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IMPACT OF IMPROVED AGRICULTURAL TECHNOLOGIES ADOPTION ON FARM HOUSEHOLD INCOME IN EAST SHEWA ZONE, ETHIOPIA

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ABSTRACT

Background: Promoting and provision of improved agricultural inputs technology innovations-, is key to increase the productivity through intensification of smallholders farms. However, there are limited rigorous impact evaluations on the contributions of such combinations of improved technologies on household income. This paper investigates the impact of improved agricultural technology use on farm household income in East Shewa Ethiopia.

Methods: The study uses a multi stage sampling procedure to select 400 sample households. Data were collected using a household survey, a focus group discussant (FGD) and key informant interviews. Binary logistic regression model and propensity score matching (PSM) were used to analyse the data collected.

Results: Results of the propensity score matching analysis showed that households using improved agricultural technologies had on average the annual income higher than the adopters by Ethiopia Birr 14,407.96. We found the importance of promoting complementary agricultural technologies among rural smallholders.

Conclusions: The farmers are using improved agricultural inputs widely and their status may be vary from farmer to farmer based on availability, accessibility and lack of awareness of the issues involved. The adoption of multiple combinations of improved technologies has substantial effects that improve the agricultural productivity status of smallholders in the study areas. We suggest that rural technology generation, promotion, dissemination and adoption interventions be strengthened.

Keywords: Improved agricultural technologies, Impact, propensity score matching, Farm income, Ethiopia

INTRODUCTION

Agriculture, particularly of smallholder farmers, is a principal economic activity in Sub-Saharan Africa (SSA) and plays a crucial role in growth and development, overcoming poverty and enhancing food security (Bihon, 2015; Biru *et al.,* 2019; Department for International Development (DFID), 2014). However, agriculture is often characterized by dependency on rainfed, low use of modern technology and low productivity, and feed millions of people living under extreme poverty (Beegle *et al.,* 2016; Tilahun *et al.,* 2019). And yet 62% of the population depends on agriculture for their livelihoods (Asfaw, Shiferaw, Simtowe, and Lipper, 2012).

Like in the case of most Sub-Saharan countries, smallholder farmers' agriculture is widely acknowledged that mixed crop-livestock agricultural plays a great role in feeding rural and urban population and considered as an economic pillar sector in Ethiopia (Agricultural Transformation Agency (ATA), 2018). The sector employs the largest labor force about 72.7%, produces 90% of export earnings and sources up to 90% of the raw materials for manufacturing industries in the country, and contributes 32.7% of Gross Domestic Products (GDP) (Central Statistics Agency (CSA) and World Food Program (WFP), 2019; National Bank of Ethiopia (NBE), 2019/20).

In Ethiopia, different strategies and polices have been devised and implemented to improve agricultural production and productivity, enhance food security, accelerate agricultural commercialization, value chain promotion, and improve rural livelihoods of smallholders since the economic growth strategy of Agricultural Development Led Industrialization (ADLI) of 1992 to latest launched 5 year Growth and Transformation Plans (GTP-I and II) since 2010/11 as key tenet to achieving the agricultural growth is the adoption of improved technologies together with management practices that will augment yields and increase household incomes for smallholder farmers by realizing its contribution to the country's economy (Chanyalew *et al.,* 2016; International Fertilizer Development Corporation (IFDC), 2012; United Nation Development Programme (UNDP), 2018).

Agricultural production remains poor in performance and slows in progress towards the expected agricultural transformation in Ethiopia (Bachewe *et al, 2015 and* Getachew, 2018). They argued that the agriculture sector remains poor in performance and slows in progress towards the GTP and Agricultural Growth Program (AGP) goals. Such poor performance can be attributed to very low use of improved agricultural technology inputs. This has been evidenced in CSA (2016), abstract report that depicted in 2015/16 production year, the farmers use improved seed for cereal cropped 15%, oil seeds was 0.8% and 1.6 % of the total pulse and cultivated land under fertilizer was 57%, and fertilizers applied was 97kg/ha all crops, this is still far below the recommended 200 kg/ha in Ethiopia. Similar report (CSA, 2018), for 2017/18 production season stated that only 34% farmers have adopted full packages of crop technologies.

In order to accelerate diffusion and adoption of agricultural technologies in a country, the Ethiopian Institute of Agricultural Research (EIAR), Regional Agricultural Research Institutes (RARIs), and Universities have been experimenting and releasing several improved agricultural technologies in crops, livestock and natural resource management. In addition, Agricultural Technical and Vocational Education and Training colleges in the country have been training frontline extension professionals who are expected to station at the farmers' Training Centers (FTCs) established at the lowest level of administrative units throughout the country. These are some of efforts made to increase the adoption of improved agricultural technologies by smallholders in the country.

To understand the impacts of adoption of improved agricultural technologies on households' income, several studies have been undertaken across the world. Regarding crop technologies, a study in India by Singh et al. (2011) shows that introducing 'Happy Seeder': a tractor-powered machine that cuts and lifts the rice straw sows into the bare soil and deposits the straw over the sown area. It provides a considerable saving in the use of human and mechanical labor. Using improved maize seed varieties in Kenya (Wilfred and Ogada 2014), in Zambia (Khonje *et al.,* 2015), in Benin (Houeninvo et al., 2019) were found to significantly increase maize yields and farm income. A similar result on adopting improved groundnut varieties in Uganda (Kassie et al., 2011) and tissue culture banana technology in Kenya (Kabunga *et al.,* 2014) were also found an increased household income due to applications of new technologies.

In Ethiopia, various studies on impact of technology adoption on agricultural productivity and income (Ayenew et al., 2020; Berihun, 2014; Natnael, 2019; Wake and Habteyesus, 2019; Tsegaye, 2020), revealed that adoption of improved agricultural technologies has a robust, significant and positive impact on farmers' income by which adopters were better-off than their counterpart non-adopters.

The above mentioned cases are some examples of illustrating adopting a single agricultural technology and impact to productivity of smallholder. However, few studies assessed on simultaneous adoption of multiple of agricultural technologies on household well-being. Such studies can highlight complementarities among technologies and can show how one technology can have a multiplier effect by reinforcing the economic effect of the other technology. A study in Tanzania-, regarding impact of farmers adopting fertilizer micro-dosing and tied-ridge technologies on farm income (Habtemariam et al., 2019), adoption of improved agricultural technology and its impact on household income (Muluken et al., 2021). Impact of Adoption of Improved Agricultural Production Technologies on Cereal Crops Productivity and Farmers' Welfare in Ethiopia (Yonnas and Seid, 2021).

Finally, adoption of complementary agricultural technologies that involves different inputs such as improved seeds, chemical fertilizers, pesticides, agricultural credit and agricultural mechanization in country has indicated that it is one of the ways of reducing poverty level (Biru *et al.,* 2020). However, there is limited empirical study in study area regarding the status of agricultural input supply and multiple agricultural technology adoption on farmer's well-being. Hence, clear knowledge gap is noticed on status and impact of such agricultural technologies on the wellbeing of farmers in the zone under study. It is believed that the research contributes in generating new knowledge on the topic.

OVERVIEW OF RELATED LITERATURE

Agriculture is an economic activity with specific characteristics associated with knowledge, innovation and technology transfer (Simin *et al.,* 2014). Most rural households are involved in agriculture that includes crop, livestock or fish production for their livelihoods (Abimbola and Oluwakemi, 2013). Agricultural inputs are a common term for a range of materials, which may be used to improve production and productivity of the agricultural sector (Charles, 2014; Kenneth and Henrik, 2012).

To increase agricultural production and alleviate poverty, attentions need to be given to technology adoption. Agricultural new technologies constitute the introduction and use of hybrids, the greenhouse technology, genetically modified food, chemical fertilizers, insecticides, tractors and the application of other scientific knowledge (Biru *et al.,* 2019; Marenya *et al.,* 2018; Melesse, 2018;Workineh et al., 2020). Innovation adoption is a time taking process although it induced growth to improve food and nutritional security and alleviates poverty (Berihun *et al.,* 2014; Kassie et al., 2018; Solomon *et al.,* 2012).

Adoption of agricultural technology has a direct effect on farmers' income, yield and economic growth, if it is widely adopted and diffused (Ibrahim *et al.,* 2014;Yonnas and Seid, 2021). Adoption of proven technologies and improved farming practices hold great promise to boost production and productivity, to improve the living conditions of rural poor and to reduce poverty. In less developing countries, improving the livelihoods of rural farm households via agricultural productivity would remain a mere wish if the technology adoption is low (Duflo *et al.,* 2011;Udry, 2010). Therefore, new technology diffusion is an important source of economic growth.

To understand the impacts of adoption of improved agricultural technologies on households' income, several studies have been undertaken. For example, Ayenew et al. (2020) have conducted a study on Agricultural technology adoption and its impact on smallholder farmer's welfare in Misha district of Hadya Zone, Ethiopia, using double hurdle and Endogenous Switching Regression model on cross-sectional data. The estimated model revealed that adoption of improved wheat varieties has a positive and significant effect in enhancing farm household's welfare. Another study was also conducted by Natnael (2019) on impact of Technology Adoption on Agricultural Productivity and Income: The analysis was conducted using a multivariate regression model, which was developed based on the household production function. The estimated result of a linear regression confirmed that adopter farmers have generated, 24% higher farm income from the resulted increase of agricultural output due to adoption.

The study undertaken by Tsegaye (2020) evaluates the impact of adopting improved agricultural technologies (high yielding varieties) on rural household welfare measured by consumption expenditure and poverty indices by applied propensity score matching, and endogenous switching regression. The analysis reveals that adoption of improved agricultural technologies has a robust, significant and positive impact on per capita consumption expenditure and a negative impact on the poverty status of households.

Muluken et al. (2021), look at the adoption of improved agricultural technology and its impact on household income in East Ethiopia. The research employed the Propensity Score Matching (PSM) procedure to establish the causal relationship between adoption of improved crop and livestock technologies and changes in farm income and results from the econometric analysis show that households using improved agricultural technologies had, on average, 23,031.28 Birr higher annual farm income compared to those households not using such technologies. Impact of Adoption of Improved Agricultural Production Technologies on Cereal Crops Productivity and Farmers' Welfare in Central Ethiopia by Yonnas and Seid, 2021.The analysis showed that compared to the non-adopter farmers, a better net cereals crop income per land was obtained from the simultaneous adoption of improved seed and row planting, row planting and urea, and improved seed, and row planting and urea. For instance, compared to the counterfactual scenario of non-adopter, the mixed adoption of an improved seed variety with row planting technology increases net cereal crop income of farmers by about birr 14,479.64 per cultivated land.

The study of Wilfred and Ogada (2014) on investigates the impact of package adoption of inorganic fertilizers and improved maize seed varieties on yield among smallholder households in Kenya using a quasi-experimental difference-in-differences approach combined with propensity score matching. Their findings show that inorganic fertilizers and improved maize varieties significantly increase maize yields when adopted as a package, rather than as individual elements.

METHODOLOGIES

Study area and Research Design

The empirical data used for this study were collected from a sample of improved agricultural technology users and non-users households in districts of Adama and Ada'a, East Shewa Zone. These districts were selected as they are the primary producers of cereal crops in the zone and they are relatively adopting improved agricultural technologies and representativeness to the major agro-ecological zone of East Shewa. In these sampled two districts, cereals crops namely Teff, wheat, maize and pulse such as chickpea are largely produced.

The study adopted a cross-sectional survey research design as its framework to guide the process of data collection. Cross-sectional survey research design is the collection of data mainly using questionnaires or structured interviews to capture quantitative or qualitative data at a single point in time. In order to discuss the results of the finding, mixed research methods, concurrent embedded design was employed in this study.

A mixed methods research design is one in which both qualitative and quantitative techniques are used in a single study. Researchers who used mixed research methods employ philosophical and methodological pragmatism (Creswell, 2014; Onwuegbuzie and Johnson, 2006). As Creswell (2014) states that for mixed methods research, pragmatism opens the door to multiple methods, different views, and different assumptions, as well as different forms of data collection and analysis. Therefore, the philosophical stand for this research is pragmatism research philosophy.

Sampling procedure

A multi-stage sampling procedure was employed to select the sample households. In the first stage, two districts were purposively selected on the basis of its relative importance in the use of inputs and its accessibility, farmers' hopeful use of agricultural inputs, their potentials for crop production and diversity of agro-climate which represent to the major agro-ecological zones of the East Shewa zone's districts.

This study made references to the improved crops technologies (of teff, maize, wheat and chickpea), chemical fertilizers (which involves DAP, NPS and Urea), agro-chemicals (pesticides, insecticides, herbicides), agricultural mechanization equipment/tools (such as tractor, seed planting technology, grain threshing machine, modern grain storage), and agricultural credits (in cash and in kinds). These technologies were chosen following a field scoping survey and mainly focused on used improved agricultural technologies in the study areas.

During the second stage stratify *kebeles* according to agro-climate, and then 4 rural kebeles Administration (KAs) were selected from both districts using simple random sampling method. Then, at third stage, random sampling method was employed to draw sample households to each KA based on the probability proportional to size (PPS) method. Finally, a total of 400 households' heads (HHs) (200 HHs from Adama district and 200 HHs from Ada'a district) were selected randomly from sampling frame in the KAs by Kothari (2004) sample size determination formula.

Methods for data generation

This step in the research process started with the selection and training of enumerators. Eight enumerators were selected from all KAs who are fluent speakers of the local language, acquainted with the culture of the local people, and familiar with the study area. They were carefully recruited and trained by researcher for two days on the objectives of the study and orientations on how to collect data using questionnaires prepared for the research.

The developed questionnaire was pre-tested on a randomly sampled 20 non-sampled households. Based on the feedback obtained from the pre-testing exercise, some items were adjusted and additional orientations were given to the data collectors. Both qualitative and quantitative data were collected through structured questionnaire as the main data collection instrument. Alongside, the data collection was supplemented by key informant interview; focus group discussion and some information were drawn from secondary sources. It focuses on data pertaining to the socio-economic and demographic characteristics of the respondents, their farming activities, ways of accessing agricultural inputs and the impact of adopting improved agricultural technologies on their income and well-being. Further the researcher closely supervised the process of data collection and provided immediate feedback whenever necessary.

Data Analysis Techniques

This study employed descriptive and inferential statistics, and econometric model to analyse data. Data collected through household survey were processed, coded, entered into the computer and analysed using Statistical Package for Social Science (SPSS) and STATA software for further analysis. Descriptive statistics, such as mean and standard deviation, tabulation, percentage and frequency were used to present summary statistics of quantitative data pertaining to demographic, socio-economic, institutional and psychological characteristics of sample households. While as inferential statistics, such as Chi-square (χ^2) for categorical and dummy types of variables and t-test for continuous types of variables were used to assess the existence of statistically significant differences in observations between improved agricultural technology adopters and non-adopters. In this study, farm income, the outcome variable, refers to the annual income in birr obtained from their agricultural production and others sources during last production season.

The Propensity Score Matching (PSM) model used in this study makes a reference to the process of evaluating the impact of an intervention on an outcome indicator, total income of farmer. It requires conceptualizing and answering the tough question: ‘what would have happened to users of an intervention had they not participated in it?’ Referred to as ‘the fundamental problem of causal inference’ this is a serious issue since an individual can only be in a state of either participating or not participating in the program at a given time (Houeninvo *et al*., 2019; Winter *et al.,* 2011).

The alternative to the experimental approach is the use of quasi-experimental approaches, which seek to create, using empirical methods, a comparable control group that can serve as a reasonable counterfactual (Cunguara and

Darnhofer, 2011; Ojobaiyegunhi, 2020). In this study, among the available non-experimental approaches, the Propensity Score Matching (PSM) procedure is implemented due to the nature of data available for analysis.

Matching methods in evaluating treatment effects

The fundamental notion behind matching is to construct a comparable group of individuals–who are similar to the treatment groups in all relevant pre-treatment characteristics X–from a sample of untreated ones. In practice, a model Probit or Logit for binary treatment is estimated in which participation in a treatment is explained by several pre-treatment characteristics and then predictions of this estimation are used to create the propensity score that ranges from 0 to 1.

There are different approaches of implementing PSM, including the Nearest Neighbor (NN) matching, Caliper, Interval matching, and Kernel and Local Linear matching (Khandker *et al.,* 2010). In the present investigation, the Nearest Neighbor Matching (with 5-Neighbors and One-to-One matching) is implemented. There are two assumptions surrounding the implementation of the PSM.

The first one is referred to as unconfoundedness Rosenbaum and Rubin (1985), selection on observables or Conditional Independence Assumption (CIA) (Lechner, 1999). 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, ensures that groups with the same values for characteristics X have a positive probability of being both participants and non-participants of a treatment.

The overlap condition enables to compare comparable units. Nevertheless, in order to deal with the ‘curse of dimensionality’ problem, Rosenbaum and Rubin (Rosenbaum and Rubin, 1985) show that if the potential outcomes of treated (Y1) and control (Y0) are independent of treatment allocation conditional on covariates X, then they are also independent of treatment conditional on the propensity score as shown in equation. 3.1.

$$P(D = 1|X) = P(X). \text{--} \quad (3.1)$$

Generalizing the above issues, assuming that the unconfoundedness assumption holds and there insufficient overlap between the treatment and comparison groups, the PSM estimator for the Average Treatment Effect on the Treated (ATT) conditional on the propensity score can be written as.

$$ATT = \{E[|D = 1, P(X)] - E[|D = 0, P(X)]\} \quad \text{----------------------} \ (3.2)$$

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 (Caliendo and Kopeinig, 2008).

A number of techniques are available to check covariate balancing during matching process. 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 (Rosenbaum and Rubin, 1985). As a rule-of-thumb, there should not be any significant difference in means after matching. Regarding standardized bias, Rosenbaum and Rubin (1985) 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

Standardized bias

$$Before = 100 * \frac{\bar{X}_1 - \bar{X}_0}{\sqrt{0.5[V_1(x) + V_0(x)}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (3.3)$$

The standardized bias after matching can be written as

Standardized bias

$$After = 100 * \frac{\bar{X}_{1M} - \bar{X}_{0M}}{\sqrt{0.5[V_1M(x) + V_0M(x)}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.4)$$

Where,

$\bar{X}_1$ (V1) is the mean (variance) in the treatment group before matching.

$\bar{X}$ 0 (V0) the corresponding values for the comparison group.

$\bar{X}$ 1 M (V1M) and X $\bar{0}$ M (V0M) are the mean (variance) values for the matched samples.

Sianesi (2004) suggests the comparison of Pseudo-R^2 before and after matching as a method to check balancing. 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 (LR) test on the joint significance of all covariates in the (Logit) model should not be rejected before matching, but should be rejected afterwards (Caliendo and Kopeinig, 2008).

RESULTS AND DISCUSSION

Descriptive statistics results

Results related to demographic, socio-economic, institutional and psychological characteristics are presented in Table 1. From the results, we note that there is a statistically significant difference in sex, school years, extension service, access to credit, time of inputs distribution, price of inputs, amounts of inputs required, motivation level, family size and farm size between adopters and non-adopters of improved agricultural technologies, while the mean value for age and distance to market of respondents were found to be not significantly different between the two groups.

These observations imply that the farm households who used improved agricultural technologies were mainly male headed, educated, and have larger family size. It is widely acknowledged that male headed farmers are more likely to adopt agricultural technologies than their female headed counterparts (Bihon, 2015; Mwungu *et al.,* 2019; Obisesan, 2014). The reasons could be that female farmers have less access to any improved agricultural technologies and other norms and beliefs prevailing in the society which contributes for lower adoption of technologies in general. This finding shows that farmers who have used technologies have better education background compared to those who did not use the improved agricultural technologies. This result is consistent with that of Chowa *et al.,* 2012; Namara *et al.,* 2013; Yonnas and Seid, 2021; Zebib, 2014. However, this finding contrasts with that of Nata *et al.* (2014), that has found out household adoption of soil-improving practices and food insecurity were negatively correlated as study in Ghana indicated.

The study result also showed out that the average family size (in adult equivalent) of sampled farmers of adopters was 6.51 members, and it is higher than the mean family size of non-adopter farmers 6.0 members. However, this finding contradicts with that of Muluken et al. (2021) the mean family size of respondents was not significantly different between the two groups, adopters and non-adopters. Age of farmers did not significantly affect the adoption of improved agricultural technologies (Hailu *et al.,* 2014; Teklewold *et al.,* 2013). But, this result contrasts with that of Yonnas and Seid (2021), and Hailu et al. (2021) studies on the impact of adoption of improved agricultural production technologies on cereal crops productivity and farmers' welfare and the impact of improved agricultural technologies on household food security of smallholders in Central Ethiopia respectively. The possible reason could be older age loss of energy and short- planning horizons, as well as being more risk averse for using new technologies. Furthermore, elderly farmers do not have the required labor force to adopt labor- intensive technologies like row planting practices compared to the young people (Kassie et al., 2015).

The second categories of explanatory variables are socio-economic factors such as total annual income, price of inputs, farm land size and number of oxen. According to this result, a statistically significant difference was observed between the adopters and non-adopters in these variables. These results indicate that farm households who owned pair oxen operate a relatively large plot of farm land and had better chance of improved agricultural technologies adoption due to farm households who have oxen can plough more farm land and prepare their land well as well. Furthermore, they can sow their crop on time which will help them to get better yield and improve their food security and their income and the result is consistent with Dereje (2018), Bihon (2015). As the price of improved agricultural inputs is expensive, the households' capacity to afford decrease and the price of improved agricultural inputs was negatively related with the use of improved agricultural inputs that approved the previous expectation and match with results of Zebib (2014), Gebrerufael (2015) and Bewket (2011), if price of inputs cheap, there is a rapidly growing amount of users for improved agricultural inputs. Size of land owned by a farmer is found to have positive effect on adoption and matches with has been fund by Tilahun et al. (2019). Our result contrasts that of Varma (2019), who found that small and marginal farmers are more likely to adopt as compared to large farmers.

Among the five institutional variables considered in this study, all variables were found to have significantly different distribution between the users and non-users of improved agricultural technologies. These are: Extension contact, Access to credit, distance to market, time of input distribution and amount of inputs required. This result revealed that Farmers who have frequent contacts with development agents more likely to adopt multiple combinations of agricultural technologies. A number of extension contacts have positively and significantly influenced the adoption. The result is consistent with a prior expectation, positive, in that the frequency access of extension service is a potential force which accelerates the effective adopting of improved agricultural technologies by farmers. This was similar with the studies of Workineh et al. (2020), Agricultural technology adoption and its impact on smallholder farmer's welfare in Ethiopia; Social capital, risk preference and adoption of improved farmland management practices in Ethiopia Wossen et al. (2015).

There is a positive and significant correlation between access to credit service and household decisions to adopt technologies. Results indicate that access to credit has a positive and significant effect on the adoption of improved agricultural technologies. This result is parallel with the previous studies by Tesfaye et al. (2016) and Hailu *et al.* (2015). If market distance is far from the homestead, farmers will face higher transportation cost given poor infrastructure and thereby accessibility of new technology becomes difficult. The result is in line with our prior expectation and consistent with Ayenew *et al.* (2020) and Solomon (2016).

The analysis showed significant association between number time of inputs delivery and adoption of improved agricultural inputs were positive correlation. The result is consistent with a prior expectation, positive, in that inputs of delivery time is a probable dynamism which quickens the active adopting of improved agricultural technologies by farmers. This result is similar to the findings of Workineh *et al.* (2020) and Wossen *et al.* (2015). The investigation shows significant association between amounts of inputs delivered and adoption of improved agricultural inputs were negative correlation. The result is consistent with a prior expectation, negative, in that the accesses of required amounts of inputs are suppressed asset which speed up the effective adopting of improved agricultural technologies by agriculturalists. This result is also correlated to the findings of Tesfaye *et al.* (2016) and Hailu *et al.* (2015).

Adopters who were motivated using new technologies to their agricultural production produce more than the non-adopters. Therefore, there was a positive relationship between adopters of improved agricultural technologies and production motivation status and match with the previous expectation and consistent with study of Zebib (2014).

Regarding the outcome variable, i.e., farm income, we find that, on average, adopters of improved agricultural technology obtained 34,149.87 Birr per year while the non-adopters obtained 19,741.91 Birr per year. Adopters tend to earn more income per annual than the non-adopters and the mean difference of it is statistically highly significant as shown in Table 1.

Table 1 Descriptive result. Mean values; standard deviations in parenthesis

	Adopter (n=134)	**Non-adopters (n=266)**	**t-test/ χ^2 -test (P-Value)**
Outcome variable			
Farm income (Birr)	34,149.82 (13819.80	19,741.91 (6072.2)	0.000*** (26.448)
Demographic variables			
Male household head[b]	116	229	0.017** (18.43)
Age (years)	52.12 (11.913)	53.3)	0.152 (2.062)
Education (years)	77	93	0.000*** (33.845)
Family size (Number)	6.5 (2.254)	6.0 (1.908)	0.014** (6.107)
Socio-economic variables			
Price of inputs (Birr)	92	259	0.000*** (68.54)
Land farm size (ha)	3.24(1.235)	2.94 (1.0)	0.000*** (16.032))
Owned oxen (Number)	120	134	0.000*** (64.26)
Institutional variables			
Extension service (number)	75	17	0.000*** (123.682)
Market distance (Km)	3.02 (0.74)	3.43 (0.618)	0.387 (0.751)
Credit access[b]	32	14	0.000*** (30.45)
Time of inputs delivered (yes)	45	10	0.000***(66.82)
Amounts of inputs distributed (yes)	119	1	0.000*** (27.16)
Psychological Variables			
Motivation level	23	12	0.000*** (101.02)

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

b percent (proportion) of the sample

Source: Survey study, 2023

Econometric results

The causal effect of improved agricultural technology use on farm income is estimated using the Propensity Score Matching (PSM) procedure. The analysis employed Nearest Neighbour Matching (with 5–neighbors and one-to-one (no replacement) matching algorithms) using psmatch2 command implemented on STATA 11.0 platform. In what follows, the results pertaining to estimation of propensity scores, Average Treatment Effect on treated (ATT), and post-matching quality analyses are presented.

Estimation of propensity score

Propensity score is the conditional probability that an individual chooses the treatment. That 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 farm income and for which observational data were available. The results are given in Table 2. Overall, the model is statistically significant as shown in the Table 2. Based on the findings, we note the existence of a statistically significant difference between treated (n=134) and control (n= 266) households regarding the age, educational level, price of inputs, own oxen, extension contact, time of inputs distributed, amounts of inputs required and level of motivation to new technologies.

Table 2. Propensity Score estimation

Independent variables	Coefficient	Std. Err	Z
Sex	0.93	0.400	0.873
Age (year)	1.05	0.023	0.029**
Education level (years)	1.49	0.265	0.023**
Family size (numbers)	0.99	0.103	0.938
Farm size (ha)	1.60	0.684	0.269
Price of inputs (birr)	0.077	0.043	0.000***
Own oxen (yes)	39.81	48.49	0.002***
Extension contact (yes)	6.88	2.33	0.000***
Credit access (yes)	1.37	0.786	0.573
Market distance (km)	0.66	0.176	0.118
Time of input delivered (yes)	8.04	4.362	0.000***
Amount of input required(yes)	13.57	16.703	0.034**
Motivational level (rank)	0.42	0.104	0.000***
Constant	-3.544	1.876	0.059*

Log likelihood	-125.189
Number of observations	400
Likelihood ratio (LR) X^2 (13)	259.75
Prob> X^2	0.000
Pseudo R^2	0.043

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

Source: Model output

As depicted in Table 2, these factors were responsible for households' differential participation in improved agricultural technology adoption. Our findings show that the age of farmers was found significantly affect adoption of improved agricultural technologies positively and the finding is consistent with studies result of Martey *et al.* (2019) in Ghana, and Varma (2019) in India. Education is vital for any occupation to understand and interpret the information coming from external source. It also increases farmer's ability to obtain;-, process and use information relevant to adoption of a new technology (Lavison 2013; Namara *et al.,* 2013). This is because better education level influences respondents' attitudes and thoughts making them more open, rational and able to analyse the benefits of the new technologies.

Price of inputs of improved agricultural technology was significantly and negatively influences adoption. It was hypothesized that those farmers who cannot buy improved agricultural technologies due to expensive input price are in most cases find it difficult to use improved agricultural technology. This result was consistent with study of Natnael (2019), the impact of that technology adoption has on agricultural productivity and income.

The effect of number of oxen was seen on the adoption of agricultural improved technologies, in that households' heads who own many oxen, adopt more agricultural improved inputs which is significant at less than 1% probability level. Therefore, this is in line with our prior expectation that number of oxen positively affects household adopting improved agricultural technologies. The result is consistent with Dereje (2018), Bihon (2015) and Bryant (2010), farm households who have oxen can plough more farm land and prepare their land well as, they can sow their crop on time which will help them to get better yield and improve their food security and their income.

We found that improved agricultural technology users participated more in extension service than the non-users. The observation of this variable is inconsistent with prior expectation and it was positively and statistically significant to influence of adoption improved agricultural technology. This agrees with the finding of Amsalu *et al.* (2017) and (Melese, 2018), who reported that farmers who had frequent contacts with development agents on agricultural development matters were the ones who got more access to information and encouraged to interact continuously with such knowledge and technology generation and adopt technologies easily. Timely distributions of inputs to farmers are positively and significantly related with household adopting of improved agricultural technologies. This shows that those households who got input timely are more users of improved agricultural inputs at significantly higher levels than those who got the inputs late. This fits with the finding of Tesfaye (2006), those farmers who timely access inputs are more users of improved agricultural inputs since they often ready to plant earlier.

The investigation shows significant association between amounts of inputs delivered and adoption of improved agricultural inputs were positive correlation at less than 1% probability level. The result is consistent with a prior expectation, positive, in that the accesses of required amounts of inputs are suppressed asset which speed up the effective adopting of improved agricultural technologies by agriculturalists. This result is correlated to the findings of Tesfaye *et al.* (2016) and Hailu *et al.* (2015). As stated in Table 3 of propensity score, level of motivation negatively affected adoption of improved agricultural technologies means farmers need motivation in order to take a risk for the newly accepted technologies. The finding is consistent Zebib (2014) and Macire *et al*. (2016), the more educated farmers the more motivated to accepted new agricultural technologies, means education can assist farmers accepting and adopting technologies.

Estimation of average treatment effect (ATE)

The estimation of average treatment effect (ATE) is performed using the nearest neighbors matching (with 5-Nearest neighbors and One-to-One matching algorithms).

The results are presented in Table 3. In addition to the mean values of the outcome variable, Table 4 contains mean differences between treated and control groups (column 3) and bootstraps standard errors (with 50 replications) on the mean difference (column 6). Overall, we found convergence of results between the two matching algorithms (column 7). However, the discussion in this section is based on the results obtained using the one-to-one matching algorithm as this resulted in a higher level of statistical significance.

Accordingly, the results show a statistically significant gain in household farm income as a result of using improved agricultural technologies in the study area. More specifically, we found that households using improved agricultural technologies obtained, on average 14,407.96 Birr higher annual farm income compared to those households not using such technologies. This is a significant result implying that adoption of improved agricultural technologies and practices resulted improved welfare of the farmers in the study area. Our result is consistent with previous empirical results of Cunguara and Darnhofer (2011) in Mozambique, who showed an improved household income as a result of adopting improved seeds and tractor; Muluken et al. (2021) in Ethiopia, who showed an improved household income as a result of adopting improved seeds and livestock technologies; Habtemariam et al. (2019) in Tanzania, who indicated the positive income effect of adopting fertilizer micro-dosing and tied-ridge technologies and Teklewold et al. (2013) and Hailu et al. (2014) in Ethiopia, who documented a positive income effect of adopting sustainable agricultural practices and improved seeds and fertilizer, respectively.

Table 3. Nearest Neighbour matching Results of Average Treatment Effect on the Treated (ATT)

Outcome variable	**Sample**	**(1)Treated**	**(2)Control**	**(3) Difference**	**(4) Std.Err**	**(5) T-stat**	**(6) Booststrap Std.Err[a]**	**(7) z**
Farm income[b]								
5-Nearest Neighbors	Unmatched	38,692.05	18,706.26	19,985.80	995.64	20.07		
	ATT	34,149.87	19,674.71	14,475.16	1,666.00	8.69	49.7	1.20
One to-one matching	Unmatched	38,692.05	18,706.26	19,985.79	995.64	20.07		
	ATT	34,149.87	19,741.91	14,407.96	1,564.50	9.21	49.3	2.33*

Note: ATT Average treated Effect on the treated

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

[a] Boostrap Standard Errors (Std.err.) on the difference (with 50 replications)

[b] 266(all) untreated and 76(out of 134) treated households found on the common support region were used

Source: model output

Matching quality analyses

The matching quality analyses were performed using t-test and standardized percentage Bias (Table 4, column (1) and (2), respectively and other measures of covariate imbalance (Table 5).

Looking at the t-test results after matching (column1, Table 4), we found that the statistically significant difference between treated and control 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 4) appears to be in the acceptance range, complementing the post-estimation t-test results and implying further that the PSM performed well in yielding unbiased estimates of ATT. In addition to the post-estimation t-test and standardized percentage bias results, other measures of covariate imbalance (Table 5) also indicate that the matching process is effective in balancing the pre-treatment characteristics.

Table 4. matching quality analysis: t-test and standardized percentage bias

	(1)t-test		(2) Standardized Percentage Bias	
	5-Nearest Neighbour	**One-to-one**	**5-Nearest Neighbour**	**One-to-one**
Sex	-0.98	-0.65	-1046.4	-681.7
	0.13	0.13		
Age (year)	1.10	0.31	-40.4	61.9
	-1.26	-1.26		
Education level (years)	0.18	0.75	95.2	79.3
	5.89	5.89		
Family size (number)	-1.23	0.26	23.4	84.9
	2.43	2.43		
Farm size (ha)	0.50	0.54	32.4	27.5
	1.14	1.14		
Price of inputs (birr)	1.53	-0.81	69.1	86.8
	-9.49	-9.49		
Own oxen (yes)	-0.32	-1.00	97.5	93.6
	5.76	5.76		
Extension contact (yes)	-0.10	0.33	98.4	94.6
	10.81	10.81		
Credit access (yes)	0.31	0.92	90.1	71.7
	5.72	5.72		
Market distance (km)	0.31	-0.88	90.6	75.0
	-6.02	-6.02		
Time of input delivered (yes)	0.48	1.00	91.2	82.4
	8.93	8.93		
Amount of input required(yes)	0.45	0.58	90.3	87.8
	5.38	5.38		
Motivational level (rank)	-1.29	-1.8	80.2	80.6
	-11.13	-11.13		

Source: Model output

Table 5. Other matching quality tests

Matching method	(1)Pseudo R^2	(2)LRX^2	(3)P>X^2	(4) Mean bias	(5)Median bias
5-Nearest Neighbors	0.052	10.96	0.614	10.7	7.3
One-to-one	0.041	8.59	0.738	10.4	10.4

Source: Model output

Finally, the propensity score graph (psgraph) in figure 1 presents treated and untreated households that are found on the common support region (i, e., 76 and 266, respectively) and the fifty eight treated observations that are off the support region.

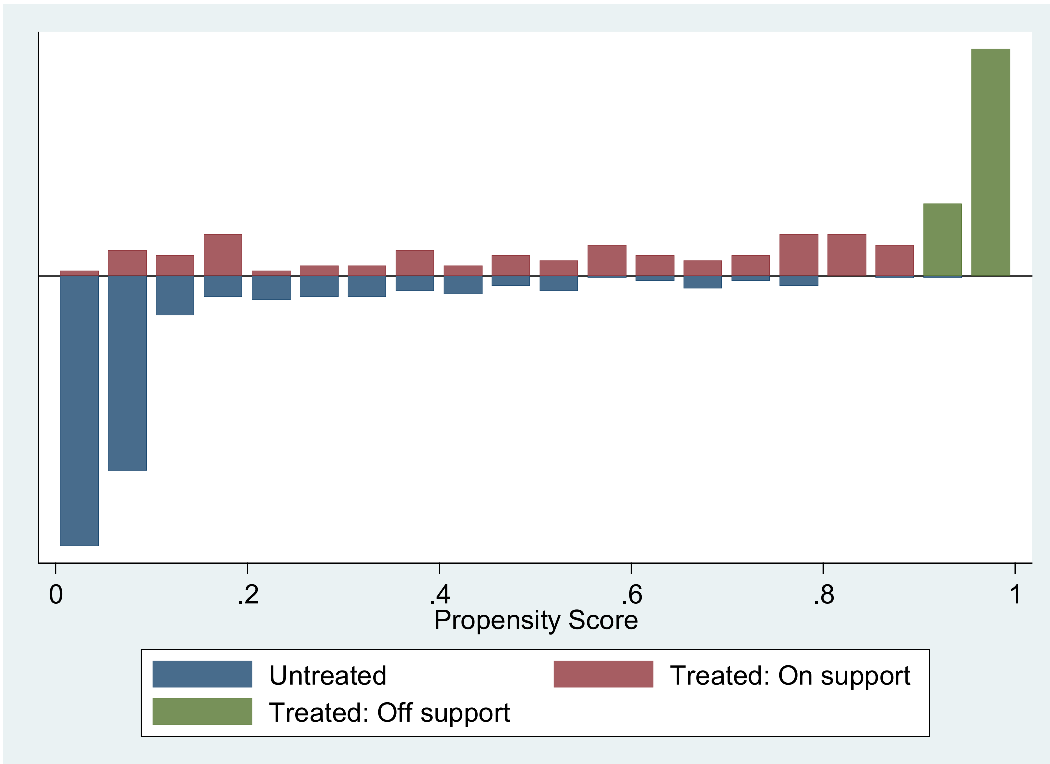

Figure 1: Propensity score graph all (266) untreated and 76 out of 134 treated observations are on common support region

CONCLUSIONS AND POLICY IMPLICATIONS

This study analyzed the impacts of a combination of improved agricultural technologies adoption on farm household income in East Shewa Zone, Ethiopia. The adoption of multiple combinations of improved technologies has substantial effects that improve the agricultural productivity status of smallholders in the study areas. While the use of improved teff seed, and wheat, chemical fertilizers, and pesticides, and agricultural mechanization such as tractor, thresher were identified as the major agricultural technologies adopted in the study areas.

The farmers are using improved agricultural inputs widely and their status may vary from farmer to farmer based on availability, accessibility and lack of awareness of the issues involved. Due to this the majority of sample households' welfare was improved and their incomes were increased.

In the study area, it is better to improve system of using improved agricultural technologies, make uniform among the farmers, and cluster and to reduce the variation observed in rate of application kilogram per hectare among farmers in using improved agricultural technologies especially in teff varieties and chemical fertilizers via facilitating availability, accessibility and affordability of technologies on time.

To improve more the farm households' welfare, productions and their incomes, the major constraints that affect adoption of improved agricultural technologies such as high interest rate of credit, high price of inputs, insufficient of extension service, delayed time of inputs delivery and farmer's level of motivation to wards to improved technologies should be solved.

We suggest that rural technology generation, promotion, dissemination and adoption interventions be strengthened. In addition, the linkage among research centers, Universities and farmers needs to be enhanced via facilitating concerned stakeholders innovation platform.

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