AGRICULTURAL TECHNOLOGY ADOPTION AND ITS IMPACT ON HOUSEHOLDS' WELFARE IN RURAL ETHIOPIA: A PANEL DATA ANALYSIS

BY

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ADDIS ABABA, ETHIOPIA

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ADDIS ABABA UNIVERSITY

COLLEGE OF BUSINESS AND ECONOMICS

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Declaration

I, the undersigned, hereby declare that the work contained in this thesis is my own original work and that I have not previously in its entirety or in part submitted at any university for a degree.

Signature: ______________________ Date: _________________________

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School of Commerce

This is to certify that the thesis prepared by ***Anteneh Demeke***, entitled "***Agricultural Technology Adoption and Its impact on households' welfare in rural Ethiopia: A Panel Data Analysis"*** *submitted* in partial fulfillment of the requirements for the Degree of Master of Science in Development Economics; complies with the regulations of the University and meets the accepted standards with respect to originality and quality.

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Advisor: ____________________ Signature: _______________ Date: __________

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Chair of Department or Graduate Program Coordinator

Dedication

This thesis is especially dedicated to my wife who fulfilled my desire and supported my success.

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LIST OF ABBREVIATION AND ACRONYMS

ATE	Average Treatment Effect
ATT	Average Treatment on Treated
CIA	Conditional Independence Approach
CIMMYT	International Maize & Wheat Improvement Center
CSA	Central Statistics Authority
DiD	Difference in Difference
DiD PSM	Difference in Difference Propensity Score Matching
ESS	Ethiopian Socioeconomic survey
GDP	Gross Domestic Product
HYV	High Yielding Varieties
KM	Kernel Matching
LSMS-ISA	Living Standards Measurement Study-Integrated Surveys of Agriculture
NNM	Nearest Neighborhood matching
OLS	Ordinary Least Square
PSM	Propensity Score Matching
RM	Radius matching
SM	Stratification Matching
SNNP	Southern Nation Nationalities & People
TAM	Technology Acceptance Model
TLU	Tropical Livestock Unit

Abstracts

This study examined factors affecting agricultural technology adoption and its impact on farming households' welfare in rural Ethiopia. Agricultural technology adoption can positively contributes to the welfare of smallholder farming households via improving crop yield and productivity. However, in most of the rural areas of Ethiopia the adoption rate is very low. Therefore, this study examines the determining factors in adopting agricultural technologies and its implied impact on welfare status of farming households. The study utilizes balanced panel data of Ethiopian Socio-economic Survey (ESS); which was collected by CSA of Ethiopia in collaboration with the World Bank in three rounds of wave during 2011/12, 2013/14 and 2015/16 in all regions of the country. The study employed logistic regression model as estimation criteria and the casual impact of technology adoption estimated by Difference-in-Differences combined with Propensity Score Matching (DID-PSM) techniques so as to assess the results robustness and their implied impact on households' welfare. This helps to estimate the true welfare effect by controling unobserved heterogeneity and handle the problem of selection bias in treatment effects. The results show that adopters of agricultural technology had higher nominal total consumption expenditure per adult equivalent, per capita food consumption expenditure and per capita non-food consumption expenditure than non-adopter but the change was insignificant on per capita education expenditure; and this confirms that adoption of agricultural technologies has a positive and significant impact on household's consumption apart from per capita education expenditure. The study concluded that the need of a wide-ranging policy framework to confront constraints that promote the adoption of agricultural technologies so as to improve welfare of farming households in rural Ethiopia.

Keywords: households' welfare, technology adoption, DiD-PSM, rural Ethiopia.

CHAPTER ONE

INTRODUCTION

1.1. Background of the Study

The agricultural sector in Ethiopia has been an engine for the economic development for years. The sector accounts for nearly 43 % of Gross Domestic Product (GDP), and 84 % of exports and 80% of employment creation (CSA, 2018). It is also the source of food that they consume and cash for their expenditure in need, so that boosting agricultural productivity is very important to farming households.

A study conducted by Natnael, (2019) states that even if agriculture is very important to the people at large and it contributes more to the GDP of the country, the sector has been still dominated by the smallholder and the level of production is very low due to less use of the modern agricultural technology and limited adoption of best agronomic practice.

Despite the improvements made over the last four decades in the agricultural sector, a combination of declining soil fertility, population growth, low uptake of external inputs, and climate disruption has resulted in a dramatic fall in per capita food production (Melesse, 2018). According to Tewodros, (2016), various researches has indicated the potential benefits of technology adoption, but experience suggests that successful adoption depends on a favorable confluence of technical, economic, institutional, and policy factors.

In Ethiopia the agricultural technology adoption is still limited due to different factors while it's very essential in reducing poverty and ensuring food security (Melesse, 2018). Perhaps one of the main reasons for studying economic development is to understand better how individuals are able to make the transition out of poverty. Increasing productivity in agriculture depends on adopting production enhancing technologies and the innovativeness of farmers (Awotide et al., 2016)

Although several technology packages have been introduced in Ethiopia over the past four decades while some studies in the past have tried to evaluate the characteristics behind the adoption behavior of farming households, they were either restricted to location and commodity specific approaches. As a result, the adoption and welfare impact of these technologies has not been satisfactorily and comprehensively assessed at a national level (Natnael, 2019; Melesse, 2018; Sebsibie et.al, 2014)

Against this backdrop, this study examined the socio-demographic factors, institutional factors as well as resource ownership which exert significant influence on the adoption behavior of farmers. In addition, the study also aimed at investigating the farming households' characteristics in adopting agricultural technologies and evaluates their welfare impact. Therefore, the general objective of the study attempts to analyses on agricultural technology adoption on chemical fertilizers, improved seed varieties and crop protection chemicals and their impact on household's welfare in rural Ethiopia.

1.2. Statement of the Problem

In Ethiopia the agricultural sector contributes for 43% of GDP, over 84% of export, and nearly 80% of employment. Besides, the major share of income of the rural farming households comes from agriculture (CSA, 2018). Realizing the importance of agriculture sector governmental and non-governmental organizations has been committing huge resources for technology development and promotion of new and improved technologies in the country. According to Getachew, (2020) the government has registered in social, economic and infrastructural development, as well as on policy experimentation over past decades.

However, the rate of technology adoption and its intensity in the country is very low even by sub-Saharan standard. For instance, the average adoption rate of modern fertilizer is estimated to be less than 33% of the total cultivated land and the average level of use of modern fertilizer is only 11kg per hectare which is very low compared to 48kg per hectare in Kenya (Sebsibie et al, 2015).

In addition to this, for the top five major cereal crops, the use of any types of fertilizers ranges from approximately 38 % of sorghum to 83 % of wheat grain fields. Besides, improved seed is relatively common for maize 31%. Improved seed application in the remaining crops ranges from 2 to 8% of crop fields (ESS, 2015/16). Low technology adoption, low use of improved farm inputs and traditional farming are the major constraints behind the low productivity of the agriculture sector in Ethiopia (Melesse, 2018).

Agricultural productivity can be enhanced through the use of improved agricultural technologies. It also plays a significant role in fighting poverty, lowering per-unit costs of production, boosting rural incomes and reducing hunger (Kassie et al., 2011). Increasing productivity in agriculture depends on adopting production enhancing technologies and the innovativeness of farmers (Awotide et al., 2016).

Although a number of studies have been conducted in Ethiopia, and showed that many factors can be associated with a lower rate of agricultural technology adoption. Besides, the systematic analysis of the adoption and welfare impacts of these technologies has been scarce. According to Mekonen and Karelplein (2014) adoption of improved seeds and chemical fertilizer alone will increase crop productivity by 7.38 and 6.32% per year of each in Ethiopia.

In addition, a study by Mekonen (2017), shows the use of high-yielding varieties increases marketable surplus production grew by 7.4% per annually, while inorganic fertilizer use increased by 2.3%. The multiple adoptions of the two technologies jointly increase the surplus by 6%. Despite this in Ethiopia regardless of the positive impact on production and productivity, a large extent of rural farm households are under deplorable living conditions.

However, there are some impact assessment studies that showed direct and indirect positive welfare effects of technology adoption on the farm households (Sebsibie et al, 2015; and Hailu et al, 2014). But, many of the aforementioned studies show the impact of single agricultural technology on productivity and welfare, and also the impacts of single technology on specific crop productivity and on poverty or welfare. Hence, none of them showed farmers' decision to adopt multiple agricultural technologies and their expected benefits for a different combination of technologies. Some studies also have limited area coverage and small samples, and may not be useful in concluding the impact of agricultural technology adoption on households' welfare at the national level (Challa and Tilahun, 2014; and Hailu et al, 2014).

Furthermore, a main weakness of many studies is that they do not explicitly point to a causal effect of agricultural technology adoption on the farm household's wellbeing, or in other words, they can not to establish sufficient counter factual condition and identify the true causality of change Mabaya, (2017). Indeed, so as to assess the impact of agricultural technology, the author explores what it would have been like if agricultural technology had not been adopted by farming households, i.e., the counterfactual situation. Thus, make use of a panel data household survey, the author revealed the causal effect of agricultural technologies adoption on improving welfare of farming households by employing the Difference in Difference (DiD) combined with propensity score matching (PSM) method.

Therefore, this study sought to contribute to the limited knowledge on the impact of agricultural technology adoption that would have good policy relevance on the enhancement of smallholder farming household's welfare. With this background and understanding, examining the impact of agricultural technology adoption on smallholder household's welfare in Ethiopia.

1.3. Objectives of the Study

1.3.1. General Objective

The general objective of the study is to examine the impacts of agricultural technology adoption on farming households' welfare in rural Ethiopia.

1.3.2. Specific Objectives

The specific objectives of the study are:

- To identify factors that influences the adoption of agricultural technologies by farming household in rural Ethiopia.
- To measure the impacts of agricultural technology adoption on welfare of farming households in rural Ethiopia.

1.4. Research Questions

The study tried to answer the following questions:

- What are the factors that influence agricultural technology adoption decision in rural Ethiopia?
- Does adoption of agricultural technologies affects the welfare status of farming households in rural Ethiopia?

1.5. Significance of the Study

The study sought to examine the socio-demographic, institutional as well as resource ownership characteristics of farming households in decision to adopt agricultural technology so as to improving wellbeing within a general framework that recognizes the complexity of this relationship, and emphasize at the same time the relevance of macro-level evidence for policy and research implications. It also provides and generates valuable information about technology adopters and which may also help policy makers to take relevant decisions and intervene in diffusion of relevant technologies.

The study strongly believed to add the list of existing literature on agricultural technology adoption since the average treatment effects (ATE) technique has not been applied abundantly in the study of technology adoption and welfare impact in Ethiopia. For that reason it extends the application of this technique. Unlike most previous studies, this study is utilized ESS panel dataset and combinations of two impact evaluation methods to check the robustness of the results and minimizing biases.

In empirical literature on agriculture technologies and their impact on welfare, several studies have used single econometric model either Endogenous Switching Regression (ESR) Model, Propensity Score Matching (PSM), Fixed Effect Regression (FE) Model, or Difference-in-Difference (DiD) Model. The problem with using a single model is that the estimates may not be robust enough because each model has its own limitations. Unlike most previous studies, this study utilized ESS panel dataset and combinations of two impact evaluation methods to check the robustness of the results and minimizing biases.

Precisely, the study applied the propensity score matching (PSM) technique, with particular attention given to average treatment effects of difference in difference-in-difference (DiD) estimation, to measure the agricultural technology adoption gap and evaluate the drivers of agricultural technology adoption in rural Ethiopia.

1.6. Scope and Limitation of the Study

For this study, the author utilized a nationally representative survey data of the three rounds of waves of Ethiopian socioeconomic survey (ESS) 2011/12, 2013/14 and 2015/16 panel data, collected by Central Statistics Agency (CSA) of Ethiopia in collaboration with the World Bank (WB). The survey covered Amhara; Oromia; Tigray; and Southern Nations, Nationalities, and Peoples (SNNP), the four main regions of the country, plus Somali region.

Though this study utilized a panel data which is ideal for time-variant impact evaluation study and the data is the only macro-survey data that is available online that can be downloaded. Hence, the most recent data is the third wave (2015/16); which is 5 years old from the date that this study is conducted. But it is believed that the data will somehow approximate the current farming household welfare status of the country. The other challenge in conducting this study was presence of missing data values, but they were treated accordingly to get minimum error from true value at each time interval.

In terms of content scope, the study undertook an investigation of the farming households' socio-economic, institutional as well as resource ownership characteristics of farming households that impacts up on agricultural technology adoption and welfare effect; in terms of household demographic status, asset ownership and access (landholding, livestock), family labor use, market access, credit access and per capita expenditure on food, non-food items, education.

1.7. Organization of the Study

This study has been organized in to five chapters; chapter one provides a brief introduction about the study. Chapter two contains a brief theoretical and empirical literature review as well as formulation of the conceptual framework. Chapter three deals with methodology used to answer the research questions. Chapter four presents results and analysis of the study. Chapter five concludes and finally forwards some policy recommendation and area for future study.

CHAPTER TWO

LITERATURE REVIEW

This chapter presents about conceptual and theoretical literature review related to agricultural technology adoption and farming households' welfare. The empirical literature reviewed on agricultural technology adoption and its implied impact on farming household welfare around the world and in rural Ethiopia in particular. At the end of the chapter, conceptual framework on the impact of agricultural technology adoption and factors that determine agricultural technology adoption were discussed.

2.1. Theoretical Foundation and Agricultural Technology Adoption

2.1.1. Definition and Concepts of Agricultural Technology

There are many definitions given for agricultural technology in economic literature. Among many definitions that has been given by Matunhu (2011) defines agricultural technologies that includes the introduction and use of improved seeds, chemical fertilizers, pesticides, tractors, the greenhouse technology, genetically modified food, and the use of other scientific knowledge. So, adoption refers to the decision to use or not to use a new technology, method, practice, etc. by a firm, farmer or consumer.

Melesse, (2018) defined adoption behavior as the practice by which agricultural technology is transferred through certain channels overtime among the members of a social system. According to Mabaya, (2017) adoption can be interpreted as extended term adaptation of modern farming practices to farming households. Adoption, however, is not a permanent feature. In the context of the study, adoption refers to the decision to use or not to use agricultural technology at a point in time.

Thus, this study concentrated on adoption agricultural technologies more particularly chemical fertilizer, improved seed varieties and crop protection chemicals that have been the central patterns of the welfare improving orientations.

A. Chemical Fertilizer

Fertilizer is a material that furnishes one or more of the chemical elements necessary for the proper development and growth of plants. The most important fertilizers are fertilizer products (also called chemical or inorganic fertilizers), organic manures, and plant residues (Sebsibe et.al, 2018). A chemical fertilizer is a material produced by industrial process with the specific purpose of being used as a fertilizer (Tefera, 2020).

According to Mideksa et.al, (2021) fertilizer is one of the most entrenched and widely used agricultural inputs so far as the Ethiopian government is concerned. It has also been a product, which has been receiving continuous government support for its promotion, and market development, as it is directly contributing to food production increase. Use of yield enhancing purchased inputs like fertilizer is very low

Previouse studies show that only 30–40% of Ethiopian farmers use fertilizer and those who do use apply on average only 37–40 kg/ha (NPS+Urea), which is below the recommended rate (Hailu, 2016). However, it is generally agreed that optimum use of fertilizer at farm level have the tendency of improving soil fertility leading to rise in agricultural productivity and the profitability of a given technology (Abubakar, 2014).

B. Improved Seed

In this study, 'improved seed' refers to seed that was originally developed in the research laboratory of a seed company or agricultural research Centre and released to the public. Seed is a key input for improving crop production and productivity. Increasing the quality of seeds can increase the yield potential of the crop by significant folds and thus, is one of the most economical and efficient inputs to agricultural development. As improved seed varieties can be higher-yielding than local seed (or are designed to exhibit desirable traits, such as disease resistance or stress tolerance), the adoption of improved seed has the potential to enhance the farming outcomes and overall welfare of farm-households (Abate et al., 2017; Alwang et al., 2019).

Generation and transfer of improved technologies are critical prerequisites for agricultural development particularly for an agrarian based economy such as of Ethiopian.

Agriculture, particularly crop farming, has a greater effect on both the rural and the urban poor who spend more than a half of their incomes on food. When there are different seed sources available and farmers get access to them there is high probability of adoption of improved varieties. An enhanced seed availability though formal or informal or both sources will improve smallholder farmer's access to seed and enhance improved variety adoption (Girma et. al, 2017).

In practice, whenever a farmer is talking about getting a new seed it implies that she or he is deciding to adopt a new variety. According to FAO (2017), the ultimate goal of a farm household in a risk prone agro-ecology is to obtain seed with characteristics suitable to farmers' agro-ecological and socio-economic condition. Similarly, seed is pivotal in the improvement of food security and farm household livelihood.

C. Crop Protection Chemicals

Pesticides are any substance or mixture of substances intended for preventing, destroying, repelling, or mitigating any pest. Pests can be insects, mites and other animals, unwanted plants (weeds), fungi, or micro-organisms like bacteria and viruses. Although usually misunderstood to refer only to insecticides, the term "pesticide" also applies to herbicides, fungicides, and various other substances used to control pests or growth of plants as approved by the relevant authority for application to crops or the growth of plants (Singh, 2014).

According to Al-Ahmadi, (2019), pesticides are a group of chlorine agents used in plant protection, public health programs, and household sprays and for disinfection of storage warehouse for the protection of agricultural protection. In agriculture, as Zenawi (2018) cited, the use of pesticides starts from the pre-sowing stage. The soil is treated against nematodes (worms) before sowing. Then, the seeds are treated against seed-borne diseases. The standing crops are treated with pesticides against damage from pests, insects, rodents, etc. However, according to Belay et.al (2015), the use of pesticides can cause adverse effects on human health and on the environment. But, it is important to realize that the biological factors cause a loss of about 35 per cent of world agricultural outputs. According to Menale et.al (2020), this includes 14 per cent due to harmful insects, 12 per cent due to diseases, and 9 per cent due to weeds.

2.1.2. Importance of Technology in Agriculture

According to Mabaya, (2017) technology is transferred from sources such as extension agents and the media to the farmer depending on the farmer's characteristics, farmers factor endowments and determined by the prevailing agro-ecological, socioeconomic and institutional factors.

Other studies have also established several factors ranging from physical, socioeconomic, as well as mental that play a crucial role towards the adoption of technology. However, Uaiene, (2011) explained that it is important for farmers to understand their perceptions of the technology provided is vital in the generation & diffusion of improved technologies and information distribution.

Fuglie et al., (2020) asserts that understanding farmers' behavior regarding adoption of new agricultural technologies and how policies might accelerate diffusion has been the subject of hundreds of studies since at least the early days of the Green Revolution.The economic constraint model limits input variability and technology adoption decision in the short run, such as land, labor, credit loans bounds production flexibility and conditions technology adoption decisions.

2.1.3. Overview of Agricultural Technology Adoption in Ethiopia

Ethiopia is among the poorest countries in the world, highly drought-prone and has an agricultural sector that accounts for 85% of employment (Dercon et al., 2012). Despite the efforts made in the recent years, and fastest economic growth recorded over the last decade, food production and distribution is still a major challenge in the country. Hence, improving living conditions and food security of smallholder farmers through increasing agricultural growth remains the main objective of decision makers in the country (Admassie and Ayele, 2010).

Many studies suggested that the way forward is fostering smallholders' productivity, which mainly depends on the adoption of suitable new or improved agricultural technologies (Admassie and Ayele, 2010; Tura et al., 2010). Farm sizes have been rapidly declining, increasing the need for agricultural intensification. Therefore, increasing the productivity of smallholder farmers through improved technology has become a policy priority for the government of Ethiopia (Abebaw & Haile, 2018).

Agricultural technology adoption is assumed to improve the welfare of adopters through higher crop yields, reduced per unit cost of production which leads to higher own personal consumption and disposable income (Zeng et al., 2017). However, agricultural technology adoption remains very low in Ethiopia. For example, in 2014/15 cropping season, adoption rate of fertilizers, improved seed, pesticides and irrigation were 55.06%, 8.55%, 22.32% and 6.15%, respectively (Shita et al., 2018). These indicate that a lot of works need to be done to make sure that farmers perceive agricultural technologies as important contributor of agricultural productivity and ensure better adoption at the farm level.

Several studies have been conducted on the determinants of agricultural technology adoption in Ethiopia as shown by the increasing number of publications (for example, Kassa et al., 2014; Ketema et al., 2016). Their findings revealed that different factors such as; demographic, institutional, socio-economic characteristics hindered adoption of improved and/or new agricultural technologies in Ethiopia. As a result, it had not been possible to benefit from existing/new agricultural technologies which would have been contributed to the achievement of national/regional goals such as eradicating poverty, ensuring food security, and overall economic development.

A study conducted by Tura et al. (2016) showed that agricultural technology adoption decision of the farmers is influenced by land ownership, credit access, distance to the nearest market, livestock holding. The authors also indicated that agricultural technology adoption has significant and positive effect on farmers' income.

Another study conducted by Masresha et al. (2017) on adoption of improved white haricot beans revealed that the decision to adopt white haricot beans variety was influenced by various factors. The study found that frequency of extension visits, land size allocated to haricot beans, agricultural income, price perception, training obtained, and perception on fertility enhancement benefit of the crop positively affected farmers' decision to adopt improved variety, and distant to market, ownership of haricot beans farm land (tenure) and nutritional perception of the crop affected negatively.

2.2. Welfare Measurement and Indicators

According to Musa et al., (2016), households' welfare can be estimated from two standpoints: income and expenditure. When he explains, mostly developed countries measure welfare makes use of the income approach, while list developed countries prefer the expenditure approach. This is due to the fact that households' income is quite easy to measure in developed countries, while expenditure is not as simple as it could be and hard to estimate. Contradictory to this, in list developed countries income is a bit complex to measure as household members earn it from self-employment, but expenditure is more straight forward and easier for estimation.

According to Zenaye (2016) the major indicators of welfare of a given household are income, food security, educational welfare, health welfare and asset holding of the household, which can classified as monetary and non-monetary welfare indicators. The monetary welfare indicators are income and consumption expenditure of the household. But, non-monetary welfare indicators are associated to health, nutrition, literacy, social relations, to insecurity, and to low self-confidence and powerlessness.

A. Monetary welfare indicators

The monetary welfare indicators are income and consumption expenditure of the household.

Income: Income is the amount of money received over a period as payment for work, either goods, or services, or as profit on capital.

Consumption Expenditure: This denotes money spent on the purchase of consumable items by the household such as food, drinks, clothes, education, and medication. Consumption expenditure in this study was limited on the expenses spent on foods and drinks due to the fact of lack of privet school and clinic in study area. In addition, expenses on clothing – which happen (rarely) i.e. once or twice a year – were not considered. Previous impact assessment studies have used income and consumption expenditure as welfare indicator to measure household wellbeing (Asfaw, 2010 and Mulubrhan *et al*., 2011).

B. Non-monetary welfare indicators

Welfare is associated not only to income or consumption expenditure of the household, but also to outcomes related to health, nutrition, literacy, social relations, to insecurity, and to low self confidence and powerlessness. In some cases, it is feasible to apply the tools developed for monetary welfare measurement to non-monetary indicators of wellbeing (Edward, 2017).

2.3. Empirical Literature Review

2.3.1. Determinants of Agricultural Technology Adoption

The literature on adoption of agricultural technologies in developing countries points towards a number of factors operating in a quite complex and interactive ways that condition the adoption decision of farmers. Identifying the factors of adoption of agricultural technologies is an important intervention to enhance the adoption of agricultural technologies, which finally results in improving welfare of the farming households.

A multitude of factors is found in the literature that affects the decision of farmers to adopt new agricultural technology and the level of adoption of these technologies. The set of explaining variables in the empirical models can be categorized under demographic factors, Socio economic factors and Institutional factors (Melesse (2018), Mabaya, et al, (2017), Ogada et al. (2014), Tewodros (2016), Gebresilassie and Bekele (2015))

The adoption of agricultural technologies depends on different demographic and socio-economic factors. In this section recent studies conducted on factors influencing adoption of agricultural technologies in Ethiopia are reviewed. Hence, the data they used, their method of estimation and results obtained are presented. For the purpose of convenience, the reviewed studies are presented chronologically.

According to Aynalem et al., (2018), a report on the adoption of improved technology in Ethiopia was conducted with 1920 farm household heads from four national regional states. The Logit and Probit model found that farm size and extension service have a positive impact on technology adoption, while distance to market and the age of the household head have a negative impact. Furthermore, they used the Tobit model to examine variables that influence fertilizer use intensity and discovered that, while farm size, family size, literacy, and extension touch all have a positive impact, age and distance have a negative and important impact on fertilizer use intensity.

Based on a cross-section sample of 700 farmers Aynalem et al., (2018), investigated the determinants of agricultural technology adoption and their effect on farmers' incorporation into the output market in Ethiopia. The results of the Double-Hurdle model shows that awareness of existing high yielding varieties, perceptions of high yielding varieties' attributes, household resources such as farm land and livestock, and the availability of an active family labor force are all major determinants of agricultural technology adoption.

Based on a cross-sectional study in the Southern Tigray Zone of Northern Ethiopia, Berihun et al. (2014) used both the Probit model and the OLS to classify factors affecting technology adoption and their effect on farm income. Age, irrigation use, off-farm income, plot distance, and distance to market were found to be determinants of high yield variety in Ethiopia, while sex, irrigation use, off-farm income, plot distance, and distance to market were found to be determinants of fertilizer adoption. Furthermore, the OLS findings showed that adopting technology has a positive and important impact on farm income, with adopters outperforming non-adopters.

Using Probit and Ordinary Least Square (OLS) regression models, Hailu et al. (2014) found that irrigation use, land ownership right protection, credit access, distance to the nearest market, plot distance from the homestead, off-farm involvement, and tropical livestock unit all influenced farm households' adoption of agricultural technologies.

A study by Tigist (2017) used survey data from 1500 rural households in four regions to investigate the effect of technology adoption on productivity and welfare in Ethiopia. Improved technology adoption, such as HYVs and inorganic fertilizer, has a positive and substantial impact on rural households' crop production and welfare, as measured by real per capita consumption expenditure, according to the estimate of an endogenous treatment effect model.

In their paper, Hussein et al. (2017) examine the impact of social capital on technology adoption among Ethiopian farmers, using socio-economic data from 398 farming households and a Probit estimated model. They found that being a member of informal conflict resolution increased the likelihood of soil and water conservation practices, as well as productivity-enhancing technologies like fertilizers and pesticides. It was also discovered that while members of the informal funeral community iddir were 18.2% more likely to practice soil and water conservation, they were 12.8% less likely to use productivity-enhancing technologies.

Dawit (2018) used descriptive statistics and an econometric model to examine the determinants of adoption and strength of adoption of improved highland maize varieties in his paper (Tobit). Farm size, household income, access to credit, interaction with extension agents, training participation, and field day were all positively and significantly influenced by the model, whereas household age and market distance were negatively influenced by adoption & intensity of use of high yielding maize varieties in the study region.

In Ethiopia, Aynalem et al. (2018) analyzed recent research on agricultural technology adoption and its determinants. The effect of new agricultural technology on the growth of agricultural productivity has been recorded in the literature. Furthermore, credit availability, farm size, and distance from market, as well as oxen ownership and level of education, were found to be significant determinants of agricultural technology adoption in Ethiopia in the majority of studies. As a result, they conclude that government policies and interventions on agricultural technology adoption and intensity usage should pay attention to and step in tandem with those variables that have a direct impact on adoption and intensity of use of new agricultural technology.

Mesele (2019) uses ESS-LSMS-IAS cross sectional data collected from 2316 rural Ethiopian households during 2015/16 to examine agricultural technology adoption effect on poverty reduction in rural Ethiopia. The results showed that farm households' decisions to implement farm technologies are primarily affected by household socioeconomic characteristics, access to knowledge and infrastructure facilities, institutional variables, plot characteristics, and geographic location. The findings revealed that adopters of each of the study's technology packages have higher per adult food and total consumption per year, confirming that agricultural technology adoption has a clear and important effect on household consumption and poverty reduction for Ethiopia's rural poor. Furthermore, relative to adopting a single agricultural technology, the use of a mix of alternative technologies results in higher annual per adult food and overall intake.

Workineh et al. (2019) used cross-sectional data and a double hurdle and Endogenous Switching Regression model to investigate the impact of improved wheat variety adoption on household welfare in Ethiopia. Credit access, extension visits, soil fertility, plot size, off-farm jobs, age of household head, distance from input sector, and farm experience all played a role in the improved wheat variety adoption decision and intensity. The estimated model showed that adopting improved wheat varieties improves farm household welfare in a positive and important way.

Bekele (2020) investigated the determinants of agricultural technology adoption in Ethiopia using a meta-analysis study. A random effect model was used to identify the determinants of technology adoption. The results of the random effect model confirmed that the age of the household head, education level, farm size, livestock holding, access to extension services, access to credit services, cooperative membership, and distance from the market were all significantly associated with technology adoption. As a result, policymakers and other stakeholders should concentrate on the common variables found to influence technology adoption.

Muluken et al. (2021) used the Propensity Score Matching (PSM) estimation approach to examine the adoption of improved agricultural technology and its effect on household income. They discovered that improved agricultural technology usage resulted in an average annual farm income per household of 23,031 birr higher than non-use of such technologies.

Mesele (2021) looks into the effect of agricultural technology adoption on poverty reduction in Ethiopia's Amhara region's north Shewa zone. Using a selection model, he discovered that the sex of the household head, credit access, saving, extension visits, farm cooperatives, and distance from market all affect farm households' decisions to implement agricultural technologies. He discovers that adopters of agricultural technologies have higher food consumption expenditure per adult using an endogenous switching regression model.

Furthermore, the real and counterfactual scenarios have a large difference in food consumption expenditure per adult equivalent. The study's findings indicated that agricultural technology adoption has a clear and substantial effect on rising household consumption expenditure while also reducing poverty. The study's findings indicate that rising farm household welfare through increasing access to and adoption of agricultural technologies.

2.3.2. Welfare Impacts of Agricultural Technology Adoption

Empirical studies argue that adoption of agricultural technologies can reduce poverty both directly and indirectly (Becerril & Abdulahi, 2010; Moyo et al. 2007) cited on Mabaya (2017). Agricultural technology adoption on the way to food security has been recognized as a key step Tsegaye (2020). Smallholder farmers have the potential to enhance their food security situation as well as their welfare if they adopted improved agricultural technologies (Langyintuo et al., 2008) cited on Mabaya (2017).

The study on role of adoption of agricultural technology on market participation among rural households by Asfaw et al. (2011) cited on Ayanalem et al., (2020) suggested that the higher productivity from improved agricultural technologies translates into higher output market integration. This study has employed treatment effect model and propensity score matching (PSM) techniques to estimate the potential impact of adoption by taking in to account for heterogeneity & unobservable characteristics of farming households in the adoption decision.

Di Zeng et al. (2014) undertook similar study in Rural Ethiopia on adoption of improved maize varieties and its impact on child nutrition by using instrumental variables and quintile instrumental variable regressions. The result indicates that the positive impact of adoption of improved technology on the general welfare of rural households children nutrition improvement.

However, existing literature evidenced in Ethiopia revealed the positive productivity and welfare implication of improved agricultural technologies. According to (Asfaw et al., 2012; Mekonen and Karelplein, 2014) cited on Workineh et al., (2019), adoption of improved seeds and chemical fertilizer alone will increase crop productivity by 7.38 and 6.32% per year of each in Ethiopia. Despite this in Ethiopia regardless of the increasing rate of adoption and its positive impact on production and productivity, a large extent of rural farm households are under deplorable living conditions.

The main drawback of many adoption studies is that, they do not explicitly point out the causal effect of improved agricultural technologies adoption on farm household productivity and welfare, and they fail to establish an adequate counterfactual situation Workineh et al., (2019). To identify the true impact of technologies, it is important to look at the counterfactual situation and identify the true causal effect. Simple comparison between the performance of adopters and non-adopters may lead to misleading policy implications since there are many factors that influence the decisions of households towards technology adoption. This is an important methodological issue in evaluating the potential impact.

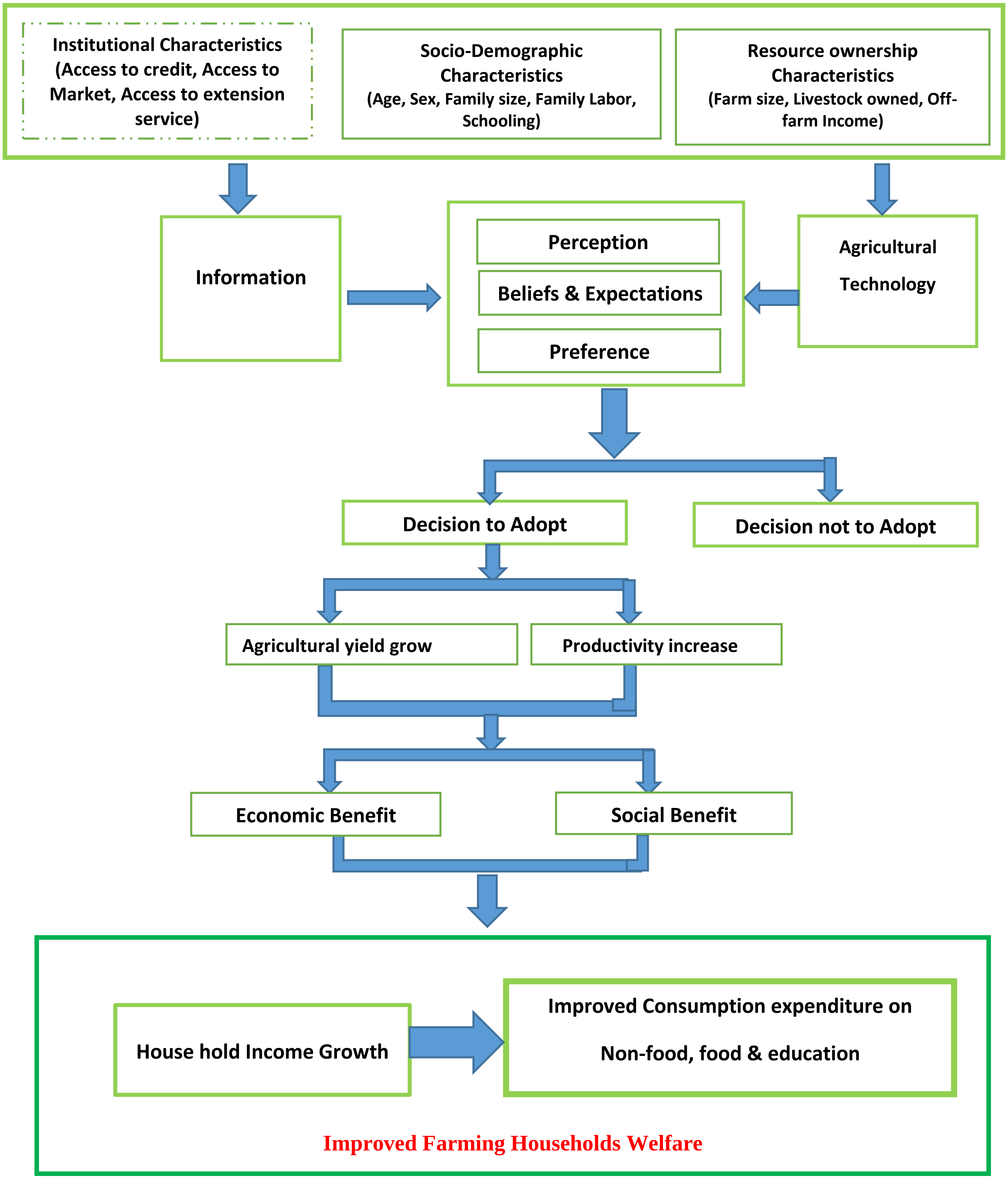
Therefore, examining the reason behind the low adoption rate of agricultural technologies and its impact on the farming households' welfare, can give a clue on the urgencies, on condition that feedback to future study, guiding public policy makers and those who take part in technology diffusion to have a better knowhow on the way to improved technologies diffusion.

2.4. Conceptual Framework of Adoption & Impact Estimation

It is assumed that farming household's decision to adopt or reject agricultural technology at any time is influenced by the combined effect of a number of factors related to their objectives, opportunities and constraints. The conceptual model used the Technology Acceptance Model (TAM) of Venkatesh and Bala (2008) and (Asfaw & Shiferaw, 2010).

Thus, the conceptual model consolidates Socio-demographic factors along with Institutional factors, Behavioral factors, Information sources and Farming households Perception, integrating various dimensions. Then after, adoption of improved agricultural technologies is expected to have considerable economic advantage in terms of increase in yield, increase in productivity of farm households and ultimately in enhancing household welfare status.

Figure 1. : Integrated Model of Households' Characteristics, Agricultural Technologies Adoption and Welfare Effect. Conceptualized from (Venkatesh & Bala, 2008, Asfaw & Shiferaw, 2010)…



CHAPTER THREE

METHODOLOGY

3.1. Source of Data and the Type of Data

The panel data for this study comes from the Ethiopian Socioeconomic survey (ESS), representing the years 2011/12, 2013/14 and 2015/16. The ESS data are a collaborative project of the Central Statistics Agency of Ethiopia (CSA) and the World Bank Living Standards Measurement Study- Integrated Surveys of Agriculture (LSMS-ISA) project (CSA 2017).

The ESS data collection covered major region of the nation, from which enumeration areas (EAs) were selected proportionally based on the regional population. A total of 290 EAs were selected from rural areas and 43 EA from small towns were selected. The survey covers rural areas, large towns and small towns in all regions except some exceptional zones of Afar and Somali region. The sample units were selected using stratified two stage sampling procedure and the sampling frame for rural areas was based on Agricultural sample survey (CSA 2017).

The ESS data sample for the first round was 3,969 households and had sample representation for the nation as a whole and provides reliable estimates of key socioeconomic and demographic, institutional variables as well as resource ownership. In the second round, all original households were targeted for revisit. The sample size for the second round subsequently expanded to 5,262 households and for the third round was a sample size of 4,954 households (CSA 2017).

Finally, as the table 00 shows, the panel household sample size balanced to 3,897 households in each three waves for the further analyses. The study analyzed agricultural technology adoption and its impact on welfare using household level data which is collected from rural part of Ethiopia.

Table 01: Balanced Agricultural Technology Adopters and Non-adopters households Sample

Year	**1**= Households that had adopted at least one of the technologies	**0** = Households that had not adopted any of the technologies	Total
2011/12	963	2,934	**3,897**
2013/14	985	2,912	**3,897**
2015/16	1,052	2,845	**3,897**
Total	**3,000**	**8,691**	**11,691**

Source: Author's calculation using ESS panel data (2011/12, 2013/14 and 2015/16) (2021)

3.2. Methods of Data Analysis

The study employed both descriptive and inferential methods of data analysis. First, Descriptive statistics used to analyze and compare the socio economic characteristics and institutional variables, between adopters and non-adopters. These include summary statistics, tabulations (mean & percentage), t-and t-test and Chi Square tests. Then, the casual impact of technology adoption estimated by Difference-in-Differences combined with Propensity Score Matching (DID-PSM) techniques so as to assess the results robustness and their implied impact on households' welfare.

3.3. The Analytical Framework and Empirical Model

3.3.1. Impact Evaluation and its Problem

In impact evaluation the standard problem that involves the inference of the causal connection between the treatment and the outcome. There are two specific related problems with regards to evaluating the impact of an intervention on targeted individuals; thus (i) the selection bias problem and (ii) the problem of missing data for the counterfactual (Blundell and Costa Dias 2000 ; Wooldridge , 2001) cited on Solomon et.al.,(2012).

The selection bias problem emanates from the fact that most program interventions are targeted at specific groups with specific characteristics and that the intervals targeted are not randomly selected. There is a problem of missing data because it is not possible to measure the impact on the same individuals as at each moment in time each individual is either under the intervention being evaluated or not and thus he or she can not be in both. This implies that we can not observe the outcome variable of interest for the targeted individuals had they not participated at the same time.

Most of the previous studies on impact evaluation first and foremost focuses on empirically verify that the changes in welfare or other outcome interest are indeed the result of intervention or adoption and not to other factors. That means; there are several theoretical reasons that can justify adoption of agricultural technology brings about improvement on households welfare, but how someone can be sure that the welfare of adopting households can be matched to non-adopting households?

These evaluation methodologies can be conducted using quantitative methods (that is, survey data collection or simulations) and qualitative (that, understands the local socio-economic, cultural and institutional context) between before or after an intervention is introduced. But qualitative methods cannot assess outcomes against relevant alternatives or counterfactual outcomes. That is, it cannot really indicate what might happen in the absence of the program. While quantitative impact evaluation is the use of an explicit counterfactual analysis. Since one has to assess the impact of adoption a technology on welfare effect, the author tried to assess the situations like what if the agricultural technology had not been adopted? If not, that can lead to misleading policy implications.

3.3.2. Model Selection and its Impact on households' welfare

The study aims at indentifying the causal effect of adopting agricultural technology on consumption expenditure using non-experimental panel data. However, the treatment assignment is not often random because of the purposive placement and individuals' self-selection into the program that is, agricultural technologies are placed according to the need of the individuals, and based on the information they have. Self-selection could be based on observed or unobserved factors, or both. The endogeneity problem mostly arises in the choice of adoption.

According to Khandker et al, (2010), they argued that there seem like to be a backward and forward linkage between technology adoption and household welfare status; more precisely technology adoption might result in increased yield productivity, in that way results additional income, but it may also be that additional income conveys to more adoption.

Examining the welfare impact as a result of adopting agricultural technologies through by non-experimental observations is not trivial; this is due to the need to identify the counterfactual situation as the households had not adopted the agricultural technology. This situation, in experimental studies, is resolved by assigning treatment and control groups randomly. However, the two groups are not randomly distributed. But rather they make their own choices of technology preferences accordingly.

Thus, the likely self-selection as a result of observed and unobserved characteristics of farming households' member ability to understand and use technologies, perceptions, expectations, motivation and skills makes it hard to conduct treatment effect of improvements from technology adoption make use of only observational data (Awudu and Wallace (2014). The adoption of these combinations may not be random; instead, farmers may endogenously self-select into adopt or not-to-adopt decisions, and are likely to be influenced by unobservable characteristics and may be correlated with the outcomes of interest, such that combination of techniques adopted (Khandker et al, 2010).

Therefore, the adoption of agricultural technology and its implied implications in terms of an outcome of interest i.e., modeling the impacts on welfare of farming households by using Difference-in-Difference combined with Propensity Score matching Method (DiD-PSM). Unlike most previous studies, this study is utilized ESS panel dataset and combinations of two impact evaluation methods to check the robustness of the results and minimizing biases.

3.4. Model specification

In this part, the study has examined an econometric model to identify the impact of agricultural technology adoption on household welfare outcomes. Moreover, determinants of agricultural technology were focused. In order to meet our objective, two models were developed. In the first part, the household decision to adopt agricultural technology was modelled as function of various determinant factors using a logit estimation. In the second part, the impact of household adoption of agricultural technologies on welfare outcomes was modelled. This particularly focused on the Propensity Score Matching (PSM) method in combination with the Difference-in-Difference estimator (DID). The PSM controls for observable differences between households that adopted and those who did not. However, it does not control for unobserved heterogeneity (the unobserved difference in mean counterfactual outcomes) between adopters and non adopters of agricultural technology. To address this shortcoming of the PSM impact estimator, the DID impact evaluation technique was employed on the data balanced via the PSM. The DID method eliminates unobservable time-invariant differences between a participant and nonparticipant households.

3.4.1. Estimation Techniques

The estimation is conducted using panel econometric techniques. In this study, non-linear probability model is used to identify determinants of the decision to engage in adopting agricultural technology by following Rosenbaum & Rubin (1983). To examine the decision to adopt, a logit model was employed (Verbeek, 2012). A one way error component model with insignificant time effects is used. It takes the following specification form:

$$\boldsymbol{Y_{it} = \beta X_{it} + \alpha_i + \mu_{it}} \text{ ………………………………..…………………………}\textbf{(1)}$$

t = 1, 2,…T, is the time period (in our case it is the wave), Y_{it} dependent variable, X_{it}, the independent variables, α_i unobserved individual hetrogeneity, and μ_{it} residual (and so not observed) that varies both over time and across individuals. This model assumes that time effects are insignificant and it is called a one way error component model (Baltagi 1995). A choice is made among the Fixed Effects Model a Model by use of the Hausman test.

3.4.2. Treatment Effects Model

A. PSM (Propensity Score Matching) Method

Propensity score matching (PSM) constructs a statistical comparison group that is based on a model of the probability of participating in the treatment, using observed characteristics. Participants are then matched on the basis of this probability, or propensity score, to non-participants. The average treatment effect of adopting agricultural technologies is then calculated as the mean difference in outcomes across these two groups (Khandker et al, 2010). .

Treatment evaluation is the estimation of the average effects of a program or treatment on the outcome of interest. In other word it is comparison of outcomes between treated and control observations. There are two types of treatment effect studies, that are controlled experiments (assignment into treated and control groups is random) and non-expermental or Quasi experimental observational studies (assignment into treated and control groups is not random).

Moreover, using the framework of Rosenbaum and Rubin (1983), the 'treatment effect' defines as the difference between the well-being of household *i* receive in the two states of the world. Assigning the farming household adopts technology, T= 1, and the farming household does not adopt technology, T = 0. Treatment $\boldsymbol{\tau}$ is a binary variable that determines if the observation has the treatment or not.

$$\boldsymbol{\tau_i = Y_i(1) - Y_i(0)} \quad \text{……………………………………………………………………..}\textbf{(2)}$$

The average treatment effect ATE is well-defined as the expectation of the treatment effect by all households. A problem arises when using non-experimental data because only one of these states is actually observed; that is, either $Y_i\,(1)$ or $Y_i\,(0)$ is observed for each farming household i, but not both. The unobserved well-being is called the counterfactual well-being. Accordingly, it is convenient to express the ATE as:

$$\boldsymbol{E(\tau_i) = P.\big[\big(\,E(Y^1\big|T=1\big) - \big(E(Y^0\big|T=1\big)\big] + (1-P).\big[\big(E(Y^1\big|T=0\big) - \big(E(Y^0\big|T=0\big)\big],..(3)}$$

Where : $\boldsymbol{P}$ is the probability of observing a farming household adopting agricultural technology. In Equation (3), the ATE for the whole sample is the weighted average of the technology (treatment) effect for adopters and non-adopters.

In estimating the ATE, both counterfactual well-beings, $\boldsymbol{E\ (Y^0|\ T=1)}$ and $\boldsymbol{E\ (Y^1|\ T=0)}$, should be constructed. Because of the associated complications, many studies focus on one or the other of the respective counterfactuals. The most prominent evaluation parameter is the so-called 'average technology effect on the treated' (adopted) (ATET). ATET is the difference between the outcomes of treated and the outcomes of the treated observations if they had not been treated.

$$\boldsymbol{\tau_{ATET} = E(\tau|T=1) = E[Y(1)|T=1)] - E[Y(0)|T=1)]\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(4)}$$

Given Equation (4), the problem of selection bias is straightforward to see, because the second term on the right-hand side is unobservable. If $E[Y\,(0)\,|\,\boldsymbol{T}=0] = E[Y\,(0)\,|\,\boldsymbol{T}=1]$, the non-adopter can be used as an adequate comparison group.

However, as discussed above, this condition is rarely satisfied with non-experimental data. A possible way forward is to use a 'matching' approach. The basic idea is that one infers the behavior of a given adopter by matching them with an observationally equivalent non-adopter. In so doing, the author hopes to create a situation similar to what would have been observed in a random experiment. For empirical estimation each treated observation $\mathbf{i}$ is matched $\mathbf{j}$ control observations & their outcomes Y (0) are weighed by $\boldsymbol{w}$.

$$\boldsymbol{ATET = \frac{1}{n_1}\quad \textstyle\sum_{i\in\{T=1\}}\big[Y_{1,i} - \sum_j w(i,j)y_{0,j}\big]\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(5)}$$

Two assumptions need to be satisfied to apply this approach. The first is the assumption of '***conditional independence***': given a series of observable covariate *X*s, which are not affected by technology adoption, the potential well-being is independent of technology assignment:

$$\boldsymbol{Y^0, Y^1 \perp T | X, \forall X,} \quad \text{……………………………………………………………………}\textbf{(6)}$$

Where $\perp$ denotes independence. If the assumption is fulfilled, holding the observable covariates constant, the non-adopter's well-being has the same distribution that adopters would have experienced had they not adopted the technology. hence, technology can be deemed as randomly assigned. It follows that the ATT can be expressed as follows:

$$\boldsymbol{\tau_{ATT} = E(\tau | T = 1) = E[Y(1) | T = 1), X] - E[Y(0) | T = 1), X]} \quad \text{……………………}\textbf{(7)}$$

A problem arises when there are many observable covariates that determine farming households' well-being. For example, if *X* contains *s* covariates that are all dichotomous, the adopter must be matched with a non-adopter having identical values for all 2*S* variables. This is obviously a problem when *S* is relatively large and/or the sample size is relatively small.

To deal with this dimensionality problem, Rosenbaum and Rubin (1983) suggest using a balancing scores method. The method shows that if potential well-being is independent of technology adoption conditional on covariates *X*, it is also independent of technology adoption conditional on a balancing score. The propensity score, defined as the possibility of farming household adopting technology conditional on covariates *X*, is one possible balancing score:

$$\boldsymbol{P_i(X) = Prob(T = 1 | X)} \quad \text{…………………………………………………………}\textbf{(8)}$$

This conditional probability is the propensity score, which allows one to identify similar farm households. The second assumption is ***the common support or overlap condition***. It rules out perfect predictability of *T* given *X*, so that: For each value of x, there are both treated and control observations. For each treated observation, there is a matched control observation with similar x.

$$\mathbf{0} < P(\boldsymbol{T} = \mathbf{1}|\boldsymbol{X}) < 1 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \textbf{(9)}$$

This condition confirms that households with the same characteristics values have a positive probability of being both an adopter and a non-adopter. In view of that, ATE is only defined in the region of this common support. Households subsiding outside this region are not included in the estimation of ATE.

The common support assumption improves the matching quality by excluding farming households at the tails of the propensity score (p-score) distribution. It guarantees that characteristics observed in the agricultural technology adoption group can also be observed among the non-adopters. A disadvantage of the common support assumption is that it reduces the sample size. If the proportion of missing farming households is too large, this might raise concerns that the remaining households are insufficiently representative of the population, thus casting doubt on the associated ATE estimates. Supposing that both the conditional independence and common support conditions hold, the propensity score matching estimator for ATT can be expressed as follows:

$$\boldsymbol{\tau}_{\boldsymbol{ATT}}^{\boldsymbol{PSM}} = \boldsymbol{E}_{\boldsymbol{P}(\boldsymbol{X})|\boldsymbol{T}=\mathbf{1}}\{\boldsymbol{E}[\boldsymbol{Y}(\mathbf{1})|\boldsymbol{T} = \mathbf{1}, \boldsymbol{P}(\boldsymbol{X})] - \boldsymbol{E}[\boldsymbol{Y}(\mathbf{0})|\boldsymbol{T} = \mathbf{0}, \boldsymbol{P}(\boldsymbol{X})]\} \ldots\ldots\ldots\ldots\ldots\ldots \textbf{(10)}$$

Equation (10) reveals that the propensity score matching estimator is simply the mean difference in the well-being of the two groups (adopter and non-adopter) over the common support area. The first step in Propensity Score Matching techniques (PSM) is estimation of the propensity scores. This makes sure that the balancing condition to be satisfied so as to estimate the ATT of the outcomes of interest. For most of non-random interventions, the problem of selection bias should be taken into consideration when identifying and evaluating the treatment effect.

For treatment effect estimation given that matching produces consistent estimates under weak conditions, a practical advantage of PSM over ordinary least squares (OLS) is that it reduces the number of dimensions on which to match participants and comparison units. Nevertheless, consistent OLS estimates of the ATE can be calculated under the assumption of conditional exogeneity.

One approach suggested by Hirano et al. (2003) cited on (Khandker et al, 2010) revealed that to estimate a weighted least squares regression of the outcome on treatment T and other observed covariates X unaffected by participation, using the inverse of a nonparametric estimate of the propensity score. This approach leads to a fully efficient estimator, and the treatment effect is estimated by $Y_{it} = \alpha + \beta T_{i1} + \gamma X_{it} + \varepsilon_{it}$ with weights of 1 for participants and weights of $\hat{P}(X)/(1-\hat{P}(X))$ for the control observations. T_{i1} is the treatment indicator, and the preceding specification attempts to account for latent differences across treatment and comparison group that would affect selection into the treatment group as well as resulting outcomes. For an estimate of the ATE for the population, the weights would be $1/\hat{P}(X)$ for the participants and $1/(1 - \hat{\hat{P}}(X))$ for the control groups.

B Difference-in-Differences (DiD) Method

The Difference-in-Differences model is applied when panel data on outcomes are available before (1) and after (0) the experiment occurs. The Difference-in-Differences model is an improvement over the one-period model. This estimation technique evaluates treatment effect by comparing the outcome differences of treated and control group before and after the intervention, technology adoption in our case. Assuming that an intervention takes effect from a baseline period (t_0) to a follow-up period (t_1), then Difference-in-Differences estimator captures the treatment effect as:

$$\boldsymbol{ATT = DiD = E\left(Y_1^T - Y_0^T \middle| \mathrm{T}_1 = 1\right) - E(Y_1^C - Y_0^C \,|\mathrm{T}_1 = 0} \text{ ……………………..……. } \mathbf{(11)}$$

That is, given a three-period setting where t = 0 before (other than 2015/16) and t = 1 after (2015/16), letting $\boldsymbol{Y_t^T}$ and $\boldsymbol{Y_t^C}$ be the respective outcomes for adopters and non-adopter farming households in time t. The first term refers to the differences in outcomes before and after the treatment for the treated group. This term may be biased if there are time trends. The second term uses the differences in outcomes for the control group to eliminate this bias. To apply the Difference-in-Differences model instead of the outcomes for the treated andcontrol groups, we use the differences in outcomes after the treatment and before the treatment. The rest of the analysis is the same.

The Difference-in-Difference (DiD) estimate can also be calculated within a regression framework; the regression can be weighted to account for potential biases in DiD. In particular, the estimating equation would be specified as follows:

$$\boldsymbol{Y_{it} = \alpha + \beta T_{i1} + \rho T_{i1} + \gamma t + \varepsilon_{it}} \quad \text{...}\textbf{(12)}$$

To understand the intuition better behind equation (12), we can write it out in detail in expectations form (suppressing the subscript *i* for the moment):

$$\boldsymbol{E(Y_1^T - Y_0^T | T_1 = 1) = (\alpha + did + \rho + \gamma) - (\alpha + \rho)} \quad \text{..............................}\textbf{(13a)}$$

$$\boldsymbol{E(Y_1^C - Y_0^C | T_1 = 0) = (\alpha + \gamma) - \alpha} \quad \text{..}\textbf{(13b)}$$

Following equation (12), subtracting (13b) from (13a) gives Diffference-in-Difference. Note again that Difference-in-Difference is unbiased only if the potential source of selection bias is additive and time invariant. This technique eliminates bias caused by observable and unobervable time invariant effects, that means the time-constant linear selection bias and the time effect of common trend across the two groups can get controlled.

Thus, the key assumption of Difference-in-Differece (DiD) method is that unobserved characteristics of farming households affecting adoption decsion do not vary over time with treatment status, i.e treatment and control outcomes move in parallel in the absence of treatments (Angrist & Pischke, 2015). For the above DiD estimator to be interpreted correctly, the following must hold:

first, the model in equation (outcome) is correctly specified. For example, the additive structure imposed is correct. secondly, the error term is uncorrelated with the other variables in the equation: $\mathbf{Cov}(\boldsymbol{\varepsilon_{it}, T_{i1}}) = \mathbf{0}$, $\mathbf{Cov}(\boldsymbol{\varepsilon_{it}, t}) = \mathbf{0}$ **and** $\mathbf{Cov}(\boldsymbol{\varepsilon_{it}, T_{i1}\, t}) = \mathbf{0}$**.** The last of these assumptions, also known as the ***parallel-trend assumption***, is the most critical. It means that unobserved characteristics affecting adoption of agriculturlal technologies do not vary over time with treatment status.

C Difference-in-Differences propensity score matching (DiD-PSM) method

This method first applied and implemented by Heckman et.al, (1997) in handling the bias from unobserved household characterstics. However, if the unobserved characterstic are time-invariant, the effect can be removed with the combination of Propensity score matching and Differece-in-Differences (DiD-PSM). This condition relaxes the CIA to the extent that in as much as as sharing the common trend, the counterfactual outcome of the treated can be different from the observed outcome of the untreated.

Unlike PSM alone, the DD estimator allows for unobserved heterogeneity (the unobserved difference in mean counterfactual outcomes between treated and untreated farming households) that may lead to selection bias. Conjontly with the matching assumption , the average treatment effect on the treated **(ATT)** can be estimated by the Difference-in-Differences **(DiD)** in means between the treatement & control groups:

$$\mathbf{ATT} = \frac{1}{N} \sum_{u \in \{T\}} (Y^{t1}_{1,u} - Y^{t0}_{o,u}) - \sum_{v \in \{T\}} W(U,V)(Y^{t1}_{1,v} - Y^{t0}_{o,v})) \ldots\ldots\ldots\ldots \mathbf{(14)}$$

Where **w(u,v)** is the same weight using the propensity score matching approach, given to the **V** from the control group in matching with the **U** from the treatment group. From previous discussion, the propensity score can be used to match treatment and control groups in the base year, and the treatment impact is calculated across treated and matched control groups within the common support. For DiD estimate for each treatment area i will be calculated as :

$$DiD_i = \left(Y^T_{i1} - Y^T_{i0}\right) - \sum_{j \in C} \omega(i,j)(Y^C_{j1} - Y^C_{j0}) \ldots\ldots\ldots\ldots \mathbf{(15)}$$

Where, $\omega(i,j)$ is the weight using a PSM approach given to the jth control area matched to treatment area i.

Interms of regression framwork, Hirano et al. (2003) cited on (Khandker et al, 2010) show that a weighted least sequare regression, by weighing the control observations according to their propensity score, yields a fully efficient estimateror:

$$\Delta Y_{it} = \alpha + \beta T_i + \gamma \Delta X_{it} + \varepsilon_{it}, \beta = DiD \ldots\ldots\ldots\ldots \mathbf{(16)}$$

The weights in the regression in equation (16) are equal to 1 for treated households and to $\hat{P}(X)/(1-\hat{P}(X))$ for comparison groups.

Thefore, PSM method deals with observable characterstics and then reduces the time-variant factors of heterogeneity, thus increasing the credibility of the parallel trend assumption of the difference-in-difference estimator; and the difference-in-differences enhances the propensity score matching method by eliminating the time-variant unobserved heterogeneity. So, difference-in difference propensity score matching (DiD-PSM) estimator works further to control of heterogeneity and to handle the problem of selection bias. Though, in this study the matching methods that were employed jointly are Radius (RM), Nearest Neighborhood (NNM), stratification (ST) and Kernel (KM).

3.5. Description of Variables and Hypothesis

3.5.1. Dependent Variable

Adoption of agricultural technology: is the dependent variable for the Logistic analysis, and is dichotomous. Hence, it has exactly two values, i.e. 1 and 0, where 1 stands for respondents (farming households) who have adopted chemical fertilizer, improved seeds or crop protection chemicals over the three waves of data collection survey period and the value of 0 if the farmer has not adopted any of these technologies.

3.5.2. Outcome variable:

Welfare Impact: Welfare can be estimated from income and expenditure standpoints. Typically developed countries measure welfare using the income approach, but in less developed countries they utilize the expenditure approach. This is because; much of this rises from self-employment, while expenditure is clearer and thus simpler to estimate Musa et al., (2016). Differing to this, in less developed countries measuring income is a tough job as they earn it from self-employment, whereas expenditure is more straight forward and hence easier to estimate. On condition that, the information on consumption expenditure obtained from a panel data of Ethiopian Socioeconomic Survey (ESS). In this study, farming households' welfare was measured by consumption expenditure and is expressed in per capita food consumption, per capita non-food consumption, per capita education consumption & also total consumption expenditure per adult equivalent terms.

3.5.3 Independent Variables

It is assumed that farming households' decision to adopt or reject a technology at any time is influenced by the combined effect of a number of factors related to their objectives, opportunities and constraints. The list of factors that may influence adoption could be very long. The following eleven categories of factors were hypothesized to affect the adoption behavior of farming households in this particular study. These independent (explanatory) variables are defined as follow:

Age of the household head: Age is one of the factors assumed to affect adoption of agricultural technologies. It is a continuous variable and is measured in years. Young farmers are more likely to adopt new technologies than the older farmers, because they may have more schooling than older farmers and have been exposed to new ideas and hence more risk takers (CIMMYT, 1993).

Gender (sex) of the HH head: Gender is also one of the different other factor assumed to affect adoption of agricultural technology. It is a dummy independent variable indicating sex of the household head and is measured as binary variable; 1=Male, 0=Female. Female headed households are not likely to adopt new technology due to many factors as compared to their male counterpart (CIMMYT, 1993). The hypothesis therefore is, male farmers are more likely to adopt agricultural technologies.

Education level of the HH head: Education is also one of the other factors assumed to affect adoption of agricultural technology. It is a continuous variable measured in years. It is expected that, education of the household head is positively related to the adoption of agricultural technologies. According to CIMMYT (1993) Education is one of the many factors that positively affect agricultural technology adoption in a manner that it may enhance the efficiency of adoption decisions.

Total family size: It is a continuous variable and is measured in terms of number of individuals living in one family. The more the family size grows, the more the demand for food will be. So as to meet the growing family‘s demand for food, it requires to cultivate more crops on a given limited farm land. This will be possible by adopting agricultural technologies and be able to harvest twice in a given one season. By doing so, one contributes to food security. Hence, it is hypothesized that the value of the coefficient for household size is different from zero and adoption of agricultural technologies has a significant positive relationship with family size. Household who has many active family labor, the probability of technology adoption also increase positively (Negera and Getachew, 2014) cited on Asnake (2019).

Family Labor: is about availability of enough labor force to provide required support in the farming practice. It is dummy explanatory variable measured in terms of 1= yes, 0= no. The hypothesis is that, the value of the coefficient (β) for active labor force availability to be different from zero and adoption of agricultural technologies has a significant negative relationship with the explanatory variable; availability of labor force. Fabiyi (2015) cited on Asnake (2019) states that, house hold size affected adoption of agricultural technologies positively and significantly. However, Shaw (2014) states that, the availability of labor does not significantly impact modern agricultural technology adoption decisions.

Farm size (Owned farm land holding): is continuous independent variable measured in terms of hectare. It is expected that, the value of the coefficient for house hold‘s farm land holding size to be different from zero, and adoption of agricultural technologies to have a significant positive relationship with farm size. That is to say, the smaller the land size is, the lower would be the probability of adoption rate. CIMMYT (1993) states, Farm size influences adoption of agricultural technologies positively and significantly.

Non-farm income: is a binary independent variable and is measured in terms of (1= yes or 0=otherwise). It is assumed to have a positive relationship with adoption of agricultural technologies. That is due to the fact that, non-farm income adds value to the financial capacity of the smallholder farmers to have easy access to technological inputs, such as improved seeds, inorganic fertilizer and the likes; as the cost of agricultural inputs are increasing. Hence, it is expected that the value of the coefficient for non-farm income to be different from zero and adoption of agricultural technologies to have a significant positive relationship with non-farm income. Hassen *et al.,* (2012) cited on Asnake (2019) states, the more off or non-farm income, the farmer makes the higher he or she resolves his or her financial constraints and the faster to adopt.

Livestock holding: A household with large livestock holding can obtain more cash income from the sales of animal products. This income in turn helps smallholder farmers to adopt agricultural technologies. Hence, livestock possession by farming household is hypothesized to be positively related to the agricultural technology adoption. The study conducted by Asnake (2019) states, livestock holding influences adoption of agricultural technologies positively and significantly.

Access to nearest market: is a continuous variable and is measured in killo meter. Hence, the hypothesis is that, the value of the coefficient (β) for access to nearest market has a significant positive relationship with the dependent variable; According to study conducted by Kinyangy, (2014) cited on Desalegn (2019) market availability has a positive and significant ($p<0.05$) influence on adoption of agricultural technology.

Access to credit: is about availability of credit services to the farmers during their needy time to purchase farm inputs and is measured as; 1=have access or 0=otherwise. Hence, the hypothesis is that, the value of the coefficient (β) for access to credit is different from zero and adoption of agricultural technologies has a significant positive relationship with the explanatory variable; which is access to credit. Mesfin (2017) cited on Desalegn (2019) states, Credit access have significantly influence on adoption of agricultural technologies.

Frequency of extension contact: Is about frequency of the extension agents visit made to the farmers to provide technical support. It is therefore a continuous variable measured in days. The hypothesis is that, the value of the coefficient (β) for frequency of extension contact to be different from zero and adoption of agricultural technologies has a significant positive relationship with the explanatory variable; frequency of extension contact. CIMMYT (2016) also found that the frequency of extension contact has a significant positive effect on adoption of agricultural technologies.

Table 02: Description of Variables used in the Study

No	Variable	Variable description	Variable value	Description	Expected sign
Dependent variable					
1.	Agricultural Technology Adoption*	Chemical Fertilizer, Improved Seed and Crop Protection Chemicals	Dummy	1 = if Yes, 0= if No	
Independent variables					
2	Age	Age of the household head	Continuous	Measured in years	Negative
3	Sex	sex of household head	Dummy	1 = Male	Positive
4	Family size	Number of Family size	Continuous	In number	Positive
5	Education level	Education of the household head	Continuous	Measured in years	Positive
6	Land size	Total Land size	Continuous	In hectare	Positive
7	Non-farm Income	Non-farm income in the past 12 months			
8	Access to market	Distance to market	Continuous	In KM	Negative
9	Livestock holding	Total livestock herd	Continuous	In TLU	Positive
10	Access to credit	Credit access	Dummy	1= if they have access	Positive
11	Extension Contact	Extension services	Dummy	1 = if they have contact	Positive
12	Area Indicator	Rural – Urban Indicator	Categorical	1 =if they are in rural	Indeterminate
13	Dummy-Region	Regional heterogeneity	Categorical	1-9	Indeterminate
Outcome Variable					
14.	Welfare status				
	- Nominal Total expenditure of the household per adult equivalent - Per capita Food consumption expenditure - Per capita Non-food consumption expenditure - Per capita education expenditure	In Birr	Continuous	Measured in birr	Positive

*Adoption refers a farming household who used at least one technology in one of crop fields.

CHAPTER FOUR

EMPIRICAL RESULTS

4.1 Results of the Descriptive Analyses

The socioeconomic and demographic variables, institutional variables and also resource endowments that are expected to influence the adoption of agricultural technologies above and beyond the welfare outcomes are included in the analysis. Precisely this study considered three different sorts of agricultural technologies to be specific chemical fertilizer, improved seed and crop protection chemicals like pesticide, herbicide and fungicides.

In the first place, the agricultural technology adopters were those farm households who utilize any type of chemical fertilizers, improved seeds or crop protection chemicals in their farm land. The non-adopters were those who did not use any of the technologies in their farm land. By using the adoption responses of farming households the author tried to compare and identify the associated welfare impact and related measures. It also shows which agricultural sectors need policy interventions or extension service staff intervention. This is due to the fact that utmost previous researches used a single agricultural technology and did not compare combinations of multiple agricultural technologies and their implied welfare impacts. Thus, an analysis and comparison of combined technology adoption impact on farming households' welfare measured by consumption expenditure is a contribution of this study.

The descriptive statistical summary in the table below shows about 27% households are technology adopters; that means they have adopted at least one of the technologies either chemical fertilizer, improved seed varieties or crop protection chemicals or the combination of two or three of them during 2011/12, 2013/14 and 2015/16 cropping season in their farm land.

Regarding with the socioeconomic characteristics of technology adopters and non-adopters; average age of household head is about 45 years for both adopters and non-adopters category. The proportion of female-headed households in the non-adopters category was slightly higher than that of adopters but the difference is not significant. The average schooling of household heads' concerned, the result shows that there is significant difference between technology adopters and non-adopters. This suggests that education level of household head might be correlated with the decision to adopt agricultural technology by farming households.

As regards to resource endowment status on the decision to adopt technology concerned, there was insignificant differences between adopters and non-adopters in terms of average active family labor force availability, farmland size owned, number of livestock owned and non-farm income involvement by any member of household.

As regards to institutional variables, no significant difference observable between adopters and non-adopters the extent of average walking distance to the main market. But Adopters were more likely to have access to credit access and extension service than adopters; this suggests that ease of credit access and enhancement of extension service might be correlated with the decision to adopt agricultural technology by farming households.

As far as welfare outcome is concerned, technology adopter groups can be distinguished in nominal total consumption expenditure per adult equivalent, per capita consumption expenditure and non-food consumption expenditure but not in terms of per capita education expenditure consumption. As table 02 indicates a descriptive statistical summary that shows on average the technology adopter households spent more nominal total consumption expenditure per adult equivalent (6,422 Birr), which is significantly higher than non-adopter households' total consumption expenditure per adult equivalent (6,035 Birr). There were also major variation between adopters and non-adopters, according to the test results.

In terms of per capita food consumption expenditure, as determined by the average value of per capita food consumption expenditure, adopter households had higher per capita food consumption, with a value of 3,883 Birr per year on average, compared to 3,668 Birr per year for non-adopters. The test also revealed that technology adopters and non-adopters spend significantly different amounts on per capita food consumption.

In terms of non-food consumption, adopter households had a higher non-food consumption of 1,290 Birr per year on average, compared to 1,213 Birr for non-adopters. In addition, the results indicate statistically significant differences between the two groups. In terms of per capita education spending, however, there was no substantial difference between adopters and non-adopters.

After correcting for all confounding variables, a robust empirical model is estimated to confirm whether these differences in average per capita consumption expenditure remain unchanged. It is important to bear in mind when estimating the impact of agricultural technology adoption those households that adopt technology may earn a lot of income, which may lead to higher consumption expenditure.

In this initial analysis, it is important to note that there are significant differences in socio-economic and demographic characteristics, access to institutional factors, and wealth ownership across farming households between adopter and non-adopter groups. However, determining whether these variations are due to agricultural technology adoption or other pretreatment characteristics is the most difficult part of assessing this variation. The author used Propensity Score Matching (PSM) method in conjunction with Difference-in-Difference approach for the estimation analysis to assess and compute these variations, or to find the impact of agricultural technology adoption.

Table 03: Descriptive summary of statistics

Variables	Description	Adopters	Non_adopters	t-sta (Chi-Square χ^2)
Outcome Variable				
tot_nom_cons_exp_aeq	Total nominal consumption expenditure per adult equivalent	6422.346	6034.572	-3.0989***
pc_food_cons	Per capita food consumption expenditure	3883.253	3668.237	-2.7788***
pc_nonfood_cons	Per capita annual nonfood consumption expenditure	1289.666	1112.627	-3.6981***
pc_educ_cons	Per capital annual expenditure on education	93.76562	93.48769	-0.0249
Dependent Variable				
CF_IS_CP_Adoption	1= adopters and 0= non adopters	0.27	0.77	
Independent Variable				
sex_hh_head	1= male and 0= female	.6933333	.727074	3.5453
age_hh_head	Age of household age	45.16121	44.78129	-1.1437
edu_hh_head	The highest grade the head of the household completed	4.437333	3.99022	-2.2428***
total_family_size	Number of household members	4.490333	4.772178	5.6032
family_labor	Household members who are greater than or equal to 15 years of age	4.489333	4.769647	5.5687
hh_farm_size	Land size in hectares	50.6979	55.65794	0.1970
livestock_holding	Number of livestock owned	1.355447	.6309608	-8.3467
non_farm_inc	Nonfarm income involvement by any member of the household in the past 12 months	.3003333	.3400069	3.9874
market_access	Nearest market access in km	53.5572	66.22646	12.0496
credit_acc	Credit access 1= Yes 2 = No	.1163333	.080428	-5.9441***
ext_cont	The hh_head contacted extension agent worker	.5553333	.2836267	-27.7083***

Note: Statistical significant at the 99% (***), 95% (**) & 90% (*) confidence levels. T-test & chi-square (χ^2) used for categorical & continuous variables respectively.

Source: Author's calculation using ESS panel data (2011/12, 2013/14 and 2015/16) (2021)

4.2 Econometric Results

4.2.1. Determinants of adoption of agricultural technology

In this section, factors that affect household's adopting agricultural technology in rural Ethiopia are discussed from three period panel data. Table 04 reports the panel logistic regression result. And in the table coefficients for both the discrete and continuous independent variables and their standard errors were presented.

The result shows that 11,691 households in the data set were used in the analysis. The Wald chi2(11) of 958.81 panel structure of data, respectively with p-value of 0.000 indicates that our model as a whole is statistically significant; that is, it fits significantly better relative to model without predictors. In other words it shows, at least one of the regression coefficients in our model affects the adoption of agricultural technology. Rho = 0.0057 indicates that 5.7 % of the variance is due to differences across panels. Logistic regression result reveals that livestock holding, non-farm income involvement, market access, credit access and extension contact were significantly affects the adoption of agricultural technology at 1% level of significance, whereas age of the household head was significant at 10% level of significance.

Among the variables that significantly affect agricultural technology adoption, livestock holding, credit access and extension contact have positive coefficient. This implies that an increase in the predictor leads to an increase the probability of adoption in agricultural technology. Whereas age of household head, livestock holding, and non-farm income involvement has negative coefficients and it indicates that an increase in the predictor leads to a decrease in the probability of adoption in agricultural technology.

A male headed household were into less participated in adopting agricultural technology than their female counterparts, holding other factors constant at their means. This result contradict with CIMMYT (1993). The marginal effect for male headed household result implies that the probability of participation in adopting agricultural technology for a male headed household lowers by 1.5 % than a female headed household, holding all other variables at their means. The result was statistically significant at 10% level of significance.

Holding other factors constant at their means, households who have more livestock (in TLU) on average tend to adopt more agricultural technology. And this result confirms with the previous study such as Asnake (2019) found the positive effect of livestock owning on agricultural technology adoption. The marginal effect of livestock can be interpreted as follows. If owning livestock which is measured by tropical livestock unit (TLU) increases by one unit, the probability of households' adoption increase by 0.6 % when allowed for panel structure of data and the coefficients are statistically significant at 1% level of significance. This may be because an household with large livestock holding can obtain more cash income from the sales of animal products. This income in turn helps smallholder farmers to adopt agricultural technologies.

Any member of a family of farming household involvement in non-farm income activities in the past 12 months negatively affects the mean predicted probability of adoption in agricultural technology by 3%, holding other factors constant at their means. The result of non-farm income activities contradict Hassen *et al.*, (2012). And the marginal effect was statistically significant at 1% level of significance.

Distance to nearest market negatively affects the predicted probability of adopting agricultural technology by 0.07%, holding other factors constant at their means. The result is contradict Kinyangy, (2014), and the marginal effec was statistically significant at 1% level of significance.

Having access to credit increases the probability of adopting agricultural technology by 5.3% panel structure of data results than having with no access to credit, holding other factors constant at their means. The coefficient was significant at 1% level of significance. This result is supported by the previous study such as Mesfin (2017) and Desalegn (2019). Credit solves liquidity problem in rural areas and thereby increases the probability of adopting agricultural technology.

Frequent visit by the extension agent so as to provide technical support for the farming household increases the probability of adopting agricultural technology by 21% panel structure of data results than having with no extension contact, holding other factors constant at their means. The coefficient was significant at 1% level of significance. This result is supported by the previous study such as CIMMYT (2016). Frequent visit by extension agent increases the probability of adopting agricultural technology.

Table 04 : Determinants of agricultural technology adoption

CF_IS_CP	Coeff.	Std.Err.	t-value	p-value	[95% Confi	Interval]	Sign
sex_hh_head	-.015	.009	-1.65	.1	-.033	.003	*
age_hh_head	0	0	-0.41	.68	-.001	0	
edu_hh_head	0	0	0.01	.991	-.001	.001	
total_family_size	-.017	.035	-0.48	.63	-.087	.052	
family_labor	.013	.035	0.37	.709	-.056	.083	
hh_farm_size	0	0	-0.48	.63	0	0	
livestock_holding	.006	.001	6.49	0	.004	.008	***
non_farm_inc	-.029	.008	-3.52	0	-.046	-.013	***
market_access	-.001	0	-9.16	0	-.001	-.001	***
credit_acc	.054	.014	3.93	0	.027	.081	***
ext_cont	.213	.008	25.93	0	.197	.229	***
Constant	.26	.017	15.42	0	.227	.293	***

Mean dependent var	0.257	SD dependent var	0.437
Overall r-squared	0.076	Number of obs	11691.000
Chi-square	958.814	Prob > chi2	0.000
R-squared within	0.043	R-squared between	0.145

Note: Sta.sign at the 1%(***), 5%(***), & 10% (*) probability levels resp.

Source: Author's calc using ESS data (2011/12,2013/14 & 2015/16) (2021)

4.2.2. Impacts of Technology Adoption on Household's Welfare

The analysis included the treatment status of farming households socio-demographic, and institutional factors reflecting access to various services, as well as credit access and extension communication. The author used the PSM method. To begin, a series of steps must be followed in order to carry out this process. When using PSM, the author first performs a Logit regression and then checks the propensity score balancing conditions. The balancing test determines whether adopters and non-adopters have the same tendency score distribution. The specification applied in the study satisfied the balancing tests since it is the most comprehensive and robust specifications.

The quality of the match can be checked if the density of the propensity scores overlaps technology adopters and non-adopters, which necessitates a visual examination to see if the propensity score densities have "common support". For this purpose, the author used the common support approach for all PSM estimates. The Logit model was estimated again for the common support sample to obtain a new set of propensity scores to be included in the match. The succeeding action was matching adopters with non-adopters using four different matching estimators: nearest neighbors (NNM), radius (RM), caliper (KM) and stratified matching (SM). The balancing properties of the data were also retested. All the balancing tests that passed are reported in the study are based on specification. Then matching the technology adopters and non-adopters observations by four PSM techniques. The standard errors of the impact estimates are calculated by bootstrap using 5 replications for each estimate.

A. The Common Support Region: Treated and Untreated Groups

The propensity score matching (PSM) is to match each technology adopters based on an identical common characteristic with non-adopters. Thus, the distribution helps to identify the impact of agricltural technology adoption on household's welfare based on consumption expenditure score. In line with this the density distribution of propensity scores for adopters and non-adopters is shown in (Figure 2) below. The bottom half of each graph shows the propensity score distribution of non-treated (non-adopters) while the upper-half refers to treated individuals. The y-axis indicated the frequency of the propensity score distribution. To that end, the variance in covariates between the treatment and control groups, as well as the propensity score, were investigated.

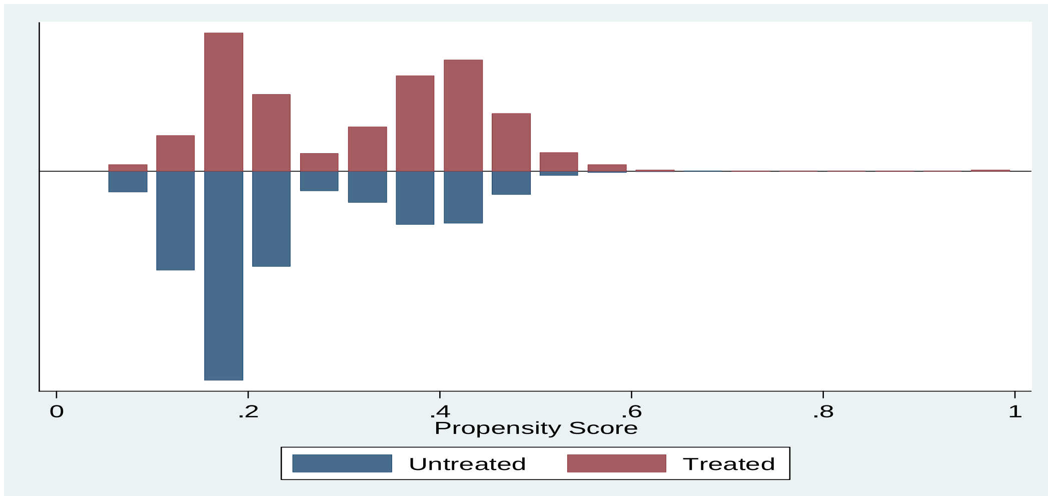


Figure 2: Histogram of p-score distribution & common support for Propensity score estimation

As a result, after matching, the gap between the two groups in terms of propensity score bias was significantly reduced to 0%. As the test indicates, some variables had statistically significant discrepancies before matching, but after matching, the covariates were balanced, demonstrating the effectiveness of the PSM method, which ensures that the two groups will match based on common support restricted areas.

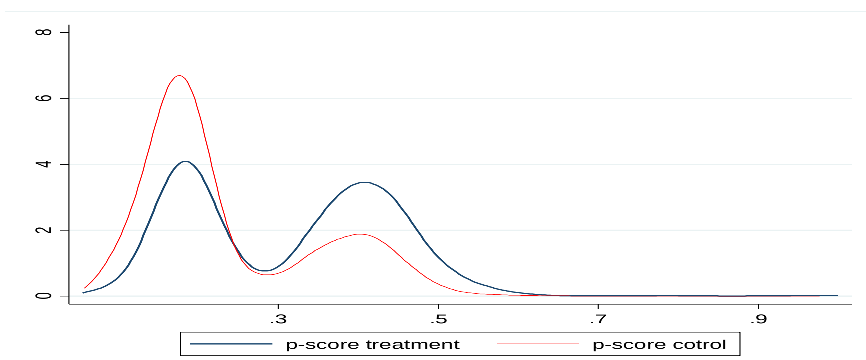


Figure 3: Two-way graph of p-score distribution & common support for Propensity score estimation

B. Balancing Covariates Testing

The main purpose of the covariate balancing is to estimate the propensity scores in order to balance the distributions of the variables in both groups. he balancing power of the estimates is ascertained by considering the reduction in the median absolute standardized bias between the matched and unmatched models.

Table 05: Testing of covariance balance using propensity score (evaluation of quality of match)

Covariates (Variable)	Unmatched / Matched	Mean		% reduction		t-test		V(T) / V (C).
		Treated	Control	% bias	bias	t	p>|t|	
sex_hh_head	U	0.693	0.727	-7.400	-3.540	0.000	.	.
	M	0.693	0.690	0.700	90.100	0.280	0.780	
age_hh_head	U	45.161	44.781	2.400	1.140	0.253	1.060	1.01
	M	45.161	44.798	2.300	4.400	0.880	0.379	
edu_hh_head	U	4.437	3.990	4.700	2.240	0.025	1.16*	1.07
	M	4.437	4.277	1.700	64.200	0.630	0.526	
total_family_size	U	4.490	4.772	-11.800	-5.600	0.000	1.060	1.09*
	M	4.490	4.560	-2.900	75.400	-1.130	0.258	
family_labor	U	4.489	4.770	-11.700	-5.570	0.000	1.060	1.09*
	M	4.489	4.560	-2.900	74.900	-1.150	0.252	
hh_farm_size	U	50.698	55.658	-0.500	-0.200	0.844	0.11*	1.49*
	M	50.698	38.826	1.200	-139.300	1.120	0.261	
livestock_holding	U	1.355	0.631	14.300	8.350	0.000	5.72*	1.23*
	M	1.355	1.235	2.400	83.400	0.740	0.459	
non_farm_inc	U	0.300	0.340	-8.500	-3.990	0.000	.	.
	M	0.300	0.287	2.800	67.200	1.110	0.269	
market_access	U	53.557	66.226	-26.700	-12.050	0.000	0.68*	1.07
	M	53.557	52.953	1.300	95.200	0.560	0.578	
credit_acc	U	0.116	0.080	12.100	5.940	0.000	.	.
	M	0.116	0.116	0.200	98.100	0.080	0.936	
ext_cont	U	0.555	0.284	57.300	27.710	0.000	.	.
	M	0.555	0.554	0.300	99.500	0.100	0.917	

C. Testing the Matching Quality

As shown in the table below, the standardized mean difference used in the propensity score for the characteristics of farming households was around 14.3% before matching and reduced to 1.7 % after matching for overall covariates. The pseudo R^2 has also fallen dramatically, from approximately 6.7% prior to matching to 0.1% after matching. After matching the joint significance of the covariates was rejected, but it was never rejected before matching, according to the p-values of the likelihood ratio test.

However, before matching the likelihood ratio (LR chi2) test was statistically significant, but after matching, it became insignificant. As a result, the low pseudo R^2 (PsR^2) indicates that the propensity score; as it was effective in balancing the covariates of distribution between the two groups, and the insignificant p-values of the likelihood ratio (LR chi2) test after matching imply that the propensity score specification was successful in balancing the covariates of distribution between the treatment and control groups.

Table 06: Quality Test of Covariate Balance Indicators (before & after Matching)

Sample	Ps R^2	LR chi^2	p>chi^2	Mean Bias	Med Bias	B	R	%Var
Unmatched	0.067	889.970	0.000	14.300	11.700	63.8*	1.250	57
Matched	0.001	8.450	0.673	1.7	1.7	6.2	4.92*	57
*** if B>25%, R outside [0.5; 2]**								

Source: Author's calculations using ESS data (2011/12,2013/14&2015/16) (2021)

4.2.3. Estimation of Average Treatment Effect on the Treated (ATT)

The results on impact of household's decision to adopt on welfare outcomes from propensity score matching (PSM) in combination with difference-in-difference (DID) estimation was presented in this section. The average treatment on treated (ATT) of agricultural technology adoption on farming households is estimated. Adopters and non-adopters households were balanced from PSM in terms of observable characteristics.

To ensure conditional independent assumption (CIA) was met, data from 2015/16 was used to generate the propensity scores for households' participation in 2011/12 and 2013/14. households who adopted and who did not adopted the agricultural technologies were balanced based on the covariates such as sex of household head, age of household head, the highest grade the head of the household, number of household members, household members who are greater than or equal to 15 years of age, land size in hectares, number of livestock owned , nonfarm income involvement by any member of the household in the past 12 months, nearest market access in km, credit access and the house hold head contacted extension agent worker. was met.

Before our main estimation, the study applied panel estimation; random effect estimation for both continuous and binary outcome variables. Since PSM estimation does not control endogeneity from unobservable characteristics. To overcome the limitations of PSM, the study applied PSM-DID estimation which utilizes three period data. Matching on full sample with difference-in-difference estimation was employed at first level. The results show a positive and significant effect of agricutural technology adoption on farming househlods nominal total consumption expenditure per adult equivalent, per capita food consumption expenditure, per capita non-food consumption expenditure but it has insignificant effect on per capita education expenditure.

The results of ATT estimation methods were shown in Table 4, with using four matching methods the agricultural technology adoption effect on households welfare outcomes. In this part, household who were adopted in 2015/16 only were taken as treatment groups and households who did not adopted in both periods (i.e., 2013/14 and 2015/16) were taken as control groups. The analysis on this study, the impact of agricultural technology adoption addressed the endogeneity problem. This problem is controlled for by way of using propensity score matching (PSM) on observable sources of endogeneity and unobservable sources of endogeneity were controlled through difference-indifference (DID) estimation.

A. Estimation of ATT for Nominal Total Consumption Expenditure:

The average treatment effect on the treated (ATT) results of the outcome variable using DiD-PSM method tells us that participant's households in adoption of agricultural technology show a significant positive impact on nominal total consumption expenditure. As the table 00 shows that the overall average increment of nominal total consumption expenditure of adopting agricultural technology using the DiD-PSM method ranged from 176 Birr to 339 Birr under the four matching algorithms, this indicates that nominal consumption expenditure per adult equivalent for farmers who adopted agricultural technology was significantly higher than that for non-adopters.

Table 07: Estimation of ATT for Nominal Total Consumption Expenditure

Matching Method	No of Treatment	No of Control	ATT	Std.Err	t-value
Nearest Neighbor (NN) Matching	3000	2210	175.603	113.858	0.731
Radius Matching (RM)	3000	8691	339.259	73.964	4.587
Kernel Matching (KM)	3000	8691	315.471	191.917	1.644
Stratification Matching (SM)	3000	8691	224.700	143.356	1.568

Source: Author's calculations using ESS data (2011/12,2013/14 & 2015/16) (2021)

B. Estimation of ATT for Per Capita Food Consumption Expenditure:

As regards to the second outcome variable which is per capita food consumption expenditure concerned; the average treatment effect on the treated (ATT) results of the outcome variable using DiD-PSM method tells us that adoption of agricultural technology have a significant positive impact on per capita food consumption expenditure. As the table 08 shows that the overall average gain of per capita food consumption expenditure for adopting agricultural technology using the DiD-PSM method ranged from 83 Birr to 181 Birr under the four algorithms; therefore, this result indicates that households that had adopted of agricultural technology have higher expenditure on per capita food consumption.

Table 08: Estimation of ATT for Per Capita Food Consumption Expenditure

Matching Method	No of Treatment	No of Control.	ATT	Std.Err	t-value
Nearest Neighbor (NN) Matching	3000	2210	83.25	113.858	0.731
Radius Matching (RM)	3000	8691	180.534	77.280	2.336
Kernel Matching (KM)	3000	8691	159.167	95.676	1.664
Stratification Matching (SM)	3000	8691	116.981	32.432	3.356

Source: Author's calculations using ESS data (2011/12, 2013/14 & 2015/16)(2021)

C. Estimation of ATT for Per Capita Non-Food Consumption Expenditure:

As regards to the third outcome variable which is per capita non-food consumption expenditure concerned; the average treatment effect on the treated (ATT) results of the outcome variable using DiD-PSM method tells us adoption of agricultural technology have a significant positive impact on percapita non-food consumption expenditure. As the table 09 shows that the overall average gain of per capita non-food consumption expenditure for adopting agricultural technology using the DiD-PSM method ranged from 115 Birr to 168 Birr under the four algorithms; therefore, this result indicates that households that had adopted of agricultural technology have higher per expenditure on capita non-food consumption. This disparity in non-food intake per capita between adopter and non-adopter households confirms the statistical description analysis described earlier and demonstrates that there was a significant difference.

Table 09: Estimation of ATT for Per Capita Non-Food Consumption Expenditure

Matching Method	No of Treatment	No of Control	ATT	Std.Err	t-value
Nearest Neighbor (NN) Matching	3000	2210	132.351	113.850	1.163
Radius Matching (RM)	3000	8691	167.885	66.724	2.554
Kernel Matching (KM)	3000	8691	152.586	89.265	1.709
Stratification Matching (SM)	3000	8691	115.123	64.052	1.797

Source: Author's calculations using ESS data (2011/12,2013/14 & 2015/16) (2021)

D. Estimation of ATT for Per Capita Education Consumption Expenditure:

The last outcome variable which is per capita education consumption expenditure concerned, the average treatment effect on the treated (ATT) results of the outcome variable using DiD-PSM method tells us that adoption of agricultural technology had insignificant impact on education consumption expenditure. As the table 10 shows that the overall average gain of per capita education consumption expenditure for adopting agricultural technology using the DiD-PSM method ranged from -10.50 Birr to -1.80 Birr under the four algorithms; therefore, this result indicates that households that had adopted of agricultural technology have slightly lower per-capita education consumption expenditure. Though the gap in per capita education consumption between adopter and non-adopter households was not significant, it supported the statistical description analysis discussed earlier and demonstrated that there was no significant difference. That is to say, technology adoption had insignificant impact on education spending.

Table 10 : Estimation of ATT for Per Capita Education Consumption Expenditure

Matching Method	No of Treatment	No of Control	ATT	Std.Err	t-value
Nearest Neighbor (NN) Matching	3000	2210	-9.658	26.810	-0.360
Radius Matching (RM)	3000	8691	-1.850	9.929	-0.181
Kernel Matching (KM)	3000	8691	-6.417	12.995	-0.494
Stratification Matching (SM)	3000	8691	-10.497	12.503	-0.840

Source: Author's calculations using ESS data (2011/12,2013/14 & 2015/16) (2021)

In Ethiopia, particularly in rural areas, for both adopters and non adopter farming households expenditure on eductaion is the same. Since almost all eductaion service is provided by government and any member of a farming households can attend primary and secondary school in their near by town without any fee. That is why the expenditure on eductation do not have difference among technology adopter and non adopter households.

In general, households that adopted agricultural technologies saw an increase in their overall nominal consumption and non-food consumption expenditure (except education expenditure) as a result of higher yields and revenues. The adoption of agricultural technology had a positive and significant impact on nominal total consumption per adult equivalent and per capita non-food consumption expenditure of adopter households.

The impact on nominal total consumption expenditure per adult equivalent, per capita food consumption expenditure, and per capita non-food consumption expenditure also yielded the same results. The final outcome variable is per capita education expenditure, regardless of whether or not a household adopted a technology. The welfare impact result on technology adoption indicates no difference between adopters and non-adopters.

Table 11: Summary of DiD-PSM methods' Results on the technology adoption and its implied impact on the welfare of farming households (ATT)

Matching Method	Outcome Variables			
	Nominal Total Consumption Expenditure Per Adult Equivalent	**Per Capita Food Consumption Expenditure**	**Per Capita Non-Food Consumption Expenditure**	**Per Capita Education Expenditure**
(ATT) or (DiD-PSM)				
NNM.	175.603	83.250	132.351	-9.658
RM.	339.259	180.534	167.885	-1.800
KM.	315.471	159.67	152.586	-6.417
SM.	224.762	116.951	115.123	-10.497

Source: Author's calculations using ESS data (2011/12, 2013/14 & 2015/16)(2021)

In general, DiD-PSM estimation methods revealed significant change in the impacts of agricultural technology adoption on household nominal consumption expenditure per adult equivalent, per capita food consumption, and per capita non-food consumption expenditure. When these methods are used to estimate the impact of agricultural technologies, the findings almost consistently show significant differences between adopters and non-adopters

CHAPTER FIVE

CONCLUSION AND RECOMMENDATION

5.1. Conclusion

The impacts of agricultural technologies such as chemical fertilizer, improved seed varieties, and crop protection chemicals on the welfare of farming households in rural Ethiopia was investigated in this study. In DiD-PSM estimation methods, the results showed that agricultural technology adoption had a robust, significant, and positive impact on nominal total consumption expenditure per adult equivalent, per capita food consumption expenditure and per capita consumption expenditure of non-food items.

When the DiD-PSM method was combined with four matching algorithms, the overall average increase in per capita consumption expenditure as a result of implementing improved agricultural technologies ranged from 176 to 329 Birr, and all of them were significant at a less than 5% probability level.

The study also looked at the impact of agricultural technology adoption on per capita food consumption expenditures in rural households, and found that adopting agricultural technologies resulted in significantly higher per capita consumption expenditures for adopters. The adopters' per capita food consumption expenditures the DiD-PSM method revealed that per capita food consumption expenditures across the adopters of agricultural technologies ranged from 115 Birr to 168 Birr under the four matching methods.

The DiD-PSM method estimated results showed that per capita non-food consumption expenditure ranged from 115 Birr to 168 Birr in households that adopted agricultural technologies. As a result the findings revealed that adopting agricultural technologies had a positive and significant impact on non-food consumption expenditures.

Regarding the final outcome variable, per capita education consumption expenditure, there was no strong support for the impact of these technologies, regardless of whether a household adopted them or not. This indicates that adoption of these technologies did not result in differences in per capita education expenditure between the two groups.

5.2. Recommendations

Agricultural technologies have a positive and significant impact on nominal total consumption expenditure per adult equivalent, per capita food consumption expenditure, and per capita non-food consumption expenditure, according to the study. In addition, policy support for enhancing extension efforts and access to agricultural technology direct sales outlets that simulate agricultural technology adoption is needed. These findings also point to the need for large-scale public and private investments in agricultural research and a variety of technologies to address major growth challenges.

To reap the benefits of adopting agricultural technology, increase investments and policy support will be required to boost agricultural productivity through the dissemination of a range of services such as access to technology information, access to finance credit, extension service support, and continuous field monitoring, as well as the supply of complementary technologies such as mechanization services, irrigation schemes, competitive prices, and improving the value and market chain for reducing transaction costs associated with agricultural technology input markets, which are strongly linked to the decision to adopt them.

Other limiting factors and barriers to adoption, such as knowledge gaps among non-adopters who had adopted the technologies, were observed. These are often linked to the availability of information about certain technologies. As a result, development policies aimed at bringing agricultural transformation to rural Ethiopia must first establish a favourable climate and then aggressively increase access to and use of agricultural technologies. According to this study, such investment would have a significant impact on improving the welfare status of rural Ethiopian farming households.

Given that farming households' variety attribute preferences determined both their tendency to adopt agricultural technology varieties and their chances of successfully adopting them, agricultural technology inputs should be available through direct input sales services to meet the needs of various farming household types categorized according to resource endowments, preferences, and constraints. Integrated support is required in examining farming households' variety-attribute preferences will help to target demands in developing agricultural technology. A one-time trial or adoption of an agricultural technology will hardly change the living conditions of farming households. In farming households, agricultural technology adoption is weakly correlated with per capita education consumption expenditure; therefore, effective interventions are needed in these areas.

The findings of this study generally confirm that adopting agricultural technology has an implied impact on improving rural household welfare, since higher agricultural technology-related incomes imply higher consumption expenditure.

5.3. Area for Future Research

Though future research should look taking into account supply side factors, since the impact of agricultural technology adoption on farming households' welfare may not be realized in just one dimension. Moreover, future research is also suggested to evaluate the impact of agricultural technology adoption on welfare by applying Instrument Variable with Fixed Effect regression method using recent data; if they utilize Ethiopian Socio economic survey (ESS) data, they should get the forth wave of dataset.

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Annexes

Annex 1: Technology Adopters and Non-adopters

Year	0	1	Total
2011/12	2,934	963	**3,897**
2013/14	2,912	985	**3,897**
2015/16	2,845	1,052	**3,897**
Total	**8,691**	**3,000**	**11,691**

Note: 1= Households that had adopted at least one of the technologies

0= Households that had not adopted any of the technologies

Annex 2: Descriptive Statistics /Dependent Variable/

Variable		Obn	Mean	SD
CF_ IS _CP Adoption		**11,691**	**0.257**	**0.437**
CF= Chemical Fertilizer	**1**	11,691	0.909	0.288
	0	11,691	0.091	0.288
IS= Improved Seed	**1**	11,691	0.944	0.229
	0	11,691	0.056	0.229
CP =Crop Protection Chemical	**1**	11,691	0.852	0.355
	0	11,691	0.148	0.355

Annex 3: Summary statistics of balanced panel data

Variables	Wave-1 (2011/12) N=3897		Wave-2 (2013/14) N=3897		Wave-4 (2015/16) N=3897	
	Mean	**SD**	**mean**	**SD**	**Mean**	**SD**
sex hh head	0.747	0.435	0.704	0.457	0.704	0.456
age hh head	44.013	15.746	44.317	15.824	46.306	15.395
edu hh head	2.630	7.451	4.833	10.275	4.851	10.084
total family size	4.799	2.387	4.544	2.371	4.756	2.37
family labor	4.799	2.387	4.540	2.373	4.754	2.373
hh farm size	0.309	1.443	0.756	8.520	162.09	2055.336
livestock holding	0.862	4.320	1.123	5.480	0.466	1.342
non-farm income	0.274	0.446	0.341	0.474	0.374	0.484
market access	67.225	50.382	58.788	48.200	62.914	50.908
credit access	0.075	0.263	0.111	0.314	0.083	0.276
extension contact	0.291	0.454	0.362	0.481	0.407	0.491

Annex 3: Balanced Panel Data Test

panel variable: hhs_id (strongly balanced)

time variable: Wave, 1 to 3

delta: 1 unit

Annex 4 : Hausman Specification Test

	Coef.
Chi-square test value	74.88
P-value	0

Annex 5: Regression results

CF_IS_CP_Adoption	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
sex_hh_head	-.015	.009	-1.65	.1	-.033	.003	*
age_hh_head	0	0	-0.41	.68	-.001	0	
edu_hh_head	0	0	0.01	.991	-.001	.001	
total_family_size	-.017	.035	-0.48	.63	-.087	.052	
family_labor	.013	.035	0.37	.709	-.056	.083	
hh_farm_size	0	0	-0.48	.63	0	0	
livestock_holding	.006	.001	6.49	0	.004	.008	***
non_farm_inc	-.029	.008	-3.52	0	-.046	-.013	***
market_access	-.001	0	-9.16	0	-.001	-.001	***
credit_acc	.054	.014	3.93	0	.027	.081	***
ext_cont	.213	.008	25.93	0	.197	.229	***
Constant	.26	.017	15.42	0	.227	.293	***

Mean dependent var	0.257	SD dependent var	0.437
Overall r-squared	0.076	Number of obs	11691.000
Chi-square	958.814	Prob > chi2	0.000
R-squared within	0.043	R-squared between	0.145

*** *p<.01, ** p<.05, * p<.1*

Appendix 6a: DiD-PSM Result

Outcome Variable: --   Per Capita Food Consumption Expenditure

```
.gen time = (year>=2016)
.gen treated = (CF_IS_CP_Adoption==1)
.gen did = time*treated
.global treatment treated
.global ylist pc_food_cons
.global xlist sex_hh_head age_hh_head edu_hh_head total_family_size family_labor hh_farm_size
<livestock_holding non_farm_inc market_access <credit_acc ext_cont
.global breps 5
```

.diff $ylist, t(treated) p(time) cov($xlist)

Difference-In-Differences with Covariates
Difference-In-Differences Estimation Results
Number of observations in the DIFF-IN-DIFF: 11691

	Before	After	
Control:	5846	2845	8691
Treated:	1948	1052	3000
	7794	3897	

Outcome var.	pc_food cons	S.Err	|t|	P>|t|
Before				
Control	5090.135			
Treated	5223.897			
Diff (T-C)	133.762	95.271	1.4	0.16
After				
Control	5518.413			
Treated	5506.998			
Diff (T-C)	-11.414	129.817	0.09	0.93
Diff-in-Diff	-145.176	158.218	0.92	0.359

R-square: 0.06
* Means and Standard Errors are estimated by linear regression
**Inference: *** p <0.01; ** p <0.05; * p<0.1

. reg $ylist did treated time, vce(robust)

Linear regression

pc_food_cons	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Did	-129.872	162.247	-0.800	0.423	-447.903	188.158	
Treated	250.727	94.979	2.640	0.008	64.553	436.900	***
Time	421.661	83.936	5.020	0.000	257.131	586.190	***
Constant	3530.206	47.652	74.080	0.000	3436.801	3623.612	***

Mean dependent var	3723.412	SD dependent var	3655.116
R-squared	0.003	Number of obs	11691.000
F-test	12.533	Prob > F	0.000
Akaike crit. (AIC)	224970.212	Bayesian crit. (BIC)	224999.679

*** *p <.01*, ** *p <.05*, * *p <.1*

* PROPENSITY SCORE MATCHING WITH COMMON SUPPORT

* MATCHING_METHODS

* Nearest_Neighbor (NN) Matching

. attnd $ylist $treatment $xlist, pscore(myscore) comsup boot reps($breps) dots
.
.
Analytical Standard_Errors

No of Treat	No of Control.	ATT	Standard Err.	T
3000	2210	83.250	113.858	0.731

..
Note: the no of treated & controls refer to actual nearest_neighbor matches.

Bootstrap stat Replicat = 5 No of observation = 11,691

Variable	Rep	Obsrvd	Bias	St.Er.	[95%Conf.Interv]		
attnd	5	83.25	4.371	95.066	-180.694	347.195	(N)
					-23.022	187.603	(P)
					-23.022	187.603	(BC)

Note: N--- Normal P ….. Percentile BC….Bias-Corrected

* Radius Matching

attr $ylist $treatment $xlist, pscore(myscore) comsup boot reps($breps) dots radius(0.1)

ATT Estimation with the Radius_Matching_Method

Analytical Standard Errors

No of Treat	No of Control.	ATT	St Er.	T
3000	8691	180.534	77.28	2.336

Note: the numbers of treated and controls refer to actual matches within radius

Bootstrap stat Replication = 5 No of observation = 11,691

Variable	Rep	Obsrvd	Bias	St.Er.	[95%Conf.Interv]		
.attr	5	83.25	4.37	95.066	-160.624	521.692	(N)
					40.423	359.451	(P)
					40.423	359.451	(BC)

Note: N = normal P = percentile BC = bias-corrected
Note: the numbers of treated and controls refer to actual matches within radius

* Kernel Matching

. attk $ylist $treatment $xlist, pscore(myscore) comsup boot reps($breps) dots

ATT estimation with the Kernel Matching method

No of treat	No of Control.	ATT	Std Er.	T
3000	8691	159.167	.	.

Note: Analytical standard errors cannot be computed. Using the bootstrap option to get bootstrapped standard errors

Variable	Rep	Obsrvd	Bias	St.Er.	[95%Conf.Interv]		
.attk	5	159.167	23.334	95.676	-106.473	424.807	(N)
					55.869	302.386	(P)
					55.869	302.386	(BC)

Note: N = normal P = percentile BC = bias-corrected

ATT estimation with the Kernel Matching method
Bootstrapped standard errors

No of treat	No of Control.	ATT	St Er.	T
3000	8691	159.167	95.676	1.664

* Stratification Matching

. atts $ylist $treatment $xlist, pscore(myscore) blockid(myblock) comsup boot reps($breps) dots

ATT estimation with the Stratification method Analytical standard errors

No of treat	No of Control.	ATT	St Er.	T
3000	8691	116.951	81.928	1.427

Bootstrapping of standard errors

Bootstrap stat Num of observation = 11,691
Replicat = 5

Variable	Rep	Obsrvd	Bias	St.Er.	[95%Conf.Interv]		
.atts	5	116.951	-76.217	32.432	26.906	206.996	(N)
					-3.219	73.407	(P)
							(BC)

ATT estimation with the Stratification method
Bootstrapped standard errors

No of treat	No of Control.	ATT	Standard Err.	T
3000	8691	116.951	32.432	3.306

Appendix 6b: DiD-PSM Result

Outcome Variable: Per Capita Non-Food Consumption Expenditure

```
.gen time = (year>=2016)
.gen treated = (CF_IS_CP_Adoption==1)
.gen did = time*treated

.global treatment treated
.global ylist pc_nonfood_cons
.global xlist sex_hh_head age_hh_head edu_hh_head total_family_size family_labor hh_farm_size
<livestock_holding non_farm_inc market_access <credit_acc ext_cont
.global breps 5
```

```
. diff $ylist, t( treated) p( time) cov( $xlist), save
```

Difference-In-Differences with Covariates
Difference-In-Differences Estimation Results
Number of observations in the DIFF-IN-DIFF: 11691

	Before	After	
Control:	5846	2845	8691
Treated:	1948	1052	3000
	7794	3897	

Outcome var.	pc_non_food cons	S.Err	|t|	P>|t|
Before				
Control	2165.239			
Treated	2337.956			
Diff (T-C)	172.717	58.151	2.970	0.003***
After				
Control	2396.874			
Treated	2377.776			
Diff (T-C)	-19.098	79.237	0.240	0.810
Diff-in-Diff	-191.815	96.573	1.990	0.047**

R-square: 0.09
* Means and Standard Errors are estimated by linear regression
**Inference: *** p<0.01; ** p<0.05; * p<0.1

```
. reg $ylist did treated time, vce(robust)
```

Linear regression

pc_nonfood_cons	Coeff	St.Er.	t-value	p-value	[95% Conf	Intval]	Sign
Did	-156.845	114.245	-1.370	0.170	-380.784	67.094	
Treated	226.374	95.306	2.380	0.018	39.559	413.190	**
Time	242.959	40.556	5.990	0.000	163.463	322.454	***
Constant	1033.094	19.931	51.830	0.000	994.026	1072.162	***

Mean dependent var	1158.056	SD dependent var	2261.992
R-squared	0.003	Number of obs	11691.000
F-test	19.822	Prob > F	0.000
Akaike crit. (AIC)	213750.421	Bayesian crit. (BIC)	213779.888

*** *p <.01*, ** *p <.05*, * *p <.1*

* PROPENSITY SCORE MATCHING WITH COMMON SUPPORT

* MATCHING METHODS

* Nearest Neighbor Matching

. attnd $ylist $treatment $xlist, pscore(myscore) comsup boot reps($breps) dots

Analytical Stat Errors

No of treat	No of Control.	ATT	St Er.	T
3000	2210	132.351	74.314	1.781

Note--the numbers of treated & controls refer to actual nearest neighbor matches

Bootstrap stat   Num of observation = 11,691
Replication = 5

Variable	Rep	Obsrvd	Bias	St.Er.	[95%Conf.Interv]		
attnd	5	132.351	-9.428	113.850	-183.746	448.449	(N)
					16.429	311.126	(P)
					16.429	311.126	(BC)

Note: N-- normal P --percentile BC -- bias-corrected

ATT estimation with Nearest Neighbor Matching method (random draw version)
Bootstrapped standard errors

No of treat	No of Control.	ATT	St Er.	T
3000	2210	132.351	113.850	1.163

Note: the # of treated & controls refer to actual nearest neighbor matches

* Radius_Matching

. attr $ylist $treatment $xlist, pscore(myscore) comsup boot reps($breps) dots radius(0.1)

ATT estimation with the Radius Matching method
Analytical standard errors

No of treat	No of Control.	ATT	St Er.	T
3000	8691	167.885	66.724	2.554

Note: the numbers of treated and controls refer to actual matches within radius

Bootstrap statistics   Number of obs = 11691
Replications = 5

Variable	Rep	Obsrvd	Bias	St.Er.	[95%Conf.Interv]		
attr	5	167.885	-1.48	97.625	-103.165	438.936	(N)
					60.774	297.064	(P)
					60.774	297.064	(BC)

Note: N --normal P --- percentile BC--- bias-corrected
Note: the numbers of treated and controls refer to actual matches within radius

ATT estimation with the Radius Matching method
Bootstrapped standard errors

No of treat	No of Control.	ATT	St Er.	T
3000	8691	167.885	97.625	1.720

Note: the numbers of treated and controls refer to actual matches within radius

* Kernel_Matching

. attk $ylist $treatment $xlist, pscore(myscore) comsup boot reps($breps) dots

ATT estimation with the Kernel Matching method

No of treat	No of Control.	ATT	St Er.	T
3000	8691	152.586	.	.

Note: Analytical standard errors cannot be computed. Using the bootstrap option to get bootstrapped standard errors

Variable	Rep	Obsrvd	Bias	St.Er.	[95%Conf.Interv]		
.attk	5	152.586	58.346	89.265	-95.254	400.427	(N)
					85.984	330.151	(P)
					85.984	232.024	(BC)

Note: N-- normal P -- percentile BC-- bias-corrected

ATT estimation with the Kernel Matching method
Bootstrapped standard errors

No of treat	No of Control.	ATT	St Er.	T
3000	8691	152.586	89.265.	1.709.

* Stratification Matching

. atts $ylist $treatment $xlist, pscore(myscore) blockid(myblock) comsup boot reps($breps) dots
ATT estimation with the Stratification method Analytical standard errors

No of treat	No of Control.	ATT	St Er.	T
3000	8691	115.123	66.615	1.728

Bootstrapping of standard errors
Bootstrap statistics No of obs = 11691
Replications = 5

Variable	Rep	Obsrvd	Bias	St.Er.	[95%Conf.Interv]		
.atts	5	115.123	0.147	64.052	-62.714	292.960	(N)
					33.325	198.263	(P)
					33.325	198.263	(BC)

ATT estimation with the Stratification method

Bootstrapped standard errors

No of treat	No of Control.	ATT	St Er.	T
3000	8691	115.123	64.052	1.797

Appendix 4c: DiD-PSM Result

Outcome Variable: Per Capita Education Consumption Expenditure

```
.gen time = (year>=2016)
.gen treated = (CF_IS_CP_Adoption==1)
.gen did = time*treated

.global treatment treated
.global ylist pc_educ_cons_ann
.global xlist sex_hh_head age_hh_head edu_hh_head total_family_size family_labor hh_farm_size <livestock_holding non_farm_inc market_access <credit_acc ext_cont
.global breps 5
```

```
. diff $ylist, t( treated) p( time) cov( $xlist), save
```

Difference-In-Differences with Covariates
Difference-In-Differences Estimation Results
Number of observations in the DIFF-IN-DIFF: 11691

	Before	After	
Control:	5846	2845	8691
Treated:	1948	1052	3000
	7794	3897	

Outcome var.	pc_educ	S.Err	|t|	P>|t|
Before				
Control	157.232			
Treated	138.583			
Diff (T-C)	-18.649	13.955	-1.340	0.181
After				
Control	207.245			
Treated	206.571			
Diff (T-C)	-0.674	19.015	0.040	0.972
Diff-in-Diff	17.975	23.175	0.780	0.438

R-square: 0.03
* Means and Standard Errors are estimated by linear regression
**Inference: *** p<0.01; ** p<0.05; * p<0.1

```
. reg $ylist did treated time, vce(robust)
```

Linear regression

pc_educ_cons_ann	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Did	24.001	21.585	1.11	.266	-18.31	66.311	
Treated	-9.402	10.835	-0.87	.386	-30.641	11.836	
Time	54.216	13.166	4.12	0	28.408	80.024	***
Constant	75.74	7.18	10.55	0	61.666	89.814	***

Mean dependent var	93.559	SD dependent var	527.848
R-squared	0.003	Number of obs	11691.000
F-test	12.862	Prob > F	0.000
Akaike crit. (AIC)	179726.660	Bayesian crit. (BIC)	179756.127

*** *p* <.01, ** *p* <.05, * *p* <.1

* Propensity score matching with common support

* Matching methods

* Nearest neighbor matching

. attnd $ylist $treatment $xlist, pscore(myscore) comsup boot reps($breps) dots
.
Analytical standard errors

No of treat	No of Control.	ATT	Standard Err.	T
3000	2210	-9.658	11.579	-0.834

Note: the numbers of treated and controls refer to actual nearest neighbor matches

Bootstrap stat   Num of observation = 11,691
Replication = 5

Variable	Rep	Obsrvd	Bias	St.Er.	[95%Conf.Interv]		
attnd	5	-9.658	-6.943	26.810	-84.093	64.778	(N)
					-51.043	11.326	(P)
					-51.043	11.326	(BC)

Note: N = normal P = percentile BC = bias-corrected

ATT estimation with Nearest Neighbor Matching method (random draw version)

Bootstrapped standard errors

No of treat	No of Control.	ATT	St Er.	T
3000	2210	-9.658	26.810	-0.360

Note: the # of treated & controls refer to actual nearest neighbor matches

* Radius matching
. attr $ylist $treatment $xlist, pscore(myscore) comsup boot reps($breps) dots radius(0.1)

ATT estimation with the Radius Matching method

Analytical standard errors

No of treat	No of Control.	ATT	St Er.	T
3000	8691	-1.800	9.664	-0.186

Note: the numbers of treated and controls refer to actual matches within radius
Bootstrap statistics   Number of obs = 11691
Replication = 5

Variable	Rep	Obsrvd	Bias	St.Er.	[95%Conf.Interv]		
Attr	5	-1.800	3.087	9.929	-29.366	25.767	(N)
					-13.656	13.015	(P)
					-13.656	6.699	(BC)

Note: N = normal P = percentile BC = bias-corrected
Note: the numbers of treated and controls refer to actual matches within radius

ATT estimation with the Radius Matching method
Bootstrapped standard errors

No of treat	No of Control.	ATT	St Er.	T
3000	8691	-1.800	9.929	-0.181

Note: the numbers of treated and controls refer to actual matches within radius

* Kernel Matching

. attk $ylist $treatment $xlist, pscore(myscore) comsup boot reps($breps) dots

ATT estimation with the Kernel Matching method

No of treat	No of Control.	ATT	St Er.	T
3000	8691	-6.417	.	.

Note: Analytical standard errors cannot be computed. Using the bootstrap option to get bootstrapped standard errors

Variable	Rep	Obsrvd	Bias	St.Er.	[95%Conf.Interv]		
Attk	5	-6.417	-4.655	12.995	-42.497	29.663	(N)
					-27.644	8.710	(P)
					-13.572	8.710	(BC)

Note: N = normal P = percentile BC = bias-corrected

ATT estimation with the Kernel Matching method
Bootstrapped standard errors

No of treat	No of Control.	ATT	Sta Er.	T
3000	8691	-6.417	12.995	-0.494

* Stratification Matching

. atts $ylist $treatment $xlist, pscore(myscore) blockid(myblock) comsup boot reps($breps) dots
ATT estimation with the Stratification method
Analytical standard errors

No of treat	No of Control.	ATT	St Er.	T
3000	8691	-10.497	10.594	-0.991

Bootstrapping of standard errors
Bootstrap statistics Number of obs = 11691
Replications = 5

Variable	Rep	Obsrvd	Bias	St.Er.	[95%Conf.Interv]		
Atts	5	-10.497	0.483	12.503	-45.212	24.217	(N)
					-20.440	10.472	(P)
					-20.440	10.472	(BC)

ATT estimation with the Stratification method
Bootstrapped standard errors

No of treat	No of Control.	ATT	St Er.	T
3000	8691	-10.497	12.503	- 0.840

Appendix 6d: DiD-PSM Result

Outcome Variable: Total Nominal Consumption Expenditure Per Adult Equivalent

```
. gen time = (year>=2016)
.gen treated = ( CF_IS_CP_Adoption==1)
.gen did = time*treated

.global treatment treated
.global ylist nom_totcons_aeq
.global xlist sex_hh_head age_hh_head edu_hh_head total_family_size family_labor hh_farm_size
<livestock_holding non_farm_inc market_access <credit_acc ext_cont
.global breps 5
```

```
. diff $ylist, t( treated) p( time) cov( $xlist), save
```

Difference-In-Differences with Covariates
Difference-In-Differences Estimation Results
Number of observations in the DIFF-IN-DIFF: 11691

	Before	After	
Control:	5846	2845	8691
Treated:	1948	1052	3000
	7794	3897	

Outcome var.	tot_nom_Cons	S.Err	|t|	P>|t|
Before				
Control	9241.573			
Treated	9531.488			
Diff (T-C)	289.915	151.478	1.910	0.056*
After				
Control	10000.000			
Treated	10000.000			
Diff (T-C)	-87.641	206.404	0.420	0.671
Diff-in-Diff	-377.557	251.561	1.500	0.133

R-square: 0.09
* Means and Standard Errors are estimated by linear regression
**Inference: *** p<0.01; ** p<0.05; * p<0.1

```
. reg $ylist did treated time, vce(robust)
```

Linear regression

nom_totcons_aeq	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Did	-301.733	280.229	-1.08	.282	-851.028	247.561	
Treated	471.807	174.903	2.70	.007	128.968	814.646	***
Time	933.893	134.475	6.94	0	670.3	1197.487	***
Constant	5728.862	68.848	83.21	0	5593.908	5863.815	***

Mean dependent var	6134.078	SD dependent var	5911.501
R-squared	0.006	Number of obs	11691.000
F-test	22.788	Prob > F	0.000
Akaike crit. (AIC)	236183.868	Bayesian crit. (BIC)	236213.334

**** p <.01, ** p <.05, * p <.1*

* Propensity score matching with common support

* Matching methods
* Nearest neighbor matching

. attnd $ylist $treatment $xlist, pscore(myscore) comsup boot reps($breps) dots

Analytical standard errors

No of treat	No of Control.	ATT	St Er.	T
3000	2210	175.603	208.344	0.843

Note: the numbers of treated and controls refer to actual nearest neighbor matches

Bootstrap stat   Num of observation = 11,691
Replication = 5

Variable	Rep	Obsrvd	Bias	St.Er.	[95%Conf.Interv]		
attnd	5	175.603	23.063	208.345	-402.854	754.060	(N)
					-159.265	348.119	(P)
					-159.265	309.068	(BC)

Note: N = normal P = percentile BC = bias-corrected

ATT estimation with Nearest Neighbor Matching method (random draw version)

Bootstrapped standard errors

No of treat	No of Control.	ATT	St Er.	T
3000	2210	-9.658	26.810	-0.360

Note: the # of treated & controls refer to actual nearest neighbor matches

* Radius matching

. attr $ylist $treatment $xlist, pscore(myscore) comsup boot reps($breps) dots radius(0.1)

ATT estimation with the Radius Matching method

Analytical standard errors

No of treat	No of Control.	ATT	St Er.	T
3000	8691	339.259	137.343	2.470

Note: the numbers of treated and controls refer to actual matches within radius

Bootstrap statistics   Number of obs = 11691
Replication = 5

Variable	Rep	Obsrvd	Bias	St.Er.	[95%Conf.Interv]		
Attr	5	339.259	34.727	73.964	133.903	544.615	(N)
					267.845	450.225	(P)
					267.845	438.652	(BC)

Note: N = normal P = percentile BC = bias-corrected
Note: the numbers of treated and controls refer to actual matches within radius

ATT estimation with the Radius Matching method

Bootstrapped standard errors

No of treat	No of Control.	ATT	St Er.	T
3000	8691	339.259	73.964	4.587

Note: the numbers of treated and controls refer to actual matches within radius

* Kernel Matching

. attk $ylist $treatment $xlist, pscore(myscore) comsup boot reps($breps) dots

ATT estimation with the Kernel Matching method

No of treat	No of Control.	ATT	St Er.	T
3000	8691	315.471	.	.

Note: Analytical standard errors cannot be computed. Using the bootstrap option to get bootstrapped standard errors

Variable	Rep	Obsrvd	Bias	St.Er.	[95%Conf.Interv]		
attk	5	15.471	39.179	91.917	-217.376	8.318	(N)
					158.736	637.344	(P)
					158.736	637.344	(BC)

Note: N = normal P = percentile BC = bias-corrected

ATT estimation with the Kernel Matching method

Bootstrapped standard errors

No of treat	No of Control.	ATT	St Er.	T
3000	8691	315.471	191.917	1.644

* Stratification Matching

. atts $ylist $treatment $xlist, pscore(myscore) blockid(myblock) comsup boot reps($breps) dots

ATT estimation with the Stratification method

Analytical standard errors

No of treat	No of Control.	ATT	St Er.	T
3000	8691	224.762	141.880	-1.584

Bootstrapping of standard errors

Bootstrap statistics Number of obs = 11691

Replications = 5

Variable	Rep	Obsrvd	Bias	St.Er.	[95%Conf.Interv]		
Atts	5	224.762	-35.149	143.356	-173.257	622.781	(N)
					-45.757	3307.230	(P)
					-45.757	307.230	(BC)

ATT estimation with the Stratification method

Bootstrapped standard errors

No of treat	No of Control.	ATT	St Er.	T
3000	8691	224.7	143.356	1.568