analysis result show that households that adopted agricultural technologies had, on average, 8.97 higher Food Consumption Score (FCS) and 1.22 higher Household Dietary Diversity Score (HDDS) compared to those not using improved technologies. This shows that households adopting agricultural technologies are more likely to have higher food security compared to non-users. This suggests that promotion of improved agricultural technologies in the study area can enhance household food and nutrition security.

1. Introduction

Smallholder agriculture is the main instrument for development and poverty reduction in many countries in Sub-Saharan Africa (SSA). The sector contributes to development and survival of smallholder farmers in various ways: as a source of growth, a source of livelihoods (employment and income), as a source of food and as a provider of services related to the environment [44]. Smallholder agriculture produces foods for rural and urban population, as well as income, employment and export earnings [44]. The association between agriculture development and poverty reduction is stronger in Africa than any other continent. For example, smallholder agriculture in Ethiopia contributed 95% of agricultural outputs [9], employed over 85% of the working population [32], and is the main source of foreign exchange earnings in Ethiopia. A 5% annual growth in the agricultural sector of Ethiopia over five years was estimated to reduce poverty by 26.5% [41] suggesting the importance of the sector to national development and smallholder farmers. Hence, Agriculture Development-Led Industrialization (ADLI) has been the major strategy within the Ethiopian government's development policy with a focus on increasing agricultural productivity and commercial orientation of smallholder farmers.

However, smallholders in Ethiopia in general and eastern Ethiopia in particular operate under difficult circumstances. The production and productivity of these farming households is limited by size and quality of land, technological options, knowledge, capital, policy environment, market access, and volatile food and energy prices [12,21]. These households also rely mainly on their own family labour with limited opportunity for employment out of agriculture and are heavily dependent on rain-fed agriculture [5,21,34]. In order to address some these problems, the Ethiopian agricultural extension system promotes

* Corresponding authorDepartment of Rural Development and Agricultural Extension, Haramaya University, P.O.Box 138, Dire Dawa, Ethiopia | |
E-mail address: mgw.tud@gmail.com (M.G. Wordofa).

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improved agricultural technologies. The Ethiopian Agricultural Research Institute, Agricultural Colleges and Universities as well as the public agricultural extension were active players in generating and disseminating improved agricultural technologies to smallholders throughout the country. However, various empirical studies regarding the impact of improved agricultural technologies on household dietary outcomes found mixed results [11,29]. Some authors indicated that agricultural interventions positively contributed to the dietary outcomes of household members [2,15]. For example, a recent impact assessment study in South Africa indicated an increase in the food security of smallholder households as a result of adopting improved maize varieties [40]. The authors reaffirmed that those households who adopted improved maize varieties had a higher food security status as compared to households who did not adopt these technologies. Similarly, studies in Ethiopia on the impact of improved agricultural technologies (maize and wheat varieties) revealed that households adopting these improved agricultural technologies had higher level of consumption and increased their food security [6,35]. Another study in Eastern Ethiopia, Babille District, has also shown a positive impact of agricultural technology adoption (Groundnut seed) on household welfare [3]. [37], for example, reviewed the impact of 30 agricultural interventions on nutritional status of households world-wide. Of these, 21 agricultural interventions led to improved nutritional status while the remaining interventions did not have effect on nutritional outcomes of the target beneficiaries. Similarly, in a review by Ref. [15] on nutritional impact of targeted agricultural interventions, five studies found no impact on nutrition indicators out of 23 studies. Overall, the evidence base indicates that some agricultural interventions can have positive welfare impact [29] while others have shown no impact or little impact on nutritional outcomes. This shows debates around the impact of agricultural interventions on dietary outcomes.

This study was designed to contribute to this debate in the Ethiopian context by examining the impact of agricultural interventions on household food consumption and dietary diversity by using a university based technology transfer programs as a case. There is limited empirical evidence examining the performance of agricultural technologies disseminated by agricultural universities to smallholder households' dietary outcomes such as food security. Findings from this study is expected to generate useful lessons to Haramaya University and universities with similar programs to revise its research and extension and outreach plans and devise innovative strategies to better address the needs and priorities of the farming community. The study can also inform agricultural policy makers for alternative pathways to effectively integrate and harness the potential within agricultural universities to promote food security and livelihoods.

The current study draws a community-based technology transfer program by Haramaya University. As such the study was initiated to examine impact of selected scaled-up agricultural technologies disseminated by Haramaya University on nutritional outcomes (food consumption and dietary diversity). Haramaya University is the oldest agricultural University in Ethiopia with more than 60 years of services in teaching, research, extension and outreach activities. It has been experimenting on different agricultural technologies and disseminating them to farmers to the nearby districts in particular and the whole country in general. However, the impact of the technology on household wellbeing or food security was not adequately studied.

2. Materials and methods

2.1. Descriptions of the study areas

This study was conducted in Eastern Ethiopia. Representative districts were randomly selected from Oromia Regional State, and Harari Regional State. A total of five districts namely; Kombolcha, Haramaya, Babile, Meta and Girawa were randomly selected from East Hararghe (Oromia Regional State) while Sofi district was selected from Harari Regional State. These districts are among the major intervention areas of the University for Agricultural Technologies. The altitude of the sample districts range from 500 to 3230 m above sea level [24]. The agro-ecologies of these districts range from low land to high land which is suitable for a wide range of agricultural technologies. Several types of crops such as cereals, fruits, pulses and oil crops, vegetables, and fruits are grown in the study areas. Livestock is also an integral part of the farming system in the study areas. Both crop-livestock faming system is practiced across these sample districts.

2.2. The research process

Data for this study was collected in four distinct phases. The first phase involved inventory of agricultural technologies disseminated by Haramaya University. In this phase, activities such as baseline data gathering, document analysis, expert interviews, and identification of technologies were undertaken. The second phase involved consultative meeting with local experts, site selection and visit to study districts. The actual field work started during the third phase of the research work. During this phase, quantitative data were gathered from users and non-users of improved agricultural technologies and different stakeholders. The last stage of the research process was data analysis and write up of the research report.

2.3. Data sources and sampling technique

Primary data were collected from sample households, and key informants who had in-depth knowledge about the topic. Information related to socio-economic characteristics of sample respondents, use of agricultural technologies and impact of these agricultural technologies on household food consumption and dietary diversity were gathered from the sample respondents. The sources of information for this study includes: farm households who adopted the technology and non-users, development agents, experts, agricultural bureau officials and those stakeholders who take part in the dissemination of the agricultural technologies. The non-users were used as a comparison group. Pilot study was conducted to use as a basis for selecting potential technologies for impact assessment. Agricultural technologies with clear information which were widely scaled up and disseminated by HU from 2009 to 2016 in East Hararghe Zone of Oromia Regional State and Harari Regional State were selected. The tools of data collection were finalized after feedback from the pre-test.

Based on the selection criteria, various improved crop and livestock technologies were selected. Among the improved crop technologies, sorghum, maize, groundnut, potato, sweet potato and wheat varieties scaled up at the targeted districts were selected. Apart from these, livestock technologies have also been scaled up in the study areas. Improved poultry technologies (portable poultry houses and poultry birds), improved cattle breeds, animal feed and improved apiculture technologies disseminated by the university were also considered for impact assessment as these technologies were among the technologies disseminated by the University. The purposes of disseminating these agricultural technologies were to improve food and nutrition security of the targeted households.

Empirical data for the study comes from households residing in six districts of eastern Ethiopia. These are: Kombolcha, Haramaya, Babile, Meta, Girawa, and Sofi. These districts were selected primarily because they are in the mandate area of the Haramaya University's agricultural technology dissemination and community service activities. On top of this, representativeness to the major agro-ecological zones to represent diversity of livelihood activities, prevalence of food insecurity, and ease of accessibility were taken into account in the selection process. A multi-stage sampling procedure was employed in this study. In the first stage, six districts were purposively selected as described above. During the second stage, a list of improved agricultural technology user farmers was generated across the selected districts in consultation with

Development Agents (DAs), community/local leaders, administrators of FTCs, and representatives of district Bureau of Agriculture and Natural Resources. The generated list contained 1785 improved agricultural technology users in the six districts – Girawa (250), Kombolcha (320), Sofi (197), Meta (284), Haramaya (416), and Babile (318). In this study, an improved agricultural technology user is defined as a farm household who has been using one or more of the aforementioned improved agricultural technologies consistently for at least two years. From the total households who are currently using improved agricultural technologies, a total of 119 users were randomly selected from the prepared list. Following Probability Proportional to Size (PPS) sampling procedure, this resulted in the random selection of 17 households from Girawa, 21 from Kombolcha, 13 from Sofi, 19 from Meta, 28 from Haramaya, and 21 from Babile districts. Likewise, in order to serve as a comparison group for the purpose of impact evaluation, random samples were drawn from a list of non-users of improved agricultural technologies. This list contained a total of 1935 households – Girawa (259), Kombolcha (344), Sofi (240), Meta (297), Haramaya (458), and Babile (337). Consequently, a total of 129 households were randomly chosen and included in the study as comparison groups. Following PPS sampling procedure, this resulted in the random selection of 17 households from Girawa, 23 from Kombolcha, 16 from Sofi, 20 from Meta, 31 from Haramaya, and 22 from Babile. Hence, the overall sample size for this study is 248.

2.4. Methods of data collection and analysis

Quantitative data were collected using interviewer administered questionnaire. The interview schedule was pretested. Modifications were made on the tools of data collection after pre-test. The data were collected by enumerators who knew the culture and language of the study participants. The enumerators were given training in advance on how to approach the study participants and conduct the interview.

For this study quantitative techniques were used. Quantitative data were analyzed using descriptive statistics and Propensity Score Matching (PSM). Descriptive statistics such as mean and standard deviation were used to present the summary of the quantitative data. T-test and Chi-Square test (X^2 –test) were also used to check for existence of significant difference in observations between the comparison and treatment sampled respondents. In this research, outcome variables such as Food Consumption Score (FCS) and Household Dietary Diversity Score (HDDS) were used so as to gauge the impact of the technologies on household food and nutrition security.

Food Consumption Score is a measure of food security which is commonly used by the World Food Program [8]. It measures both the types of food groups consumed and the frequency of consumption of these food groups [45]. The FCS of the sample households was computed following [45] Technical Annex. The food composition groups encompass starches, pulses, vegetables, fruit, meat, dairy, fats and sugar. In order to capture the dietary habit of the sample households, seven days recall period was used which further reduces the risk of selection bias [10]. Frequency of consumption and weights attached to each food group are used for computing food consumption score [10]. Households with highest FCS are more food secure [8].

$$FCS = (starches * 2) + (pulses * 3) + vegetables + fruits + (meat * 4) + (dairy * 4) + (fats * 0.5) + (sugar * 0.5) \quad (1)$$

The Household Dietary Diversity Score is a measure of food adequacy indicating the number of food groups consumed at household level, which is considered to be an indicator for economic ability of households [20]. Dietary diversity refers to the number of food groups (e.g. cereals, vegetables, milk, meat, legumes, eggs and fruits) consumed over 24 h recall period [30]. The HDDS score ranges from 1 to 12. The minimum is consuming one food group over the reference period and the maximum is consuming twelve food groups [6,16].

2.4.1. Empirical strategy for impact evaluation

The process of evaluating the impact of a program on an outcome indicator of interest inevitably requires answering a daunting question: 'what would have happened to the participants of the program had they not participated in it?' Referred in the evaluation literature as '*the fundamental problem of causal inference*' or '*fundamental evaluation problem*' [23], this is a serious question to answer since an individual can only be observed at one state in a given time – either participating or not participating in the program [35,39]. The ideal way to deal with the problem of counterfactuals is to employ Randomized Control Trials (RCTs) following the *potential outcome approach* or *Roy–Rubin model* [4,13], which entails the random assignment of eligible individuals to a treatment and comparison group. Having performed random assignment of treatment and comparison groups, any observed difference in outcomes can be attributed to participation in the treatment. The treatment effect following this approach is given as $T_i = Y_{i1} - Y_{i0}$, where T_i is the treatment effect for individual i, Y_{i1} and Y_{i0} are the potential outcomes with and without the treatment, respectively. However, RCTs is not viable in the present study setting due to concerns about placement/targeting and self-selection bias.

The alternative to the experimental approach is the use of quasi-experimental approaches, which seek to create, using empirical methods, a comparable comparison group that can serve as a reasonable counterfactual [1,35]. Some common quasi-experimental approaches include Propensity Score Matching (PSM), Double Difference or Difference-In-Difference (DID) Regression Discontinuity Design (RDD), and Instrumental Variables (IV) estimation. The instrumental variable approach was considered but taking into account that in practice the assignment to treatment would be based on criteria that are not necessarily observable, such as budgetary considerations, logistics, convenience, or political priority, and acknowledging the fact that finding a valid instrumental variable is a great practical challenge, we could not proceed further.

Therefore, in the present study, the propensity score matching procedure is implemented primarily due to the nature of data available. Although PSM is based on a quite strong assumption, requires a large amount of data from participants and non-participants, and fails to account for selection bias due to unobservable characteristics, it remains an influential quasi-experimental approach to estimating the impact of an intervention in a fairly straightforward manner [1].

2.4.2. Matching methods in evaluating program/treatment effects

The fundamental notion behind matching is to construct a comparable group of individuals – who are similar to the treatment individuals/groups in all relevant pre-treatment characteristics X – from a sample of untreated ones. Then, having created this comparable group and performed matching under some identifying assumptions, any observed difference in outcome between the two groups can be attributed to the program/treatment. In practice, a model (Probit or Logit for binary treatment) is estimated in which participation in a treatment/program is explained by several pre-treatment characteristics and then predictions of this estimation are used to create the propensity score which ranges from 0 to 1. Having done this, one can compare the units (individuals or groups) which are made "close" to each other in terms of the propensity score [1].

There are different approaches of implementing PSM, including the Nearest Neighbor (NN) matching, Caliper or Radius matching, Stratification or Interval matching, and Kernel and Local Linear matching [43]. In the present investigation, the Nearest Neighbor Matching (with 5-Neighbors and One-to-One matching) is implemented.

2.4.3. Assumptions in implementing PSM

There are two assumptions to be made and verified in implementing the PSM. The first one is referred to as *unconfoundedness* [38], *selection on observables* [22], or *conditional independence assumption (CIA)* [28]. According to this assumption, the treatment needs to fulfil the criterion of being exogenous, implying that any systematic difference in outcomes between the treatment and comparison groups with the same values for characteristics X can be attributed to the treatment. The second assumption, called *common* support or *overlap*, ensures that individuals/groups with the same values for characteristics X have a positive probability of being both participants and non-participants of a program/treatment [23]. The *overlap* condition enables to compare comparable units.

Nevertheless, in order to deal with the 'curse of dimensionality' problem [38], show that if the potential outcomes of treated (Y_1) and comparison (Y_0) are independent of treatment allocation conditional on covariates X, then they are also independent of treatment conditional on the propensity score (i.e., P(D = sd1|X) = P(X)).

Generalizing the above issues, assuming that the *unconfoundedness* assumption holds and there is sufficient *overlap* between the treatment and comparison groups, the PSM estimator for ATT conditional on the propensity score can be written as

$$ATT = EP(X|D = 1\{E[Y1|D = 1,\ P(X)] - E[Y0|D = 0,\ P(X)]\} \tag{2}$$

This means, the PSM estimator is simply the mean difference in outcomes over the common support region, appropriately weighted by the propensity score distribution of treated participants [25].

2.4.4. Matching quality analysis (balance checking)

A number of techniques are available to check balancing, including mean comparisons between treatment and comparison groups (before and after matching), standardized bias, and overall measures of covariate imbalance. In terms of mean comparisons, a two-sample t-test (before and after matching) can be used to check the existence or lack of significant differences in covariate means between the treated and comparison groups [38]. As a rule-of-thumb, there should not be any significant difference in means after matching [38]. define the absolute standardized bias (for each covariate X) as the absolute difference in sample means between the matched treatment and comparison samples as a percentage of the square root of the average sample variance in the two groups.

The standardized bias before matching can be written as

$$\text{Standardized bias}_{\frac{\text{before} = 100^{*}\ \overline{X}1 - \overline{X}0}{\sqrt{0.5.(V1(X)+V0(X))}}} \tag{3}$$

The standardized bias after matching can be written as

$$\text{Standardized bias}_{\frac{\text{after} = 100^{*}\ \overline{X}1M - \overline{X}0M}{\sqrt{0.5.(V1M(X)+V0M(X))}}} \tag{4}$$

where $\overline{X}1$ (V1) is the mean (variance) in the treatment group before matching and $\overline{X}0$ (V0) the corresponding values for the comparison group. $\overline{X}1M$ (V1M) and $\overline{X}0M$ (V0M) are the mean (variance) values for the matched samples.

In addition to mean comparisons and standardized bias, there is a measure of overall covariate imbalance [7]. suggests the comparison of Pseudo-R^2 before and after matching as a method to check balance. The Pseudo-R^2 indicates how well the covariates X explain the probability of participating in the treatment. The Pseudo-R^2 has to be very low after matching to indicate success of the matching process. Moreover, the Likelihood Ratio test on the joint significance of all covariates in the (Logit) model should not be rejected before matching, but should be rejected afterwards [25].

2.4.5. Choice of variables to estimate propensity score

A crucial aspect in the estimation of propensity scores is the criteria to include/exclude variables into/from the model. The most widely followed practice in selecting variables into the model estimating propensity score is to include all the variables which simultaneously affect both participation in treatment/program and outcome variable of interest, but are not affected by the treatment or the expectation of it [25]. This implies that a variable that affects outcome but not participation should not be included. Likewise, any variable which does not affect either participation or outcome should not be included in the model [33]. In the choice of variables for the estimation of propensity score for this study, therefore, both theoretical and empirical sources were consulted. Moreover, the criteria used to select farmers were also taken into account.

3. Results and discussion

3.1. Descriptive statistics results

3.1.1. Demographic characteristics

Demographic variables such as age, educational status, family size, farming experience and gender of the household head were among the variables included in the statistical analysis. The results depicted in Table 1 show that there is a statistically significant difference in the age, gender, school years, and farming experiences of users and non-users of the agricultural technologies from HU. Details of the results are shown in Table 1 below.

Generally, respondents who used the technologies were found to be relatively older (with a mean age difference of close to 4 years) than those who did not use technologies from HU. There was significant difference between users and non-users of the technologies in terms of age at 1% significant level. This seems to correspond with the finding that the respondents who have used technologies from HU have stayed in schools and on farming activities for more number of years compared to those who did not use the technologies. On average users were found to be one more year educated and over 2 years farm experienced than the non-users. The results are statistically significant at 5% significant level. The inferential statistics also shows that there is a significant variation among users and non-users of HU's technologies in terms of gender of the household head. The information obtained from several FGDs conducted with female headed households specifically revealed that there was a frequent targeting bias against among others female farmers and this supports the finding related to gender-based differences among users of the technology. Key informants also indicated that the interventions of HU were less successful in recognizing gender sensitive preference criteria for the technologies and female targets were found to be more prone to such phenomena compared to the male counterparts. Based on the findings, therefore, relatively older male targets that have better education and farming experiences seem to be more privileged than their counterparts in accessing and utilizing the technologies generated and disseminated by HU so far.

3.1.2. Economic variables

The second category of explanatory variables is labeled as economic factors. Several variables vis-à-vis livestock owned, land size, non-farm income, irrigation access, use of conservation practices, and asset value were included under this category. According to the results (depicted in

Table 1
Descriptive results of pre-intervention demographic variables across outcome variables.

Variables	Sample Group	Observation	Mean/ Percentage (SD)	T-test/X^2-test (P-value)
Age	Comparison	129	36.40 (11.22)	-2.45 (0.007)
	Treatment	119	39.98 (11.71)	***
Gender (Male)	Comparison	70	54.30	11.34 (0.001)
	Treated	89	74.80	***
School Years	Comparison	129	2.53 (3.52)	-2.12 (0.017)
	Treated	119	3.57 (4.18)	**
Family Size	Comparison	129	6.46 (2.54)	0.99 (0.838)
	Treated	119	6.15 (1.98)	
Farming Experience	Comparison	129	19.74 (10.50)	-1.94 (0.026)
	Treated	119	22.42 (11.24)	**

, * indicate statistical significance at 5% and 1% levels, respectively.

Table 2
Descriptive results of Economic Variables across Outcome Variables.

Variables	Sample Group	Observation	Mean/ Percentage (SD)	T-test/X^2-test (P-value)
Livestock Owned	Comparison	129	1.67 (1.61)	-2.29 (0.0113)**
	Treated	119	2.14 (1.58)	
Land Size	Comparison	129	0.78 (0.65)	-1.61(0.0547)*
	Treated	119	0.91 (0.57)	
Non-Off-farm Income	Comparison	129	2852.56 (11607.67)	-0.14 (0.4432)
	Treated	119	3034.27 (7871.68)	
Access to Irrigation (Yes)	Comparison	40	31.00	0.090 (0.766)
	Treated	39	32.80	
SWC-practices (Yes)	Comparison	69	53.50	12.15(0.000)***
	Treated	89	74.80	
Asset Value	Comparison	129	3288.72 (4166.50)	0.65 (0.7409)
	Treated	119	2929.24 (4583.34)	

*,**, *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Table 2), a statistically significant differences were observed between the comparison and treatment group for three among the six economic variables. Livestock owned, land size, and SWC-Practices were the significant variables while Non-Off-Farm Income, Access to Irrigation, and Asset Value were found not significantly varying between the users and non-users group. The details of the results are indicated in Table 2 below.

The respondents who use technologies from HU were found owning significantly higher TLU (2.14) of Livestock compared to the non-users' TLU (1.67). The t-test for such a difference in livestock ownership between the two groups is significant with $p < 0.05$. In spite of such a significant difference in livestock ownership, at this stage, it will not be robust enough to establish that the difference between users and non-users was necessarily resulting from HU's livestock related interventions.

The statistical results as seen in Table 2 above indicated that the treatment category of respondents do possess significantly larger size of farm land (0.91 ha) compared to the farm land size (0.78 ha) owned by the comparison group. The result is statistically significant with $p < 0.1$. Based on an inventory of HU's technological interventions conducted prior to this study, most of the technologies generated and disseminated by the University are on-farm based ones and hence require an adequate size of plot for the farmers to participate in and draw impacts of the interventions. The fact that the non-users group possesses lesser farm size would tend to hinder them from utilizing the interventions. Apart from having a lager farm size, users were also found to be in a better position to practice SWC measures compared to the non-users. Greater proportion i.e. 89 of 119 respondents in the treatment group have used SWC technologies while only 69 out of 129 non-users were found to exercise SWC activities. This difference is statistically significant with $p < 0.01$. This finding is consistent with the results obtained from KIIs and FGDs conducted with users group which indicated that the target farmers have a long standing history working with the University on various SWC technologies among which cultivation of leguminous crops and tree species, as well as constructing SWC structures are the major ones.

3.1.3. Institutional variables

From among the seven institutional variables considered under this study, only two were found to have a significantly different distribution between the comparison and treatment groups. The two variables are Participation in FTCs and Access to Market Information. As seen in Table 3 below, the number of farmers who participated in FTCs from the treatment group is higher than the ones in the comparison group ($p < 0.01$) despite the fact that the study shows such level of participation is not favorably and adequately accompanied by DAs visit to the homes and farm lands of the farmers. Farmers from both categories equivocally said that the DAs visit them very rarely, and this visit don't exceed twice a year. Details of the results are shown in the following Table 3.

Table 3
Descriptive results of Institutional Variables across Outcome Variables.

Variables	Sample Group	Observation	Mean/ Percentage (SD)	T-test/X^2-test (P-value)
DA Visit	Comparison	129	1.77 (2.60)	1.15 (0.874)
	Treated	119	1.44 (1.81)	
Participation in FTC (Yes)	Comparison	48	37.20	18.72
	Treated	77	64.70	(0.000)***
Cooperative Participation in SWC	Comparison	23	17.80	2.01 (0.157)
	Treated	30	25.20	
Credit access (Yes)	Comparison	22	17.10	0.087(0.77)
	Treated	22	18.50	
Access to Market Information (Yes)	Comparison	96	74.40	19.70
	Treated	113	95	(0.000)***
Market Distance	Comparison	129	0.81(0.96)	2.44 (0.992)
	Treated	119	0.58 (0.35)	
PSNP Participation	Comparison	18	14	0.64 (0.43)
	Treated	21	17.60	

*** indicates statistical significance at 1% levels.

Cooperative Participation, Access to Credit, Market Distance, and PSNP Participation were the remaining institutional variables, apart from DAs visit, whose observations were not significantly varying between the treatment and comparison groups. The proportion of users who have access to Market information is, however, larger than the proportion of non-users who access to Market Information. The result for the differences is statistically significant with $p < 0.01$. Such a difference could, therefore, be attributed to the probability that HU's interventions encouraged and facilitated farmers to get access to market information.

3.1.4. Outcome variables

The mean of observations for the two impact indicators considered under this study vis-à-vis Food Consumption Score, and Household Dietary Diversity Scores were compared across Comparison and Treatment groups. The result helps to identify if there exists a significant variation among the groups in terms of the outcome variables. Nutritional outcomes refer to the dietary diversity measures such as Food Consumption Score (FCS) and Household Dietary Diversity Score (HDDS). FCS measures the types of food groups consumed and frequency of food consumption over the last seven days prior to the survey. The person who was responsible for food preparation was asked regarding the food types consumed at household level. The average FCS of users was 62 while that of non-users was computed to be 56 (Table 4). The difference between the two categories is statistically significant with $p < 0.05$. The sampled households were again categorized in to poor, borderline and acceptable food consumption based on their FCS. These scores were computed following the WFP (2008) Technical Annex. Majority of the sample households (72%) fall into acceptable consumption category while the remaining 28% fall into the lower consumption categories. This indicates that 28% of the sample households were food insecure following [8]. The

Table 4
Descriptive results of Outcome Variables for users and non-users of technology.

Variables	Sample Group	Observation	Mean (SD)	T-test/X^2-test (P-value)
FCS (Outcome 1)	Comparison	129	56.06 (23.38)	-1.83(0.034) **
	Treated	119	62.21(29.28)	
HDDS (Outcome 2)	Comparison	129	6.67(1.95)	-2.78 (0.003) ***
	Treated	119	7.56 (3.01)	

, * indicate statistical significance at 5% and 1% levels, respectively.

data was based on FCS, and hence, larger proportion of food in secured respondents should fall under non-users group signifying the probability of HU interventions to improve targets' FCS.

HDDS refers to the number of food groups consumed by households [18]. The recall period used in this case is 24 h. A list of food groups was prepared based on the types of foods consumed by the sampled households. The results were computed as the sum of food groups consumed at household level. With a reference to the 12 food groups that were reviewed to have addressed by the HU's interventions, then, users and non-users have scored HDDS of 7.56 and 6.67, respectively (Table 4). The difference in the scores is statistically significant with $p < 0.01$. The result implies that the interventions made by HU could have possibly contributed one more food group to the target households in contrast with non-users of the technologies. Information obtained from qualitative field surveys have actually revealed that crop technologies generated and disseminated by the university are able, among others, to meet the local criteria as important for household food consumption.

3.2. Econometric model results

The causal effect of improved agricultural technology use on welfare indicators – household food consumption and dietary diversity – is estimated using the Propensity Score Matching (PSM) procedure. The analysis employed Nearest Neighbor Matching (with 5-Neighbors and One-to-One matching algorithms) using *psmatch2* command [14] on STATA 15.1 platform. In what follows, the results pertaining to estimation of propensity scores, Average Treatment Effect on the Treated (ATT), and post-matching quality analyses are presented.

3.2.1. Estimation of propensity score

The conditional probability of households' participation in improved agricultural technology use is estimated using a Logistic Regression model. The model considered all observable covariates that affect participation and welfare and for which observational data is available. The results are given in Table 5. Overall, the model is statistically significant. Based on the findings, we note the existence of a statistically significant difference between treated ($n = 119$) and comparison ($n = 129$) households regarding the distributions of age, gender, family size, land size, Soil and Water Management (SWM) practices, and distance from main market (Column (3), Table 5). As depicted in the Table, these factors were responsible for households' differential participation in improved agricultural technology use. Since we are interested in computing the propensity scores, which will be used in the matching process later on, we will not go into the details of why and how each of the covariates affected households' participation in the interventions. Nevertheless, we note that as we proceed with our analysis, these before-matching differences are no longer significant in the aftermath of matching (Column (1), Table 7), which is an indication that the PSM was successful to experimentally create a comparable group of comparison individuals whose welfare outcomes can be compared to that of the treated ones.

Table 5
Propensity score estimation.

	(1) Coef.	(2) Std. Err.	(3) Z
Age (*Years*)	0.032	0.014	2.36 **
Gender (*Male*)	0.934	0.322	2.90 ***
Education (*Years*)	0.028	0.040	0.71
Family Size (*Number*)	–0.183	0.072	–2.53 **
Livestock (*TLU*)	0.134	0.094	1.42
Land Size (*Ha*)	0.413	0.236	1.75 *
SWM Participation (*Yes*)	1.049	0.322	3.26 ***
Irrigation Use (*Yes*)	–0.247	0.337	–0.73
Development Agent (DA) Visit (*Yes*)	–0.102	0.079	–1.29
Credit Access (*Yes*)	0.286	0.375	0.76
Market Distance (*Km*)	–0.599	0.340	–1.76 *
Asset Value (*Birr*)	–0.00004	0.00004	–1.23
Constant	–1.412	0.698	–2.02 **
Log Likelihood	–146.769		
Number of observations	248		
LR $chi^2(12)$	49.86		
Prob > chi^2	0.000		
Pseudo R^2	0.15		

*, **, *** denote statistical significance at 10%, 5%, and 1% level, respectively.

3.2.2. Estimation of Average Treatment Effect on the treated (ATT)

The estimation of Average Treatment Effect on the Treated (ATT) for all outcome variables is performed using the Nearest Neighbor Matching (with 5-Nearest Neighbors and One-to-One matching algorithms). All the 129 comparison and 117 treated households are used in the matching process, since these were found on the common support region (to be discussed following Fig. 1). The results are presented in Table 6. In addition to the mean values of the outcome variables, the Table contains mean differences between treated and comparison groups (Column 3) and bootstrap standard errors (with 50 replications) on the mean difference (Column 6). Overall, we found a good convergence regarding statistical significance (i.e., p-value < 0.05) between the two matching algorithms (Column 7).

3.2.2.1. Impact on food consumption score (FCS). Although the two matching algorithms resulted in similar statistical level of significance (Column 7, Table 6), we base our discussion on the FCS results obtained using the 5-Nearest Neighbor Matching, since the bootstrap standard errors (Column 6) for this algorithm are lower than that of the One-to-One matching. Accordingly, we found that households using improved agricultural technologies had, on average, a 8.97 higher FCS compared to those not using those technologies. This is a statistically significant difference suggesting that improved agricultural technologies enhanced households' FCS. This indicates that households who adopted improved agricultural technologies disseminated by Haramaya University had higher food consumption score which is an indicator for improved food security [8]. The implication of this result is that the adoption of agricultural technologies disseminated by HU had a positive impact on household food security.

3.2.2.2. Impact on household dietary diversity score (HDDS). Following a similar reasoning as for FCS above, we base our discussion of the causal effect of improved agricultural technologies on Household Dietary Diversity Score (HDDS) on the results obtained using the One-to-One

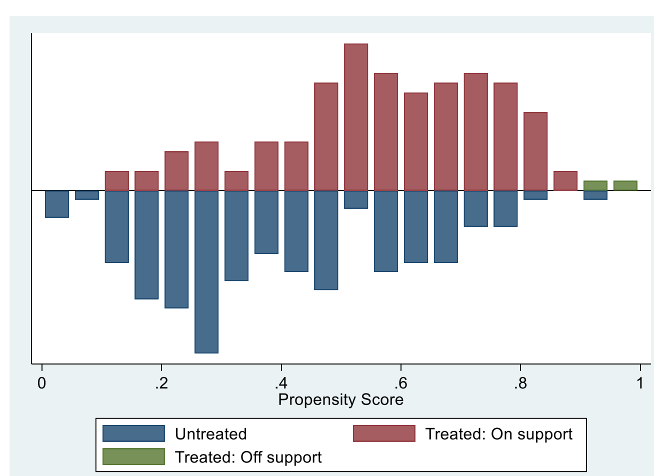

Fig. 1. Propensity Score Graph
Note: all (129) untreated and 117 out of 119 treated observations are on common support region.

Table 6
Nearest neighbor matching results of average treatment effect on the treated (ATT).

Outcome Variable	Sample	(1) Treated	(2) Comparison	(3) Difference	(4) Std. Err.	(5) T-stat	(6) Bootstrap Std. Err. [a]	(7) z
Food Consumption Score (FCS)[b]								
5-Nearest Neighbors	Unmatched	62.21	56.06	6.14	3.35	1.83		
	ATT	62.01	53.05	8.97	4.11	2.18	4.53	1.98**
One-to-One Matching	Unmatched	62.21	56.06	6.14	3.35	1.83		
	ATT	62.01	48.48	13.53	4.50	3.01	6.25	2.16**
Household Dietary Diversity Score (HDDS) [b]								
5-Nearest Neighbors	Unmatched	7.56	6.67	0.89	0.32	2.78		
	ATT	7.52	6.61	0.92	0.39	2.36	0.38	2.43**
One-to-One Matching	Unmatched	7.56	6.67	0.89	0.32	2.78		
	ATT	7.52	6.30	1.22	0.44	2.79	0.37	3.27***

Note: ATT = Average Treatment Effect on the Treated.
*, **, *** denote statistical significance at 10%, 5%, and 1% level, respectively.
[a] Bootstrap Standard Errors (Std. Err.) on the difference (with 50 replications).
[b] 129 (all) untreated and 117 (out of 119) treated households found on the common support region were used.

matching algorithm. It is evident from the results in Table 6 that treated households had, on average; a 1.22 higher HDDS compared to the comparison households, which is a statistically highly significant difference. The result from the above analysis has shown that adopters have a higher household dietary diversity score compared to non-adopters. The descriptive result also confirmed that the agricultural technology users have a higher dietary diversity. This shows that the adoption of agricultural technologies disseminated by HU has positively influenced their dietary diversity. Higher dietary diversity is an indicator for diet adequacy or economic ability of households [20]. This implies that increasing the dissemination of agricultural technologies to rural households can improve diet of households.

The findings in this study indicated that household food consumption and dietary diversity increased with adoption of improved agricultural technologies. The descriptive results also revealed that households who adopted the technologies had higher food consumption score and household dietary diversity score. This shows that households who adopted agricultural technologies were better off compared to households who didn't adopt the improved agricultural technologies. This is in line with the findings of previous studies [6,27,40]. For example a recent study in South Africa indicated an increase in the food security of smallholder households as a result of adopting improved maize varieties [40]. The authors reaffirmed that those households who adopted improved maize varieties had a higher food security status compared to households who do not adopt these technologies. Household food security increased in households who adopted improved varieties of maize and wheat varieties [6,27]. For example, a recent study in South Africa indicated an increase in the food security of smallholder households as a result of adopting improved maize varieties [40]. The authors reaffirmed that those households who adopted improved maize varieties had a higher food security status compared to households who do not adopt these technologies. Studies in Ethiopia had also shown that household food security increased in households who adopted improved varieties of maize and wheat varieties [6,27]. This suggests that household food and nutrition security can be enhanced through the introduction and promotion improved agricultural technologies.

3.2.3. *Matching quality analysis*

The matching quality analyses were performed using t-tests and Standardized Percentage Bias (Table 7, Columns (1) and (2), respectively) and other measures of covariate imbalance (Table 8). Looking at the t-test results after matching (Column 1, Table 7), we found that the statistically significant difference between treated and comparison groups that were observed for some covariates in the unmatched sample were fully removed. This implies that the matching process was effective in balancing the distributions of the covariates in the matched sample. Likewise, the Standardized Percentage Bias (Column 2, Table 7) appears to be in the acceptable range, complementing the post-estimation t-test results and implying further that the PSM performed well in yielding unbiased estimates of ATT.

Table 7
Matching quality analysis: t-test and standardized percentage bias.

	(1) t-test		(2) Standardized Percentage Bias	
	5-Nearest Neighbors	One-to-One	5-Nearest Neighbors	One-to-One
Age (*Years*)	0.56 (0.576)	0.55 (0.580)	7.4	7.2
Gender (*Male*)	−0.36 (0.717)	−1.09 (0.276)	−4.4	−12.8
Education (*Years*)	−0.51 (0.613)	−0.92 (0.358)	−6.9	−12.5
Family Size (*Number*)	−0.27 (0.784)	−1.54 (0.124)	−3.5	−19.1
Livestock (*TLU*)	−0.24 (0.812)	−1.41 (0.160)	−3.6	−24.0
Land Size (*Ha*)	−0.12 (0.907)	−0.20 (0.839)	−1.7	−2.9
SWM Participation (*Yes*)	−0.18 (0.857)	0.15 (0.882)	−2.2	1.8
Irrigation Use (*Yes*)	−0.30 (0.763)	0.56 (0.576)	−4.0	7.3
DA Visit (*Yes*)	0.15 (0.878)	−0.96 (0.338)	1.5	−10.3
Credit Access (*Yes*)	−1.46 (0.144)	−0.33 (0.743)	−20.9	−4.5
Market Distance (*Km*)	−1.02 (0.310)	−0.87 (0.386)	−7.0	−5.9
Asset Value (*Birr*)	−0.72 (0.473)	1.07 (0.286)	−9.8	12.6

Table 8
Other matching quality tests.

Matching Method	(1) Pseudo R^2	(2) LR chi^2	(3) $p>chi^2$	(4) Mean bias	(5) Median bias
5-Nearest Neighbors	0.014	4.67	0.968	6.1	4.2
One-to-One	0.034	11.18	0.514	10.1	8.8

In addition to the post-estimation t-test and standardized percentage bias results, other measures of covariate imbalance (Table 8) also indicate that the matching process is effective in balancing the pre-treatment characteristics.

Finally, the propensity score graph (*psgraph*) in Fig. 1 presents treated and untreated households that are found on the common support region (i.e., 117 and 129, respectively) and the two treated observations that are off the support region.

4. Summary, conclusion and recommendations

This study examined the impact of selected agricultural technologies on household wellbeing – dietary diversity and food consumption. Both crop and livestock technologies were considered for the impact assessment. The PSM result revealed that households using improved agricultural technologies had higher food consumption score (FCS) and dietary diversity as compared to those not using those technologies. This is a statistically significant difference suggesting that improved agricultural technologies enhanced households' food consumption and dietary diversity. In other words, the result shows that adoption of improved agricultural technologies can result in higher food consumption, and dietary diversity which in turn results in better food security. This study reaffirms that dissemination of the agricultural technologies had resulted in higher dietary diversity and food security. The study provides evidence that public policy that promotes increase in adoption of agricultural technologies for boosting the productivity of the small farm sector can lead to better wellbeing in terms of food consumption and dietary diversity. The implication of the above result is that household food access (both food consumption and dietary diversity) can potentially be improved through increased access to improved agricultural technologies. To expand the availability of these improved agricultural technologies and address large number of smallholder farmers, the university research extension office should work with local stakeholders such as district agricultural extension officials, agricultural research centers and NGOs. The university should also build the capacity of local agricultural development agents for wider dissemination of the improved agricultural technologies. This study also suggests the need for investment on agricultural technologies for improving wellbeing or food security.

This study has some limitations that should be addressed by future research. First, this study was conducted in Eastern Ethiopia and the findings cannot easily be extended to other areas of Ethiopia where the technologies were disseminated. This study used cross-sectional data and hence, it may not reflect household situation throughout the whole year and provides a limited insight into household consumption and dietary diversity over a longer period time. Moreover, the level of analysis was at household level – this suggests a future area of research especially on the impact of technologies within the household such as children and mothers. Additional indicators such as income, household food expenditure, and asset accumulation can be used apart from household dietary diversity and food consumption for measuring the impact on welfare of the targeted households.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Chanyalew S. Aweke (PhD) is an Assistant Professor of Food Business and Development. He is Director for Research, Extension, and Publication at Haramaya University.

Jemal Y. Hassen (PhD) is an Associate Professor of Agricultural Extension, leading and managing several development-related multi-partner projects.

Muluken G. Wordofa (PhD) is an Assistant Professor of Rural Development & Agricultural Extension at Haramaya University, Ethiopia. He also serves the university as a Research Theme Leader for Institutions, Innovation Systems, and Economic Development.

Getachew S. Endris (PhD) is an Assistant Professor of Agricultural and Rural Innovation Systems. He also serves as a Sub-Theme Leader for Innovation Systems and Impact Evaluation at Haramaya University.

Dereje K. Moges (MSc) is an Assistant Professor of Sociology and Social Works in the Department of Rural Development & Agricultural Extension. He is also a PhD candidate at Addis Ababa University.

Debbebe T. Rorisa (MSc) is a PhD candidate at Makerere University (Uganda) and Lecturer at Arsi University. He coordinates BENEFIT-REALIZE project.