IMPACT OF IMPROVED WHEAT VARIETY ADOPTION ON WHEAT PRODUCTIVITY USING DNA FINGERPRINTING DATA IN ETHIOPIA

M.Sc. THESIS

EFREM ASFAW

OCTOBER, 2018

JIMMA, ETHIOPIA

Impact of Improved Wheat Variety Adoption on Wheat Productivity Using DNA Fingerprinting Data in Ethiopia

By:

Efrem Asfaw

A Thesis Submitted to Jimma University College of Agriculture and Veterinary Medicine in Partial Fulfillment of the Requirements for the Degree of MASTER OF SCIENCE IN AGRICULTURAL ECONOMICS

September, 2018

Jimma, Ethiopia

APPROVAL SHEET

Jimma University College of Agriculture and Veterinary Medicine
<u>Thesis Submission Request Form (F-07)</u>

Name of Student**: EFREM ASFAW GUTEMA** ID No. RM/0013/09

Program of Study: Degree of Master of Science (M.Sc.) in Agricultural Economics

Title: Impact of Improved Wheat Variety Adoption on Wheat Productivity Using DNA Fingerprinting Data in Ethiopia.

I have incorporated the suggestion and modification given during the internal thesis defense and got the approval of my advisors. Hence, I hereby kindly request the department to allow me to submit my thesis for external thesis defense.

Efrem Asfaw Gutema ________________

Name of student Signature of student

We, the thesis advisor has evaluated the contents of the thesis and found it to be satisfactory, executed according to the approved proposal, written according to the standards and formats of the University and is ready to be summated. Hence, we recommended the thesis to be summated for external defense.

Major Advisor: Moti Jaleta (PhD)

Signature ____________________ Date 07/09/2018

Co-Adviser: Fikadu Mitiku (PhD)

Signature ______________ Date ____________

Decision/suggestion of Department Graduate Council (DGC)

____

Chairperson, DGC __________________ _____________

Signature Date

Chairperson, CGS _____________________ ______________

Signature Date

DEDICATION

I dedicate this thesis manuscript to my family for their continuous prayer in my academic success and life, especially, to my brother *Dereje Asfaw* (*Abbaa Sanyii*) who sacrificed much to bring me up to this level.

STATEMENT OF AUTHOR

I the undersigned, hereby declare that the thesis- Impact of Improved Wheat Variety Adoption on Wheat Productivity Using DNA Fingerprinting Data in Ethiopia is the outcome of my own work and all sources of materials used for this thesis have been duly acknowledged. This thesis has been submitted in partial fulfillment of the requirements for M.Sc. degree at Jimma University and is deposited at the University Library to be available to borrowers under rules of the library. I solemnly declare that this thesis is not submitted to any other institution anywhere for the award of any academic degree, diploma, or certificate.

Brief quotations from this thesis are allowable without special permission provided that accurate acknowledgement of the source is made. Requests for permission for extended quotation from or reproduction of this manuscript in whole or part may be granted by the head Department of Agricultural Economics or the Dean of the School of Graduate Studies when in his/her judgment the proposed use of the material is in the interest of scholarship. In all other instances, however, permission must be obtained from the author.

Name: Efrem Asfaw Signature: ____________

Place: Jimma University, Jimma.

Date of submission: __________________________

BIOGRAPHICAL SKETCH

The author was born on Aprill 14, 1990 in Hawa Babo *Kebele*, Hawa Galan District of Kellem Wollega Zone, and Oromia National Regional State, Ethiopia. He attended his elementary school from grade 1-8 at Terkanfi Woreksa elementary school, Secondary School at Burayu Aba Gosa and Preparatory at Kellem Comprehensive School in Dambi Dollo town. After he successfully passed EGSEC, he joined Jimma University in 2010 and graduated after three years with BSc in Agricultural Economics on June 28, 2012.

After graduation, he served in Ethiopian Institute of Agricultural Research at Jimma Agricultural Research center for about four years until he joined Jimma University on October 13, 2016 to pursue his M.Sc. degree in Agricultural Economics program.

ACKNOWLEDGMENTS

At the outset, I would like to praise the everlasting Father and the Prince of love and peace **the Almighty God** who always let the bulk of unfinished work to be completed at a moment.

My particular appreciation and deepest gratitude goes to Dr.Moti Jaleta, my major advisor, without him, the accomplishment of this research would have been difficult. Besides, his gentle advisor ship from the early designs of the work to the final write-up of the thesis by adding valuable, constructive and ever-teaching comments, frequent assistant, subsequent and unreserved technical support are commendable. I want to extend my deepest gratitude and special thanks to my teacher and co-advisor, Dr.Fikadu Mitiku for his helpful comments, advice, guidance, material support and cooperation. I am also indebted to Dr Chilot Yirga for all his help in all stages of the study. Without their encouragement, insightful and professional expertise, the completion of this work would have not been possible.

I would like to express my sincere appreciation and gratitude to Ethiopian Institute of Agricultural Research specially Agricultural Economics Directorate bureau for their institutional support to give me this opportunity. I also greatly like to thank CIMMYT, Ethiopia, for providing me with the complete data set and financial support for my study.

LIST OF ACRONYMS AND ABREVIATIONS

AgSS	Agricultural Sample Survey
ATT	Average Treatment Effect on The Treated
CGIAR	Consultative Group for International Agricultural Research
CIMMYT	International Maize and Wheat Improvement Center
CSA	Central Statistical Agency
DArT	Diversity Arrays Technology
DD	Difference in Difference
DIIVA	Diffusion and Impacts Of Improved Varieties in Africa
DNA	Deoxyribonucleic Acid
EIAR	Ethiopian Institute of Agricultural Research
ESE	Ethiopian Seed Enterprise
FAO	Food and Agricultural Organization
FAOSTAT	Food and Agriculture Organization Corporate Statistical Database
ICV	Improved Cassava Varieties
ISM	Integrated Striga Management
IV	Instrumental Variable
IWVADOPT	Improved Wheat variety Adoption
IWVs'	Improved wheat varieties
KM	Kernel-Based Matching
Mha	Million hectare
MMt	Million metric tone
MoFED	Ministry of Finance and Economic Development
NERICA	New Rice for Africa
NNM	Nearest Neighbor Methods
PASDEP	Plan for Accelerated and Sustained Development to End Poverty
PSM	Propensity Score Matching
PSNP	Productive Safety Net Program
RD	Regression Discontinuity
RM	Radius Matching
SM	Stratification Matching Method
SSA	Sub-Saharan Africa
GDP	Gross Domestic Product
MOA	Ministry Of Agriculture
Ha	Hectare

TABLE OF CONTENTS

Contents **Page**

LIST OF TABLES

Tables **Page**

LIST OF FIGURES

Figures **Page**

LIST OF THE TABLES IN APPENDIX

Appendix Table **Page**

LIST OF THE FIGURES IN APPENDIX

Appendix Figure **Page**

IMPACT OF IMPROVED WHEAT VARIETY ADOPTION ON WHEAT PRODUCTIVITY USING DNA FINGERPRINTING DATA IN ETHIOPIA

ABSTRACT

Adoption of yield increasing technologies is seen as a key driver to increase agricultural production in Ethiopia. There is, however, limited empirical evidence on the adoption and impacts of improved crop varieties grown by smallholders. The existing studies on improved crop variety adoption and impacts mainly rely on farmers' report in identifying crop varieties which is subject to error due to several factors among which farmers might not have complete information about the varieties they grow. To overcome this challenge, in this study we used DNA fingerprinting technique to accurately identify wheat varieties that farmers grow and then evaluate the role of using improved varieties on wheat yield. Varietal and plot level information were collected from 1421 randomly selected wheat plots from the major wheat growing regional states of Ethiopia. In quantifying the productivity impacts of improved varieties, Propensity Score matching method was used to empirically assess the impact of IWVs' adoption on wheat productivity using DNA fingerprinting data. According to farmers' recall method in variety identification, only 55.03% of the sample farmers used IWVs' during the study year. However, using DNA fingerprinting method, 73.61% of the respondents were using IWVs'. The discrepancy between the two approaches show that relying on household survey methods in varietal identification underestimates improved crop variety adoption rates. According to household recall Kakaba is the most popular variety and had used by 7.18% of farmers; however, contradict to this, the result of DNA finger printing showed that Kubsa is most popular wheat variety and had used by 26.11% of the farmers. The study results further show that the mean productivity of the varieties is high for high genetic purity of varieties grown. The result of both farmers' recall and DNA fingerprinting data further showed that farmer's dependence on and adopted limited number of IWVs' in Ethiopia. On average, the adoption of IWVs' enhances wheat yield by 418.51Kg/ha. The policy implication of the findings is that accurate varietal level data collection is essential in estimating adoption rates and associated productivity impacts of research and extension services in crop variety development and promotion.

Key words: *Genetic purity, adoption rate, Probit, propensity score matching, Average treatment on treated*

1. INTRODUCTION

1.1. Background of the Study

Globally, agricultural development is expected to have the potential of supporting in sinking down poverty for 75% of the world's poor, who lives in rural areas and their livelihood depends mainly on farming. Agriculture accounts for one-third of GDP and three-quarters of employment in Sub-Saharan Africa (WB, 2013).

Agriculture in Ethiopia is a basis for the entire socioeconomic structure of the country and has a major influence on all other economic sectors and development processes and hence it plays a crucial role in poverty reduction similar to many other SSA countries (Elias *et al.*, 2013). Despite the marginal decline in its share of GDP in recent years, it is still the single largest sector in terms of its contribution to GDP as agricultural GDP constitutes 41% of total country's GDP (CSA, 2014/15 as cited in Tesfaye *et al.*, 2018). It also accounts for 73% in terms of employment (UNDP, 2014) and contributes almost 90% of the foreign exchange earnings. Moreover, the livelihood of about 90% of the poor is fully or partly dependent on agriculture as a result of which, agricultural development will continue to be the basis for economic growth (GebreEyesus, 2015).

Smallholders produce a yearly average of 25.4 million tons of cereals, which is 87.42 % of total grain production in Ethiopia. From the total grain produced in the country, the left 12.58% comes from pulses and oilseeds (CSA, 2017). According to Abegaz (2011), cereal crops constitute the largest share of farming household's production and consumption activities. Accordingly, only five major cereals (barley, maize, sorghum, *teff* and wheat) account for about 70% of area cultivated.

Wheat is a key food staple that provides around 20 % of protein and calories consumed worldwide. Demand for wheat is projected to continue to grow over the coming decades, particularly in the developing world to feed an increasing population, and with wheat being a preferred food, continuing to account for a substantial share of human energy needs in 2050

(Wageningen, 2016). Ethiopia contains the majority of this cropping system in the Africa, although there are smaller areas in the highlands of Eritrea, Lesotho, South Africa, Angola, Cameroon and Nigeria. This cropping system accounts for only four % of cultivated area in SSA, but supports seven % of the regions' population (Schneider *et al*., 2010).

Wheat is the fourth most important cereal crop cultivated after *teff*, maize and sorghum; and the third in production after maize and *teff* and about 4.7 million farm households are directly dependent on wheat production in Ethiopia (CSA, 2017).Given the low productivity of traditional varieties, Ethiopia imports significant quantities, especially in drought years when deficits are large. Some of the food import stems from food aid coming into the country under relief and recovery programs. Wheat contributes 16% of the kilo calorie requirement for an individual per day (Tesfaye *et al*., 2016).

In 2016/2017 main season, the total area under wheat production was 1.69 million ha while the total production was about 4.5 million tons. Over the same period, wheat accounted for about 16.6% of the total area of cereals in Ethiopia (CSA, 2017). Ethiopia's wheat farmers are the greatest producer of wheat in sub-Saharan Africa, yet Ethiopia is not self-sufficient in its wheat production and imports an average of more than 1 million tons per annum. Thus, an increasing yield is frequently cited as an important issue for increasing food security (Bekele *et al*., 2009 and Jayne *et al*., 2010, as cited in Alan de *et al*., 2016).

While wheat is an important cereal crop in Ethiopia's production systems, wheat yields are relatively low. Previous study results show that wheat farmers in Ethiopia produce, on average, 2.1 t/ha, well below the experimental yield of above 5 t/ha (MOA, 2012). Similarly according to (CSA, 2017) the national average productivity of wheat is 2.675 tons/ha. Ethiopia also consistently lags behind average yields in Africa and beyond. In 2012, for instance, Ethiopia's wheat yield was 29 % below the Kenyan average, 13 % below the African average, and 32 % below the world average (FAO, 2014).

Despite the low yields, demand for wheat has been growing fast in both rural and urban areas in the country. Changes in dietary patterns and a rapid growth in wheat consumption have been noted over the past few decades in several countries in Sub-Saharan Africa (SSA)

(Morris and Byerlee, 1993; Shiferaw *et al*., 2011). A study by Jayne *et al*. (2010) has also confirmed rapid growth in wheat consumption as a consequence of urbanization, rising incomes, and dietary diversification in Eastern and Southern Africa.

While many countries in Africa are largely dependent on wheat imports to meet their growing demands, Ethiopia is a country where smallholder wheat production is prominent, allowing it to meet more than 70% of the demand from domestic production (Shiferaw *et al*., 2011). These statistics indicate the critical importance of improving the productivity and production of wheat through generation and development of improved wheat technologies in order to promote broad-based economic growth and poverty reduction in Ethiopia.

Cognizant of its importance, the government of Ethiopia has been investing heavily in the development and dissemination of improved wheat technologies. Over the past years, a number of wheat technologies were developed and promoted for different agro-ecological zones of the country. Besides, over the last several years, CIMMYT has been collaborating with the Ethiopian Institute of Agricultural Research (EIAR) in the development and dissemination of improved wheat varieties. Through this long-standing partnership, about 44 improved bread wheat and 30 durum wheat varieties have been released, with associated agronomic and crop protection practices (Bekele *et al*., 2014).

Despite considerable efforts to develop and disseminate several modern wheat varieties, the adoption and livelihood impacts of these technologies have not been analyzed systematically. There are many studies on the adoption and impact of agricultural technologies (Kassie *et al*., 2011; Amare *et al.,* 2012; Asfaw *et al.,* 2012; Tsegaye and Bekele, 2012; Degye *et al.,* 2013 and Di Zeng *et al.,* 2014). However, most of them focused only on identifying determinants of adoption and in analyzing the impact on livelihood outcomes by using the data conducted by household survey.

Farmers' recall estimate varietal adoption can be fairly accurate in a setting where farmers are mostly planting seeds freshly purchased or acquired from the formal seed market as certified or truthfully labeled seed, and the seed system is well-functioning and effective in monitoring the quality and genetic identity of varieties being sold by the seed vendors. However, in settings where the formal seed system is non-existent or ineffective, and farmers mostly rely on harvested grain (either from their own farms or acquired from other farmers or purchased from the market) as the main source of planting material, the reliability of estimating varietal adoption using this method is challenging(Merdia and Reyes,2015).

By implication, it also makes the results of impact assessments based on those adoption estimates questionable. The challenges stem from several confounding factors. These include farmers' inability to identify varieties by names, the inconsistency in the names of the varieties as identified by the farmers and what is in the variety registration list (i.e., varieties may have locally adapted names), and the loss of genetic identity (true to type) due to contamination by different factors. DNA fingerprinting, which is routinely used by plant breeders and is becoming widely available and affordable, offers a reliable method to address these challenges and to accurately identify varieties grown by farmers. The use of this method can thus increase the accuracy and credibility in the interpretation of results of economic analysis that estimate the causal link between the adoption of improved varieties and the impact on crop productivity (Merdia and Reyes, 2015).

It is with this background that this study was conducted to estimate varietal level adoption rate both by farmers' recall and DNA finger printing approach and focused impact study on DNA finger printing approach for better comparison and robustness of impact estimates. Yet, adoption rate of IWVs' and its impact on wheat productivity has not been determined and documented at national level using DNA finger printing data, and information on the adoption and impact of IWVs' is imperative for targeting interventions efficiently and equitably.

1.2. Problem Statement

The ultimate goal of any agricultural development strategy or program is to improve the welfare of rural households. This goal is achieved among other things by increasing productivity at farm level and by raising farmer's income and by improving their livelihood. This is possible if improved agricultural technologies are properly transferred and disseminated to farmers so as to deepen and intensify their production (Assefa and Gezahagn, 2010). Of all the inputs used in agriculture, none has the ability to affect productivity more than improved seed (Morris *et al*., 1999). Thus, if farmers can get all the information and identify the name of the varieties, obtain and adopt seed of improved varieties those perform well under local conditions, the efficiency with which other inputs are converted into economically valuable outputs increases and productivity rises. Utilizing of improved agricultural inputs for instance, (improved seed and chemical fertilizers) are important technological instrument in all crop based farming system and they are a key factors in determining the upper limit of yield (Cromwell, 1990).

Despite the fact that farming technologies such as improved seed is considered as contributing factor for development of the worldwide agriculture, Ethiopia has chronicle poverty and food insecurity problem for a sustained period of time (Yitbarek, 2017). In fact different agricultural technologies have been released to improve productivity of smallholder farmers in the country (Hailu, 2008).However, low crop production and household income remained to be common problems in the country (Dorosh and Shahidur, 2012).

Wheat (*Triticum aestivum*) is one of the most important cereal crops cultivated in wide range of agro-ecologies in Eastern Africa (George *et al*., 2014), particularly, it is the most important staple food crops grown in Ethiopia. Over the past years, a number of wheat technologies were developed and promoted for different agro-ecological zones of the country. However, there is limited robust information on varietal level adoption and impact of this crop in Ethiopia. The importance of adoption and impact study of the crop is to provide concrete evidence to return to the research and extension efforts in developing and extending the technology to farmers. Besides, it clearly would have a significantly contribution for the improvement of its productivity and assist policy makers in making informed decisions about dissemination of technologies that are under consideration.

Different scientific study on adoption of agricultural technologies and their adoption rates have been carried out within and outside Ethiopia. Most of the studies, however, are more location specific with limited national coverage rendering the information less useful to make policy recommendations at a macro level and the studies approach was based on household survey. Evidence shows that household survey approach underestimates the use of improved varieties compared to the DNA fingerprinting results (Chilot *et al.*, 2016).Based on this for more comparison and robustness of the information generated, the study was supported by two complementary data collection methods, namely, a targeted household survey for collecting varietal knowledge and use, crop-cut experiments for collecting seeds from farmer fields, and laboratory analysis were employed which is yet not much practiced in adoption and impact study of agricultural technologies.

In a nut shell, against this background, there is a need to identify the IWVs' adopted and the impact on wheat productivity using the advanced approach (DNA fingerprinting) because without accurate information on varieties and the effects, farmers, extension agents, seed companies and researchers can't make informed decisions that drive agricultural development, particularly, wheat production in Ethiopia. Therefore, this study has attempted to investigate possible answer to the following research questions.

1.3. Research Questions

1. What explains the difference between adoption rate estimates from farmers' recall method and DNA finger printing approach?
2. What is the impact of improved wheat variety adoption on small-holders' wheat yield?

1.4. Objectives of the Study

1.4.1. General objective

The general objective of the study is to assess the impact of improved wheat variety adoption on wheat productivity in Ethiopia.

1.4.2. Specific objectives

1. To compare improved wheat variety adoption rate estimates from farmers' recall and DNA finger printing approaches in varietal identification in identifying wheat variety
2. To examine the impact of improved wheat variety adoption on wheat productivity of smallholder farmers

1.5. Significance of the Study

Technological improvement is necessarily such that a greater output is achieved from a given input level. The firm would never adopt an innovation if output were not increased from given resources, or if input decreased for a given output .In other words, the firm's cost curve must be lowered. The only exception would be the case in which the innovation increased ex-ante profit expectations through risk reduction. Therefore, identification of most important improved wheat varieties those providing high productivity is the first priority. Newer DNA and a more recently developed method that use the polymerase chain reaction can allow faster identification of varieties. The new method may potentially raising genetic purity standards and enabling farmers and consumers better to utilize and benefit from increasingly productive varieties that are bred from a more diverse base of genetic resources.

Therefore, this study provides rigorous information on varietal level adoption and impact assessment for informed and evidence-based policy making, for instance, to develop and implement appropriate support policy measures for improving targeting, access and use of modern wheat varieties. Adoption and impact studies are also valuable tools for improving the efficiency of communication between institutions responsible for research, extension, and agricultural policy. Adoption and impact studies are therefore an important part of the methodology involved in agricultural development. The paper also contributes to the literature by introducing an innovative method to track improved wheat varieties and their productive effects.

1.6. Scope of the Study

This study is undertaken in four regions of Ethiopia, namely, Oromia, Amhara, Tigray and south nation and nationalities people. The data used for this study is based on a farm-household survey and DNA finger printing data. Besides, the study focused on the application of propensity score matching method to assess the impact of improved wheat variety adoption on wheat productivity.

1.7. Limitation of the Study

A variety of studies are aimed at establishing factors underlying adoption of various technologies and its impacts on livelihood of the society. As such, there is an extensive body of literature on the economic theory of technology adoption. Several factors have been found to affect technological adoption. These include government policies, technological change, market forces, environmental concerns, demographic factors, institutional factors and delivery mechanism. However, the study is concerned only with socioeconomic factors, demographic factors and institutional factors to assess factors that affect farmer's decisions to adopt improved wheat varieties.

1.8. Organization of the Thesis

This study is organized into five chapters. The first chapter outlined introduction, statement of the problem, research questions, objectives, significance and, scope and limitations of the study. Concepts and definition used in the present study along with a review of the past works are discussed in chapter two. Chapter three describes the study area and research methodology applied. Chapter four deals with descriptive results and discussions, econometric analysis results and discussions, Chapter five, deal with summary, conclusion and recommendations.

2. LITERATURE REVIEW

The literature review encompasses, the conceptual definitions/theoretical descriptions and empirical evidences related to adoption of agricultural technologies, farmers' decision making behavior in adoption of improved crop varieties, adoption and impact models concepts, overview of wheat varieties and production in Ethiopia and tracking diffusion of improved agricultural technologies with DNA fingerprinting as well as impact of agricultural technologi es adoption has been reviewed.

2.1 .Definitions and Concepts

Technology: refers practical application of knowledge especially in a particular area, manner of accomplishing a task using technical processes, methods, or knowledge and the specialized aspects of a particular field of endeavor to the practical aims of human life or changing and manipulating the human environment (Aytekin, 2012). It is an idea, object, or practice that is perceived as new by the members of the social system (Martin, M.J. 1989). It includes the use of materials, tools, techniques, and sources of power to make life easier or more pleasant and work more productive. It is systematic application and collective human rationality to the solution of the problems through the assertion of control over nature and all kinds of human processes (Olayide, 1980).

Agricultural Technology: includes both the component and process of agricultural production process like production of plant, animal breeding (including biotechnology), and introduction of new crop varieties, mechanization services, infrastructural development and other inputs. Farming technologies are new farming solutions that enabling farmers to take more output than the previous by increasing quality, quantity and cost effectiveness. Successful farming technology has been largely attributed to improved farming technologies such as fertilizer, improved seed and soil and water conservation (Gebremedhin and Johnston, 2002).

Adoption: Numerous researchers stated definition of adoption of (agricultural) technologies in different times. As pointed by Doss (2003), adoption can be defined as the continued use of recommended idea or practice by individuals over a reasonably long period of time and the adoption is not a permanent behavior. Feder *et al*. (1985) have also given definition of adoption as the integration of an innovation into farmers' normal farming activities over an extended period. Adoption is a mental practice through which a person passes from hearing about an innovation to its adoption that follows awareness, interest, evaluation, trial, and adoption stages (Bahadur and Siegfried, 2004). It can be considered as a variable representing behavioral changes that farmers undergo in accepting new ideas and innovations in agriculture anticipating some positive impacts of those ideas and innovations. Adoption is the decision-making process in which a person passes from first hearing about an innovation to final adoption (Rogers, 1962).

A distinction exists between adoption at the individual farm level and aggregate adoption within a targeted region. Adoption at the farm level reflects the farmer's decision to incorporate a new technology into the production process while aggregate adoption is the process of spread or diffusion of a new technology within a region (Feder *et al*., 1985). At the farm level for investigating the adoption process there should be a complete analytical frame work that include farmer's decision making model determining the extent and intensity of use of a new technology at each point throughout the adoption process. Aggregate adoption is measured by the aggregate level of use of a specific new technology within a given geographical area or a given population (Rogers, 1962). The adoption of a new technology can be defined in several ways. In all cases, the definition of "adoption" needs to be agreed upon. Sometimes it may be sufficient simply to report on the proportion of farmers using the technology (at some defined level), (CIMMYT, 1993).

Impact Evaluation: An impact evaluation assesses changes in the well-being of individuals, households, communities or firms that can be attributed to a particular project, program or policy. The central impact evaluation question is what would have happened to those receiving the intervention if they had not in fact received the program. Impact evaluation is aimed at providing feedback to help improve the design of programs and policies. In addition to providing for improved accountability, impact evaluations are a tool for dynamic learning, allowing policymakers to improve ongoing programs and ultimately better allocate funds across programs. Information generated by impact evaluations informs decisions on whether to expand, modify, or eliminate a particular policy or program and can be used in prioritizing public actions. In addition, impact evaluations contribute to improve the effectiveness of policies and programs (World Bank, 2016).

DNA fingerprinting: Alec Jeffery et al. (1985) developed the technique of DNA fingerprinting in human beings for the first time and the usefulness of DNA fingerprinting technique for cultivar identification was demonstrated first by Dallas (1988) in rice. It is the process through which genetic material is extracted from a sample taken from an individual plant or population of plants, in a field and then compared to a known set of genetic profiles – referred to as a "library" of reference samples. The individual sample is then matched to its closest reference sample providing a definitive answer to the question of whether the sample is or is not that variety or cultivar. DNA fingerprinting has long been used by breeders and geneticists, but it is starting to be used by economists and social scientists as a tool for data collection (James, 2018).

2.2. Theoretical Perspective of farmers' decision-making behavior

The theories of decision-making have been largely rooted in disciplines of economics and psychology. In economics, mathematical probability analysis are conducted to explain what value people assign to the utilities for alternatives outcomes of and seek to maximize their expected utility. In psychology, observations are made to describe human judgment process and how people make alternative judgments based on their perception (Simon *eta al.,* 1987).

According to Dunn (1984), decision-making is a ubiquitous activity inherent in the behavior of individuals or society. Decision can be categorized as intuitive, programmed, and analyzed. Those choices that individuals make without conscious thought as to the alternatives and the relative evaluation are known as intuitive decisions. Whereas programmed decision-making are which in principle capable of being automated. There are certain decisions that one has to analyze possible outcomes and their consequences (Gebre-Mariam, 2012).

When an individual has alternatives each with significant consequences, and that he or she in unsure about which choice is the best a decision problem exists. A decision problem consists of: (i) alternatives available to the decision maker, (ii) state of nature (rainfall, price etc), (iii) probability attached to the state of nature influencing the decision problem (iv) consequence of action, (v) process of conducting experiments to obtain additional income, (vi) process of conducting additional information about the likelihood of outcome give the state of nature, and (vii) the strategy for action which are conditional on the experimental outcome observed (Dunn, 1984). The distinction between farmers producing improved varieties or old or both key for study farmers behavior which is much complex when the environment is highly unpredictable.

Decision-making takes different aspects. According to the Rational Decision-making Model; a model in which decisions are made systematically and based consistently on the principle of economic rationality people strive to maximize their individual economic outcomes (Taher, 1996; Mendola, 2007). Information about all possible alternatives, their outcomes and the preference of decision makers is assumed available.

2.3. Methodological Perspectives

2.3.1. Discrete choice models

The study of improved agricultural technology adoption received attention of researchers and policy makers expecting that the adoption of agricultural innovation improves production. A household level adoption study considers the decision made by the household head to include new or improved variety in usual farming practice. The decision made to adopt or otherwise depend on different factors. Farmers' decision to adopt improved varieties is assumed to be the product of a complex preference comparison made by a farm household. To adopt or not to adopt a technology is often a discrete choice. Discrete choice models have widely been used in estimating models that involve discrete economic decision-making processes (Guerrem and Moon, 2004).

The two commonly used discrete choice models in the adoption studies are the probit and logit models. The results from the two models are very similar since the normal and logistic distributions from which the models are derived are very similar except for the fact that the logistic distribution has slightly fatter tails (Gujarati and Porter, 2009). The dependent variable which is normally used with these models is dichotomous in nature, taking the values 1 or 0, a qualitative variable which is incorporated into the regression model as dummy variable. In this case the value 1 indicates a farmer who adopts the IWVs' while the value 0 indicates the farmer who does not adopt. In this study, adoption of improved wheat varieties refers to a continued use of the improved wheat varieties. Here, the respondents who have cultivated improved wheat varieties and continued growing at least one of the distributed improved wheat varieties in the study area during the survey year and in any one of the years before the survey year of this study are considered as adopters. Farmers who never adopted and those who discontinued from growing of improved wheat varieties are categorized as non-adopters.

The other models used to study adoption are the Tobit model and Heckman procedure known as Double-Hurdle models. The Double-Hurdle model and the Tobit model are alternatively used to identify factors which affect adoption and the intensity of adoption (Alene *et al*., 2000; Berhanu and Swinton, 2003; Mignouna *et al*., 2011). These two models differ from the above two due to the assumption that factors that affect the farmers' choice of an option should not necessarily be the same as those that affect the intensity of use. This is because the decision to choose a particular wheat option is obviously associated with some threshold effects. Hence, the probit model was employed in this study as to the taste and convenience of the researcher in assessing farmer's propensity to adopt.

2.3.2. Impact evaluation methods

To know the impact of IWVs' adoption on wheat productivity, we must compare the observed outcome with the outcome that would have resulted had that individual not participated in the intervention. However, two outcomes cannot be observed for the same individual. In other words, only the factual outcome can be observed. Thus, the fundamental problem in any social intervention evaluation is the missing data problem (Ravallion, 2005; Bryson *et al*., 2002).

Estimating the impact of the participation requires separating its effect from involving factors which may be correlated with the outcomes. This task of "netting out" the effect of the program from other factors is facilitated if control groups are introduced. "Control groups" consist of a comparator group of individuals or households who did not involve in the intervention, but have similar characteristics as those involving in the intervention, called the "treatment groups". Identifying these groups correctly is a key to identifying what would have occurred in the absence of the treatment (Ezemenari *et al*., 1999). In theory, evaluators could follow three main methods in establishing control and treatment groups: randomization/pure experimental design; non-experimental design and quasi-experimental design. In practice, in the social sciences, the choice of a particular approach depends, among other things, on data availability, cost, and ethics to experiment. In what follows, brief descriptions of the main impact evaluation methods mentioned above are given.

Experimental Method

In a randomized experiment, the treatment and control samples are randomly drawn from the same population. In other words, in a randomized experiment, individuals are randomly placed into two groups, namely, those that involve in the program or those that not involve in the program. This allows the researcher to determine the involvement impact by comparing means of outcome variable for the two groups. According to Ezemenari *et al*. (1999), a random assignment of individuals to treatment and non-treatment groups ensures that on average any difference in outcomes of the two groups after the involvement can be attributed to the involvement. The main advantage of a randomized experiment is its ability to avoid problem of selection bias, which arises when participation in the program by individuals is related to their unobservable or unmeasured characteristics (like motivation and confidence), which in turn determine the program outcome. Obviously, randomization must take place before the program begins.

Non-Experimental Method

A non-experimental approach is used in cases where program placement is intentionally located. For intervention that is often setup intentionally, it is common to only have access to a cross-sectional survey done after the program is introduced (Jalan and Ravallion, 2003).

According to Bryson *et al*. (2002), there are two broad categories of non-experimental approach; before and after estimator and cross-sectional estimator. The essential idea of the before and after estimator of an impact evaluation approach is to compare the outcome of interest variable for a group of individuals after participating in a program with outcome of the same variable for the same group or a broadly equivalent group before participating in the program and to view the difference between the two outcomes as the estimate of average treatment effect on the treated. Cross-section estimators use non-participants to derive the counterfactual for participants in which case it becomes quasi-experimental method.

Quasi-Experimental Method

Quasi-experimental design involves matching program (in this case improved wheat varieties) participants with a comparable group of individuals who did not participate in the program. This simulates randomization but need not take place prior to the intervention (Kerr *et al*., 2000). A quasi-experimental method is the only alternative when neither a baseline survey nor randomizations are feasible options (Jalan and Ravallion, 2003). Quasi-experimental method consists of constructed (matched) control where individuals to whom the intervention is applied are matched with an “equivalent” group from whom the intervention is withheld (Ezemenari *et al*., 1999). The study used this method as there is no base line data and as the program placement is not random.

Different methods have been developed and used in the literature to address the fundamental question of the missing counterfactual. These include Randomized evaluations, Matching methods, specifically Propensity Score Matching (PSM), Double- Difference (DD) methods, Instrumental Variable (IV) methods, Regression Discontinuity (RD) design and pipeline methods, Distributional impacts, and Structural and other modeling approaches (Shahidur *et* *al*., 2010). Each of these methods carries its own assumptions about the nature of potential selection bias in program targeting and participation, and the assumptions are crucial to developing the appropriate model to assess the ex-post impacts.

These methods vary by their underlying assumptions regarding how to resolve selection bias in estimating the program treatment effect (Shahidur *et al*., 2010).

Randomized evaluation: involves a randomly allocated initiative across a sample of subjects (communities or individuals, for example); the progress of treatment and control subjects exhibiting similar pre-program characteristics is then tracked over time. Randomized experiments have the advantage of avoiding selection bias at the level of randomization.

Double- Difference: assumes that unobserved selection is present and that it is time invariant- the treatment effect is determined by taking the difference in outcomes across treatment and control units before and after the program intervention. DD methods can be used in both experimental and non-experimental settings.

Instrumental Variable: used with cross-section or panel data and in the latter case allow for selection bias on unobserved characteristics to vary with time. In the IV approach, selection bias on unobserved characteristics is corrected by finding a variable (or instrument) that is correlated with participation but not correlated with unobserved characteristics affecting the outcome; this instrument is used to predict participation.

Regression Discontinuity and pipeline methods: are extensions of IV and experimental methods; they exploit exogenous program rules (such as eligibility requirements) to compare participants and nonparticipants in a close neighborhood around the eligibility cut off. Pipeline methods, in particular, construct a comparison group from subjects who are eligible for the program but have not yet received it (Becker and Ichino, 2002).

Propensity Score Matching: in the absence of an experiment, PSM methods compare treatment effects across participant and matched nonparticipant units, with the matching conducted on a range of observed characteristics. PSM methods therefore assume that selection bias is based only on observed characteristics; they cannot account for unobserved factors affecting participation (Rosenbaum and Rubin, 1983). The basic idea behind (PSM) is to match each adopter with an identical non-adopter and then measure the average difference in the outcome variable between the two.

2.4. Overview of wheat varieties and production in Ethiopia

One of the most important inputs in agriculture is seed. Seeds form the foundation of all agriculture. Without seed, there is no next season's crop. The genetic traits embodied within seeds reflect and determine the nature of farming systems dependent on them. The genetic and physical characteristics of seed determine the productivity in line with the use of other agricultural inputs and improved cultural practices within the farming system. Improving the genetic and physical properties of seed can trigger yield increase and lead to improvement in the agricultural production and food security. In order for seed to act as a catalyst in agricultural transformation, however improved seed has to be made available to a broad base of farmers on continuing base. Many released varieties have never been widely disseminated (Rohrbach *et al.,* 2002 as cited in Gezahagn, 2008).

The use of good quality seed of adopted and improved varieties is widely recognized as fundamental to ensure increased crop production and productivity. This is even more important in SSA in the view of increasingly available land, declining soil fertility and ever growing population; those facts increase the importance of promotion and use of good quality seed as a means to intensify food production. The potential benefits from the distribution of good quality seed of improved varieties are enormous, and the availability of quality seed of wide range of varieties and crops to the farmers is the key to achieve food security in SSA. Enhanced productivity, higher harvest index, reduced risks from pest and disease pressure, and higher incomes are some of the direct benefits potentially accrued to the farmers (FAO, 2004).

The agricultural research system has been engaged in adaptation and generation of different improved varieties for most of the cereal crops. Since the start of formal crop improvement programme in early 1950s, there has been strong exchange of cereal germ plasma especially through a close collaboration with International Agricultural Research

Institutes (CGIAR centres). For example, the Ethiopian wheat and maize improvement programme has been collaborating with the International Maize and Wheat Improvement Center (CIMMYT), which has resulted in release of considerable number of varieties. The emphasis given in the Plan for Accelerated and Sustainable Development to End Poverty (PASDEP) for importation and adaptation of technologies is in line with the long ago started effort in the crop improvement programmes (MoFED, 2006).

The supply of any seed material depends on the availability of seed from the formal and the informal sectors and their ability to develop and provide seeds of the cultivars needed by the local producers. The Ethiopian formal seed sector is composed of the Ethiopian Institute of Agricultural Research (EIAR) and Universities (as crop breeding bodies) and the Ethiopian Seed Enterprise (ESE) (as seed multiplier and supplier). Unlike the formal sector where there is clear distinction between cultivar development and seed production and supply, in the informal seed sector both, the production and the supply ends are linked, as farmers are the ones who manage both. It is largely recognized in Ethiopia that farmers can obtain seed from the formal (seed companies/enterprises, agricultural research centers and universities) as well as the informal (local or traditional including farmers' saved seed, local markets exchanges, etc.) (Yealembirhan, 2006).

2.5. Overview on tracking diffusion of improved agricultural technologies with DNA finger printing

Since the pioneering research by Griliches on assessing the impact of hybrid corn adoption in the U.S. almost six decades ago, the interest in measuring the impacts of adoption of improved technology by farmers has expanded to include a gamut of agricultural technologies in both developed and developing country settings. Among the most widely assessed agricultural technologies in the developing country context is the adoption of improved varieties (Maredia, and Reyes, 2015).

Most varietal adoption and impact assessment studies in the past have relied on either the low cost method of expert elicitation (e.g., Evenson and Gollin, 2003; Alene *et al*., 2009; Walker and Alwang, 2015) or the resource-intensive, but gold-standard method of conducting farm household surveys and eliciting this information directly from farmers (e.g., Kassie *et al*., 2011; Shiferaw *et al*., 2014; Zeng *et al*., 2015). However, despite their wide use, the reliability of these approaches has never been verified, leaving the bias and standard errors of these adoption estimates unknown.

There are also other non-household based adoptions tracking methods that may be feasible for some crops such as through record keeping and collection of minimum data from Deoxyribonucleic acid (DNA) fingerprinting of grain samples collected from farmers after the harvest. DNA fingerprinting, which is increasingly used by plant breeders, offers a reliable method to accurately identify varieties grown by farmers and thus serves as a benchmark against which traditional or other innovative methods of varietal identification can be evaluated. However, despite this advantage, the use of DNA fingerprinting as part of adoption surveys is nonexistent or limited to few recent attempts such as (Rabbi *et al*., 2015; Kosmowski *et al*., 2016; Floro *et al*., 2016). With the cost of genotyping expected to decline rapidly, the use of DNA fingerprinting may be pursued as the main method of varietal identification to track and monitor the adoption of improved varieties

Given the importance of agricultural to the overall economic development of Ethiopia and the pattern of research and development investments made so far devising a credible and highly responsive system of monitoring technology use and diffusion would be a critical component in ensuring the Ethiopian crop improvement system remains targeted and capable of accomplishing its goals. To date, considerable research investments attempting to assess varietal adoption and impact in Ethiopia have been made. Previous assessments, however, heavily relied on farmer perceptions and knowledge about the use of crop varieties. Among others, the Central Statistical Agency (CSA) is by far the most important institution tasked with conducting household surveys on annual basis (Chilot *et al.*, 2016).

The CSA through its annual Agriculture Sample Survey (AgSS) has developed a crucial level of foundational knowledge on the overall usage of improved varieties across Ethiopia and the resulting farmer yields. Other studies employing household survey approach have also collected and disseminated data related to agricultural technology use in Ethiopia. However, most of the studies are more location concerned with limited national coverage rendering the information less useful to make policy recommendations at a national level. In 2010, a study on selected food crops under the project "Diffusion and Impact of Improved Varieties in Africa" (DIIVA) expanded the AgSS by providing additional details on variety-specific adoption rates (Chilot *et al.*, 2016).

Besides, providing national and location specific crop varietal use, the DIIVA study uncovered some of the challenges inherent in identifying individual varieties in the field (Walker *et.al*. 2014). These challenges called for the use of state of the art technology to develop an improved monitoring system that can help track the diffusion of individual modern varieties in a better accuracy and efficiency. In this regard, the advancement in developing accurate and low cost molecular marker technology has created an opportunity to apply in tracking varietal diffusion. It is with this background that this study was directed to track the varietal level adoption and impact of IWVs' through DNA fingerprinting in selected areas in Ethiopia.

2.6. Review of Empirical Studies

2.6 .1. Empirical studies on the adoption of agricultural technologies

Different authors have emphasized on different factors as determinant of adoption decision in agricultural technology. Similarly, the following empirical studies have been reviewed for the study.

Age is important household related variable that has relationship with adoption. Age is also assumed to be a determinant of adoption of new technology .However, with regard to age different studies report different results. For instance, older farmers are assumed to have gained knowledge and skill over time and are better able to evaluate technology information than younger farmers (Mignouna *et al*, 2011; Kariyasa and Dewi, 2011). On contrary age has been found to have a negative relationship with adoption of technology. This relationship is explained by Mauceri *et al.* (2005) and Adesina & Zinnah (1993) that as farmers grow older, there is an increase in risk aversion and a decreased interest in long term investment in the farm.

Farm related variable such as farm size influence farmers' adoption behavior as farm is an important unit where agricultural activities take place. For example a study carried out by Mwanga *et al*. (1998) in Tanzania has indicated that cultivated land size level significantly affected the adoption of improved wheat varieties. Many others, Mulugeta (2000), Tesfaye and Alemu (2001), Million and Belay (2004) and Taha (2007), also reported positive relationship of cultivated land size with adoption.

According to study by Kidane (2001) adopters of new wheat varieties were younger with a relatively, more experienced in farming, better size of livestock holding and more frequent contact with development agents than the non adopters. Similarly, Getahun (2003) indicated that access to credit was the most important factor influencing adoption of improved wheat varieties. The impacts of adoption of IWVs' also portray the increase of the farmers' production of wheat varieties and improve their incomes as farmers adopted wheat technologies.

Livestock is the farmers' important source of income, food and draft power for crop cultivation in Ethiopian agriculture. It is one of the main cash sources to purchase inputs. According to the study by Franklin *et al*. (2011) on assessment of determinants of agricultural technology adoption, ownership of livestock returned a positive and significant coefficient suggesting that households that own larger amounts of livestock have a higher propensity to adopt improved varieties of pigeon pea than those that do not own livestock. Similarly other evidence shows that household with larger TLU have better economic strength and financial position to purchase sufficient amount of fertilizer (Techane, 2002 and Legesse, 1992).

Farming experience is another important household related variable that has relationship with adoption. Experience in a particular farming area or with a given crop may not be strictly correlated with age (CIMMYT, 1993). Longer farming experience implies accumulated farming knowledge and skill which has contribution for adoption. A more experienced grower may have a lower level of uncertainty about the innovation's performance (Abadi *et al*, 1999 and Chilot *et al*, 1996), as cited in Mulgeta (2009). Farmers with higher experience appear to have often full information and better knowledge and were able to evaluate the advantage of the technology in question.

As a farm household is nearer to market places, it is expected to be more likely participating in intensive farming activities that demands adoption of new agricultural technologies. According to the study by Afework and Lemma (2015) those used probit model to study determinants of improved rice varieties adoption in Fogera District of Ethiopia ,access to main market is negatively and significant at one % significance value to participate in rice seed technologies adoption.

Proximity of farmers to all weather roads is essential for timely input delivery and output disposal. It also decreases the transport cost of inputs; hence, investment in improved road infrastructure is crucial for promoting adoption and welfare gains. The result is consistent with the finding of (Berhanu and Swinton, 2003). As farmers' gets all weather roads, they can have access to transportation facilities and relatively better support from concerned bodies to their use of improved agricultural technologies which might increase the use of technology. According to study by Solomon *et al*. (2014) on adoption of improved wheat varieties, access to all weather roads is found to be positive and significant suggesting that farmers who have access to all weather roads are more likely to adopt improved wheat varieties.

The relationship between farmers' access to extension services and adoption has been repeatedly reported as positive by many authors. For instance, according to study by Bezabih (2001) on determinants of multiple technology adoption in Ethiopia, extension services, and the qualities of the new varieties play significant roles in the adoption decision. When farmers have regular contact with extension agent, probability of using production enhancing inputs would increase through increased awareness from the extension organization. This finding is in harmony with the observations of (Kidane, 2001 and Techane, 2002); Asfaw *et al*., 2012; Mariano *et al*., 2012) those underlines the importance of extension in promoting adoption.

Regarding the relationship of household's sex with adoption of agricultural technologies, many previous studies reported that household's sex has positive effect on adoption in favor of males. A study by) Fitsum, (2003), and Legesse, (1992); Namwata *et al.*, (2010) found that sex of the household head has an impact on the adoption of new improved technologies. These studies revealed that male-headed households have more likelihood to adopt new technologies than their female-headed counterparts. For instance, Namwata *et al.* (2010) indicated that there is a positive link between male-headed households and adoption of new technologies.

The adoption study conducted by Bekele *et al.* (2000) indicated that the logit analysis revealed that access to credit is an important factor in influencing farmer's decision to adopt improved wheat technologies. Capital and risk constraints are key factors that limit the adoption of high value crops by small scale farmers because these crops generally are much more costly to produce per hectare than traditional crops and most growers require credit to finance their production. Access to credit not only relaxes the cash constraint currently existing in most farm communities, but also facilitates input availability for farmers.

Source of information such as mass media is also important in diffusion of agricultural innovations. Many studies reported the positive and significant relationship of mass media with adoption of agricultural technologies. In line with this, Yishak (2005) in his study on determinants of adoption of improved maize technology indicated that ownership of radio had positive influence on adoption of improved maize technologies. The study by Bezabih (2001) further shows that dissemination of agricultural information through radio programs positively and significantly influenced the adoption behavior.

As the study by Danso *et al.* (2017) on adoption of improved maize variety among farm households in the northern region of Ghana by using probit model shows many years in formal education is statistically significant and have a positive correlation with the adoption of maize varieties. Thus, farmers with a relatively high level of education adopt improved maize varieties than their counterparts with a low level of education. This is not surprising as many studies have reported a positive relationship between adoption of improved farm technology and farmers level of education (Mwanga *et al.*, 1998; Musa, 2015; Deepa *et al.*, 2015; Kebede & Tadesse, 2015). Similarly, carried out a study in Tanzania and found that education level significantly affected the adoption of improved wheat varieties. Besides, Tesfaye and Alemu (2001), indicated positive relationship between education and adoption

As discussed above, the empirical evidence on the adoption and its determinant generally indicate that adoption of agricultural technologies is notably influenced by farmer's demographic, socio-economic and institutional factors (sex, age, education, experience in wheat growing, model farmer, cultivated land size, number of livestock units, access to credit to by seed, contact with extension services, distance to famer cooperative, media (ownership of a radio), all weather road availability and distance to seed dealer, distance to nearest main markets. Even though there are many adoption studies throughout Ethiopia, there is a clear bias towards the information generated for policy issues. Because all the information generated were from the data collected by household survey and the studies are location specific which may not be robust information for agricultural development policy. Unlike previous studies, this study focuses on estimating the adoption of improved wheat varieties in Ethiopia which take in to consideration large data set which may provide strong and robust policy information. Besides, this study used DNA fingerprinting approach that accurately identify cultivars and give clear adoption estimates.

Previous varietal level adoption studies done by DNA fingerprinting

The following are some of the review of improved agricultural technologies varietal identification studies done by DNA fingerprinting data.

According to the study done by Yirga *et al*. (2015) on estimation of the bias of farm survey identification of the diffusion of improved wheat and maize varieties, genetic fingerprinting appears to be a technically feasible method for tracking varietal diffusion and that generates more precise estimates than farmer recall data. The results confirm widespread use of improved wheat and maize varieties in Ethiopia, but that farmer recall data underestimates the diffusion levels of improved varieties. The result shows that adoption levels of improved wheat varieties based on the farmers' recall information is 62% compared to 96% from the

DNA fingerprinting approach. In the case of maize, estimates based on farmer recall data indicate 56% adoption rate for improved varieties compared to 61 % from the DNA finger printing.

Labarta *et al*. (2015) used DNA fingerprinting to identify varieties in farmer fields to assess impacts of the adoption of modern rice varieties in Bolivia. Their results indicate that using DNA fingerprinting varietal identification the adoption rate of modern varieties is estimated in 44.96% compared with the 41.58% that is estimated when using farmers' self-identification of rice varieties. Thus, using only farmers' self-identification of varieties may lead to an underestimation of the adoption of modern rice varieties of almost 3.5 %age points.

According to the study by Leonard *et al.* (2015) on diffusion and adoption of improved rice and maize varieties in Tanzania by application of genetic fingerprinting technique, comparing the varietal identification results from DNA analysis to those from farmer recall revealed a high degree of misclassification. In the case of maize, varietal identification using DNA fingerprinting estimates diffusion levels of improved higher than the 46% reported by the survey respondent. These results suggest that the genetic material that farmers refer to as local varieties are in fact improved and therefore, the diffusion levels of improved maize varieties could be higher than those reported in the literature. By the same token, only a small proportion of rice farmers reported planting improved varieties yet the submitted material was classified into three distinct improved varieties through genetic fingerprinting. These findings appear to confirm that the varietal adoption and diffusion estimates derived from farmer recall data are less accurate compared to those generated through DNA fingerprinting.

Similarly, according to the study result by Maredia *et al*. (2016) on testing alternative methods of varietal identification using DNA fingerprinting in Ghana and Zambia, identifying farmer grown improved varieties accurately by name in a setting where there is a diversity of names by which farmers call their varieties and the seed system is predominantly informal, and is a challenge. Results for both beans and cassava indicate that in such a setting the traditional method of farmer elicitation will give an underestimate of adoption of improved varieties.

According to the study by Le *et al*. (2014) on analysis of cassava varietal adoption in Vietnam using DNA fingerprinting approach, farmer's elicitation method failed to identify the adoption level of different cassava varieties in Vietnam. Farmers use their local-adapted names and often mix up between the cultivar groups and unique variety. Using DNA fingerprinting through SNPs for stake samples taking from the farmer fields, they were able to know exactly the variety planted and document the adoption level of each individual variety.

As the result of the study by Kosmowski *et al*. (2016) on varietal identification of sweet potato varieties in southern Ethiopia using DNA fingerprinting shows, all methods(interviewee with visual-aid , enumerator observation and interviewee's self-report without visual aid) were found to be less accurate than the DNA fingerprinting benchmark in varietal level adoption estimates .. They suggested that a wider use of DNA fingerprinting seems unavoidable in varietal level adoption studies. Moreover, farmers' identification of improved varieties by name only delivered fuzzy varietal identification. Data quality may suffer since information from these methods proved to be unreliable. This also assured that DNA fingerprinting approach will provide accurate estimation of varietal level adoption studies.

2.6 .2 .Empirical studies on the impacts of agricultural technologies adoption

Several studies have showed that adoptions of improved agricultural seed varieties, though variably and incompletely, had positive impacts on productivity, income, food security and poverty reduction. Below are reviews of some of the recent studies who have applied PSM in program evaluations in Ethiopia and elsewhere.

According to the study by Ahmed *et al.* (2017) on impact of improved maize varieties on farm productivity and wellbeing in the case East Hararghe Zone of Ethiopia using propensity score matching method with endogenous switching regression, adoption of improved maize varieties leads to significant gains in wellbeing and improves farm productivity.

Using propensity score matching method with endogenous switching regression the study by Khonje *et al.* (2015) on analysis of adoption and impacts of improved maize varieties in eastern Zambia shows that adoption of improved maize leads to significant gains in crop incomes, consumption expenditure, and food security. They stated that agricultural growth (thus reducing poverty and improving food security) primarily depends on the adoption of improved agricultural technologies.

Similar study was also done on impact of improved maize variety adoption on household food security in Ethiopia by (Moti *et al.* ,2015) , employing propensity score matching method with endogenous switching regression shows that the impact of improved wheat varieties adoption on per-capita food consumption is slightly higher for non-adopters had they adopted improved wheat varieties.

According to the study by Tesfaye *et al.* (2016) on impact of improved wheat technology adoption on productivity and income in Ethiopia by employing propensity score matching method shows that improved wheat variety adoption on average increased wheat productivity of adopters by about 1 to 1.1 t ha-1 than the non adopters. Similarly, the result of the propensity score matching estimates showed that the average income of adopters was 35 to 50% greater than the non-adopters. The results provide empirical evidence that agricultural technology adoption can contribute to improving productivity and raising income of farm household.

The study in Southeastern Ethiopia by Tsegaye and Bekele, (2012) on impacts of adoption of improved wheat technologies on households' food consumption using propensity score matching method indicates that efforts to disseminate existing wheat technologies will highly contribute to food security among farm households.

According to the study by Shiferaw *et al*. (2014) on adoption of improved wheat varieties and impacts on household food security in Ethiopia by employing endogenous switching regression treatment effects complemented with a binary propensity score matching method indicates that adoption of new varieties increases food security and farm households suggesting the need for efforts to improve access to modern varieties and services and enhancing diffusion and adoption of modern wheat varieties in Ethiopia.

Similarly, Tesfaye *et al*. (2018) examined impact of improved wheat variety on productivity in Oromiya Regional State, Ethiopia by employing propensity score matching method and indicates that improved wheat variety adoption appears to significantly increase productivity. The result of the model shows that on the average adoption of improved wheat variety increases wheat productivity by 34-38% for farm households.

According to the study by Dontsop Nguezet *et al*. (2012) on productivity impact differential of improved rice technology adoption among rice farming households in Nigeria by employing local average treatment effect (LATE) shows adoption of improved varieties helped raise farmers' area harvested and yield per hectare, respectively, by 0.39 hectare and 217.9 kg/ha for NERICA and 0.51 hectare and 210.4 kg/ha for other improved varieties, thereby increasing their productivity.

Kassie *et al*. (2010) used propensity score methods to assess the ex- post impact of adopting groundnut on welfare in Uganda. The results showed that the adoption of high yielding improved varieties has a positive effect in improving the smallholder farmers' wellbeing. In the same vein, Kassie *et al*. (2012) analyzed the impact of the intensity of improved maize varieties adoption on food security and poverty in rural Tanzania. The aforementioned authors used a continuous treatment approach using generalized propensity score matching and parametric error correction approaches to reduce potential biases stemming from difference in observed characteristics. The results indicate that maize technology adoption has generated a significant positive impact on food security and that the impact varies by the level of adoption.

Awotide *et al.* (2015) used PSM to assess impact of agricultural technology adoption on asset ownership: the case of improved cassava varieties in Nigeria. Their study shows as PSM essentially estimates each cassava farmer's propensity to adopt any ICVs and it is commonly estimated using the logit regression as a function of observable characteristics of the farmers and then matches each cassava farmer with similar propensities. The result of the study showed a significant and positive effect of adoption of ICVs on asset ownership and a negative effect on asset poverty.

Similarly, a research conducted by Kijima *et al*. (2008) on the impact of New Rice for Africa (NERICA) in Uganda found that NERICA adoption reduces poverty without deteriorating the income distribution. Diagne (2006) also assessed the impact of NERICA adoption on rice yield in Cote d'Ivoire. The results show a positive and significant increase in yield. Setotaw *et al*. (2003) found that adoption of improved agricultural technologies (improved varieties and agronomic practices) have positively and significantly affected household's food security in Ethiopia.

Solomon *et al*. (2011) evaluated the adoption determinants and casual impact of adoption of improved chickpea technologies on market integration in rural Ethiopia. They estimated the causal impact of technology adoption on market integration by utilizing treatment effect model; regression based on propensity score as well as matching techniques to assess results robustness. Results of the analysis revealed that the adoption of improved agricultural technologies has a significant positive impact on marketed surplus and the findings are consistent. The results also confirmed the potential direct role of technology adoption on market integration among the rural households, as higher productivity from improved technology translates into higher output market integration.

Studies conducted in Asia also revealed similar results. Using a propensity score matching method, Mendola (2007) examined the impacts of agricultural technology adoption on poverty reduction in rural Bangladesh. Findings show a robust and positive impact of agricultural technology adoption on farm households' well-being. Similarly, Wu *et al*. (2010) conducted an impact study in rural China and found that adoption of agricultural technologies had a positive impact on farmers' well-being thereby improving household income.

The aforementioned studies revealed the significant and promising effect of agricultural technologies on the general wellbeing of the farm households. Even though there are many impact studies throughout Ethiopia, there is a clear bias towards the information generated for policy issues. Because all the information generated were from the data collected by household survey and the studies are location specific which may not be robust information for agricultural development policy. Unlike previous studies, this study focuses on estimating the impact of improved wheat varieties in Ethiopia which take in to consideration large data set which may provide strong and robust policy information. Besides, this study used DNA fingerprinting approach that accurately identify cultivars and give clear impact estimates.

2.7. Conceptual Framework

From profit maximization theory, the firm's objective is to maximize profit (Hyman, 1989). However, small-scale farmers are both consumers and producers of goods and services. As producers, they still aspire to achieve various primary objectives and not necessarily profit maximization. Some of small-scale farmers' objectives include achievement of minimum subsistence requirements, maintenance of social status, leisure and better living standards among others. Therefore, a smallholder farmer would maximize his/her objectives by maximizing output. This is only achievable through the use of improved production technologies by the farmers. However, the farmer is faced with several technologies to choose from. Based on primary objective maximization, the probability of the farmer to choose an alternative technology is determined by how best that particular technology maximizes profits, minimizes cost per unit of production or ensures achievement of a threshold level of subsistence or any other objectives as the case may be, as compared to all other alternatives in the choice set. However, the farmer's decisions to choose a given alternative technology from the available choices is influenced by many and varied factors that are observable and non-observable.

The study conceptualized that farmer's decision to adopt improved wheat varieties is being dependent on farmer's complex set of socio-economics, demographic, and institutional factors. This is based on evidence from empirical works (Makhoha *et al*., 1999, Adesina and Zinnah, 1993; Adesina and Baidu-forson, 1995; Sall, *et al*., 2000 and) that have shown farmer's complex set of socio-economic, demographic, and institutional factors do significantly impact on farmer's adoption decisions. The decision to adopt or not to adopt improved wheat varieties is dependent on farmer's demographic, socio-economic and institutional factors (sex, age, education, experience in wheat growing, model farmer, cultivated land size, number of livestock units, access to credit to by seed, contact with extension services, distance to famer cooperative, media (ownership of a radio), all weather road availability and distance to seed dealer, distance to nearest main market) as shown in Figure 1. From Figure 1 the dependent variable is decision to adopt improved wheat varieties and the independent variables are socio-economic, demographic, and institutional factors. Besides, adoption of improved wheat varieties has interrelation with impact on wheat productivity .The figure also shows how adoption decisions influence productivity. The arrows in Figure 1 represent a cause-effect relationship.

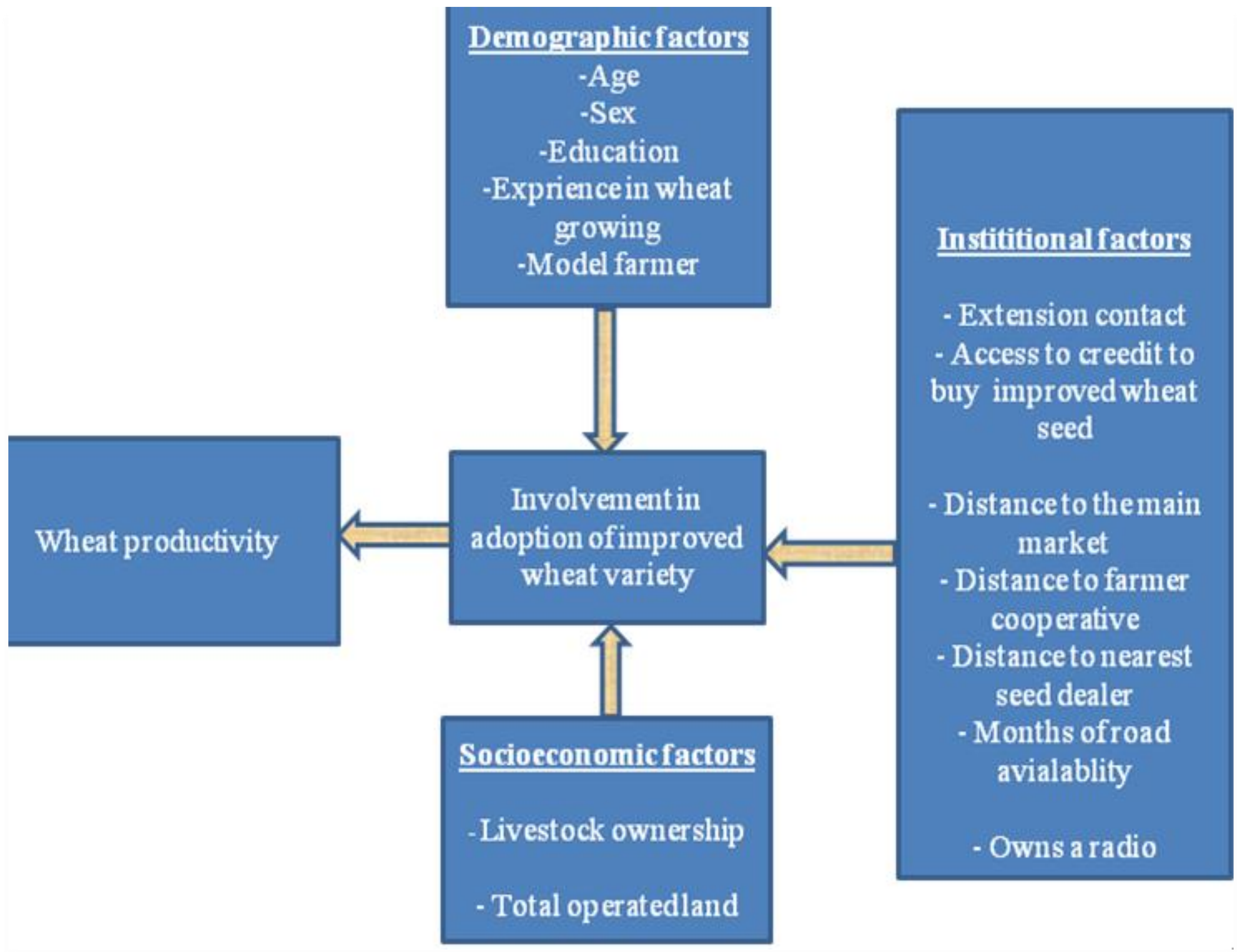


Figure 1 :Conceptual framework. Source**:** Adapted from Duvel (1991)

3. RESEARCH METHODOLOGY

This chapter provides an explanation of the methodology employed to address the objectives of the study. This chapter contains six sections. Section one describes the study area. Section two presents source and type of data. Section three and four presents sample design, data collection methods and section five gives data analysis methods. Section six provides definition of variables and working hypothesis.

3.1. Description of the Study Area

Ethiopia, situated in the Horn of Africa, has a population of nearly 102 million and a surface area of 1.2 million square kilometers, of which 65% is suitable for arable farming (WB, 2016). Agriculture is the country's largest economic sector, contributing about 41% of the country's GDP and employing more than 85% of the working population ((CSA, 2014/15 as cited in Tesfaye *et al.*, 2018). Production systems are dominated by smallholder farming under rain-fed conditions with little mechanization. Subsistence mixed farming with crop cultivation and livestock husbandry is practiced on most farms. Agriculture is highly dependent on rainfall, and hence the onset, duration, amount and distribution of the rainfall determines the performance of the agriculture sector and the economy of the country in general. More than 95% of the country's agricultural output is generated by subsistence farmers who, on average, own less than 1 ha of cultivated land with poor soil fertility as a result of continuous cropping and little input of nutrients to replace removal with harvest.

Ethiopia is known for its ecological diversity that ranges from tropical to temperate conditions. Altitude ranges from -126 meters below sea level in the Danakil Depression in the northeast to 4620 meters above sea level in the Ras Dashen Mountains in the northwest. In central highland plateaus, where major cereal crops are grown, elevation ranges from 1800 to 3000 meters above sea level with mean annual rainfall ranging from 950-1500 mm and mean annual temperature from 11-21°C. Ecological and socio-cultural diversity creates favorable conditions to support tremendous diversity of fauna and flora such that the country is a center of origin and biodiversity for many cultivated crops and their wild relatives.

About 15% of the county's area is currently used for the production of major food crops. Major staple crops include cereals, pulses, oilseeds, roots and tubers, vegetables and coffee. According to the recent Ethiopian Central Statistical Agency report (CSA, 2013), grain crops (cereals, pulses and oil crops) are cultivated on 13.9 Mha with annual production of 25.1 million metric tonnes (MMt). According to the same report, cereals, pulses and oil crops constituted 78, 15, 7% of the cultivated area and 85, 12 and 3% the total grain production of the country, respectively in the main rainy season of 2012/2013. Cereals are the most important field crops and the chief element in the diet of most Ethiopians. Principal cereals are *teff* (an indigenous principal staple crop), wheat, barley, maize, sorghum and millet.

Wheat is grown mostly between 1,500 and 2,700 meters above sea level whereas maize, sorghum and millet are cultivated at lower elevations in the warmer areas of the country. Sorghum and millet, which are drought resistant, are grown in regions with low and uncertain rainfall. Maize is mainly grown between 1,500 and 2,200 meters above sea level and requires relatively higher seasonal rainfall to ensure good harvests. These major food crops are produced in almost all regions of the country but with large variations in terms of volume of production. The area coverage of maize, wheat, sorghum and finger millet account for 47% of cultivated grain crop area of the country in the 2012/13 cropping season. However, the productivity of these crops is very low despite their large production area. National average yields for maize, wheat and sorghum, and finger millet are 3.0, 2.0 and 1.7 t ha^{-1}, respectively in 2012/2013.

Available evidence suggests that yields of major crops under farmers' management are still far lower than what can be obtained under on-station and on-farm research managed plots. This is a clear indication of large yield gaps. There are several factors believed to contribute to the low productivity including, among others, moistures stress, shortage of seeds for improved varieties, soil fertility degradation, insect pests, diseases, weeds and birds. The most important cereal farming system zones are located in the north, northwestern, central, eastern and southwestern highlands (USAID, 2010). Cereal mixed farming dominates the northern, northwestern and central highlands while maize-sorghum based cropping dominates the eastern highlands. Whilst Barley-wheat cropping dominates the Arsi and Bale highlands, coffee, maize and horticultural crops farming characterize the major farming system of the southern and southwestern highlands. The lowlands (areas below 1500 m above sea level) areas also grow short maturing maize, sorghum, wheat, and *teff* varieties along with some oil crops and lowland pulses.

3.2. Source and Type of Data

The source of data is secondary data. The data used for this study is based on a farm-household survey and DNA finger printing data collected from Amhara, Oromiya, Tigray, and Southern Nations Nationalities and Peoples (SNNP), with a purpose of wheat varietal identification adoption analysis and its impacts on wheat productivity of smallholder producers by collaboration of three organizations namely: Ethiopian Central Statistical Agency, Ethiopian Institute of Agricultural Research and International Maize and Wheat Improvement Center. The sources of data are sampled households based on the actual wheat farming practices existed in the study area, journals, websites; published thesis and dissertation are also other source of data. Quantitative data type was employed in the study.

3.3. Sample Design

Prior to the determination of the survey sample design the concerned CSA staff, senior researcher from EIAR and a staff from CIMMYT had made meetings, and in these meetings, the participants has reached a consensus to execute the survey along with the CSA Agricultural Sample Survey which is currently under operation with the objective of minimizing survey cost and time without compromising data quality and efficiency. Accordingly, survey sample design, sample size determination and sample selection and survey instrument preparation, field data collection, field supervision and quality control and …etc, were among the major activities CSA had agreed to execute.

The organization used probability sampling techniques to draw a representative sample. A stratified two-stage probability sampling strategy was employed, with enumeration areas serving as the primary sampling units and the households being the secondary sampling units. The sampling enumeration areas in each region was randomly selected following probability proportional to size technique from a list of enumeration areas compiled during the 2007 population and housing census. Then, the survey covered a total of 110 EAs' from Amhara, 136, 50 and 104 EAs' from Oromiya, Tigray and SNNp Regions, respectively.

They sampled Enumeration Areas' in each of the respective regions to have good representation of the agro-ecology, topography, type of crop grown and related agricultural practice. The sample frame used is registered household list collected through census by population and vital statistics office of the administration council with technical support of Central Statistical Authority. The list of households was used as a sampling frame to select agricultural households using systematic random sampling. A total of 1421 farm household heads were used in this study. The sample size was deducted from 2000 because it was attacked by bacteria during DNA finger printing and discarded from the analysis.

3.4. Methods of Data Collection

Identification and verification of the required data items of the survey were carried out by CSA, EIAR and CIMMYT staff. Followed by questionnaire design, translation of questionnaire and the preparation of enumerators manual and printing of the survey instrument were accomplished on time scheduled. Survey data were collected using a pre-tested structured questionnaire by trained and experienced enumerators who have good knowledge of the farming systems and speak the local language. The enumerators was trained and supervised.

Field data collection operation of the survey involved both subjective and objective data collection methods where data is being collected using subjective methods by interviewing each holders in the sampled households and crop yield data are being collected using objective method through conducting crop-cutting (harvesting) on sample plots and measuring the results using weight scales. Crop cut involves the use of appropriate sampling techniques for collecting crop samples from randomly selected wheat fields. The main objective of the crop cut is to collect wheat grain samples from farmer fields for extraction of DNA and subsequent laboratory analysis for genetic matching with known reference materials. The method was involved demarcating small subplots of rectangular shape from randomly selected crop fields and subsequent threshing, drying and weighing and recording the weight of the harvest.

In each enumeration area, five wheat fields were selected for conducting crop-cutting experiment. In each case, a 4m x 4m plot is randomly demarcated within each of the selected cropped fields and harvested from the plot. The crop cut is then were weighed (fresh weight) and the data were recorded in a format developed for the purpose. After two weeks of sun drying, the harvested sample was re-weighed several times and the figure from each weighing was compared to the previous record until a consistent figure is attained. Once, a consistent weight is achieved which suggest further drying and weighing is unlikely to lead to moisture loss, the final weight was considered the correct weight of the sample recorded. It is from the dried crop-cuts a sample of 200 grain of wheat were taken and sent to Holeta Agricultural research center for screening and shipped to DArT at Australia for laboratory analysis.

3.5. Method of Data Analysis

The data were analyzed using descriptive, inferential statistics, and econometrics models. The analytical tools were used in this study are discussed in the following sub-sections.

3.5.1. Descriptive and inferential analysis

Descriptive statistics mean, standard deviation, and %ages were used for describing the data. Chi-square and t-test was used as inferential statistical tools to compare treatment and control groups in terms of the different explanatory variables.

3.5.2. Propensity score matching (PSM) method

In this paper, the researcher used propensity score matching to empirical results.

The impact of IWVs' adoption in this study is the differences in households' mean wheat productivity generated from wheat production of the treated and non-treated groups. However, households involved in IWVs' adoption cannot be simultaneously observed in two states. A household can either be involved or non-involved. Thus, the fundamental problem of such an impact evaluation is a missing data problem. In other words, this study was interested in answering the research question what would the wheat productivity of household have been, had they not been involved in adoption of improved wheat varieties. If there is a baseline survey data the most commonly used model is differences-in differences method (Baker, 2000). This study applied a propensity score matching (PSM) non-experimental technique, which is a widely applied among other non-experimental methods because it does not require baseline data, the treatment assignment is not random and considered as second-best alternative to experimental design in minimizing selection biases.

The PSM technique enables us to extract from the sample of non-involving households, a set of matching households that look like the involving households in all relevant characteristics. In other words, PSM matches each non-involved households with involved households that has (almost) the same characteristics. PSM is preferred to the traditional regression method in several ways. These include, among others, PSM compares outcome for observations, who share similar observable characteristics and it only compares households that lie in the common support region and excludes others from the analysis.

This study was attempted to estimate the impact of IWVs' adoption on household wheat productivity farm. In this study "treatment" refers to involvement in adoption of IWVs' and impact refers to the change of productivity status generated from adoption of improved wheat varieties. On the other hand, "control" stands for households not-involved in adoption of improved wheat varieties.

3.5.2.1. Specification of the PSM method

According to Caliendo and Kopeinig (2008), the estimation of the impact of household's involvement in adoption of IWVs' on given wheat productivity (Y) is specified as:

$$\tau_i = Y_i(D_i = 1) - Y_i(D_i = 0) \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots . (\mathbf{3.1})$$

Where $\boldsymbol{\tau_i}$ is treatment effect (effect due to involvement in adoption of improved wheat variety), $\boldsymbol{Y_i}$ is wheat productivity of household i, D_i is whether household i has got the treatment or not (i.e., whether a household is involved in adoption of IWVs' or not).

However, one should notice that $Y_i(D_i = 1)$ and $Y_i(D_i = 0)$ cannot be observed for the same household at the same time. Depending on the position of the household in the treatment (involvement in adoption of improved wheat varieties), either $Y_i(D_i = 1)$ or $Y_i(D_i = 0)$ is unobserved outcome (called counterfactual outcome). Due to this fact, estimating individual treatment effect $\boldsymbol{\tau_i}$is not possible and one has to shift to estimating the average treatment effects of the population than the individual one. Most commonly used average treatment effect estimation is the 'average treatment effect on the treated ($\boldsymbol{\tau_{ATT}}$), and specified as:

$$\tau_{ATT=}E(\tau \mid D = 1)=E[\mathrm{Y}(1) \mid \mathrm{D} = 1] - E[\mathrm{Y}(0)/ \mathrm{D} = 1] \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots . (\mathbf{3.2})$$

As the counterfactual mean for those being treated, $E[\mathrm{Y}(1) \mid \mathrm{D} = 1]$ is not observed, one has to choose a proper substitute for it in order to estimate ATT. One may think to use the mean outcome of the untreated individuals, $E[\mathrm{Y}(0) \mid \mathrm{D} = 0]$ as a substitute to the counterfactual mean for those being treated, $E[\mathrm{Y}(0) \mid \mathrm{D} = 1]$.However, this is not a good idea especially in non-experimental studies, since it is likely that components which determine the treatment decision also determine the outcome variable of interest.

In this particular case, variables that determine household's decision to participate in adoption of IWVs' could also affect household's wheat productivity. Therefore, the outcomes of individuals from treatment and comparison group would differ even in the absence of treatment leading to a self-selection bias.

By rearranging, and subtracting $E[\mathrm{Y}(0) \mid \mathrm{D} = 0]$ from both sides of equation (**3.2**), one can get the following specification for ATT.

$$E[\mathrm{Y}(1) \mid \mathrm{D} = 1] - E[\mathrm{Y}(0) \mid \mathrm{D} = 0] =\tau_{ATT} + E[\mathrm{Y}(0)/ \mathrm{D} = 1] - E[\mathrm{Y}(0)/ \mathrm{D} = 0] \ldots (\mathbf{3.3})$$

Both terms in the left hand side are observables and ATT can be identified, if and only if $E[\mathrm{Y}(0)/ \mathrm{D} = 1] - E[\mathrm{Y}(0) \mid \mathrm{D} = 0] = 0$. i.e., when there is no self-selection bias. This condition can be ensured only in social experiments where treatments are assigned to units randomly (i.e., when there is no self-selection bias). In non-experimental studies one has to introduce some identifying assumptions to solve the selection problem. The following are two strong assumptions to solve the selection problem.

i**.** Conditional Independence Assumption (CIA)**.** The Conditional Independence Assumption is given by:

$\mathrm{Y}(0), \mathrm{Y}(1)\ \mathrm{U}\ \mathrm{D}/\mathrm{X}\ , \forall\ \mathrm{X}$

Where: U indicates independence, $\mathrm{Y}(0)$ is non-involvement, $\mathrm{Y}(1)$ involvement and X –is is a set of observable characteristics.

Independence indicates that given a set of observable covariates (X) which are not affected by treatment (in our case, involvement in adoption of improved wheat variety) and potential outcome (wheat productivity) are independent of treatment assignment (independent of how adoption of IWVs' involvement decision is made by the household).

This assumption implies that the selection is solely based on observable characteristics (X) and variables that influence treatment assignment (households' involvement in adoption of IWVs' decision) and potential outcomes (wheat productivity) are simultaneously observed (Bryson *et al.*, 2002; Caliendo and Kopeinig, 2008). Hence, after adjusting for observable differences, the mean of the potential outcome is the same for $\mathrm{D} = 1$and $\mathrm{D} = 0$ and

$$E[Y_0/\ \mathrm{D} = 1, \mathrm{X}] = E[Y_0/\ \mathrm{D} = 0, \mathrm{X}] \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. (\mathbf{3.4})$$

Instead of conditioning on X, Rosenbaum and Rubin (1983), suggest conditioning on a propensity score (propensity score matching). The propensity score is defined as the probability of participation for household i given a set X which is household's characteristics, $\mathrm{P}(\mathrm{X}) = \mathrm{pr}(\mathrm{D} = 1 / \mathrm{X})$. Propensity scores are derived from discrete choice models, and are then used to construct the comparison groups. Matching the probability of participation, given covariates solves the problem of selection bias using PSM (Liebenehm *et al.*, 2009). The distribution of observables X is the same for both participants and non- participants given that the propensity score is balancing score (Liebenehm *et al.*, 2009).

Matching can be performed conditioning on P(X) alone rather than on X, where $P(\mathrm{X}) = \mathrm{pr}(\mathrm{D} = 1 / \mathrm{X})$the probability of involving in the adoption of IWVs' is conditional on X. If the outcomes without the involvement in adoption of IWVs' are independent of participation given X, then they are also independent of participation given $P(\mathrm{X})$. This reduces a multidimensional matching problem to a single dimensional problem. Due to this, differences between the two groups are reduced to only the attribute of treatment assignment, and unbiased impact estimate can be produced (Rosenbaum and Rubin, 1983).

ii. Common support region assumption

Imposing a common support condition ensures that any combination of characteristics observed in the treatment group can also be observed among the control group (Bryson *et al*., 2002). The common support region is the area which contains the minimum and maximum propensity scores of treatment and control group households, respectively. It requires deleting of all observations whose propensity scores is smaller than the minimum and larger than the maximum of treatment and control, respectively (Caliendo and Kopeinig, 2008). This assumption rules out perfect predictability of D given X.

That is $0 < P(D = 1/ X) < 1$

This assumption improves the quality of the matches as it excludes the tails of the distribution of $P(\mathrm{X})$,though this is done at the cost that sample may be considerably reduced. Yet, non-parametric matching methods can only be meaningfully applied over regions of overlapping support. No matches can be formed to estimate the parameters when there is no overlap between the treatment and comparison groups. This assumption ensures that persons with the same X values have a positive probability of being both participants and non-participants.

Given the above two assumptions, the PSM estimator of ATT can be written as:

$$\tau_{ATT=} E[Y_1 - Y_0/ D = 0, P(\mathrm{X})] = E[\mathrm{Y}(1) /\ \mathrm{D} = 1, P(\mathrm{X})] - E[\mathrm{Y}(0)/\mathrm{D} = 0, P(\mathrm{X})] \ldots\ldots (\mathbf{3.5})$$

Where $P(X)$is the propensity score computed on the covariates X. Equation above shows that the PSM estimator is the mean difference in outcomes over the common support, appropriately weighted by the propensity score distribution of participants.

According to Caliendo and Kopeinig (2008), there are steps in implementing PSM. These are estimation of the propensity scores, choosing a matching algorithm, checking on common support condition and testing the matching quality.

3.5.2.2. Procedures of propensity score estimation

The first step in PSM method is to estimate the propensity scores by using either logit or probit models. The study uses probit model to estimate the propensity scores and marginal effects of the explanatory variables.

This study was intended to analyze which and how much the hypothesized repressors' were related to the involvement in adoption of IWVs' and the wheat productivity. In estimating the probit model, the dependent variable is involvement in adoption of improved wheat varieties, which takes the value of 1 if a household is involved in adoption of IWVs' and 0 otherwise.

The dependent variable, technology adoption, has a binary nature taking the value of 1 for adopters (of improved wheat variety) and 0 for non-adopters. In this regard an econometric model was employed while examining probability of farm households' agricultural technology adoption decision is the probit model. Often, probit model is imperative when an individual is to choose one from two alternative choices (Hailu *et al.*, 2014) .In this case, either to adopt or not to adopt improved wheat varieties. Hence, an individual i makes a decision to adopt improved wheat variety if the utility associated with that adoption choice ($Ui1$) is higher than the utility associated with decision not to adopt ($Ui0$). Hence, in this model there is a latent or unobservable variable that takes all the values in (-∞, +∞). According to Koop (2003) these two different alternatives and respective utilities can be quantified as: $Yi^* = V1i - V0i$ and the econometric specification of the model is given in its latent as:

$$Y_i = \begin{Bmatrix} 1, if\ Y_i^* > 0 \\ 0\ , if\ Y_i^* \leq 0 \end{Bmatrix} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \textbf{(3.6)}$$

Where: Yi takes the value of one (1) for adopters and Zero (0) for non-adopters.

$Y_i^* = X_i'\ \beta i +\ ui$

Where:

Y_i^*=is a dependent variable indicating for probability of improved wheat variety adoption

ui | x =is a normally distributed error term.

βi= is the parameters that are estimated by maximum likelihood

X_i'= is a vector of exogenous variables that explains adoption of improved wheat varieties. Therefore, on the basis of the dependent variable indicated: an improved wheat variety, probit model was applied as given below.

$IWVADOPT$=$\beta 0 + \beta 1$ AGEHH + $\beta 2$ TOPLND + $\beta 3$ TLU + $\beta 4$ HHEXP + $\beta 5$ MINMAINMRKET + $\beta 6$ NUMMONTHS + $\beta 7$ MINSOURSED + $\beta 8$ MINCOOPS + $\beta 9$EXTCONT + $\beta 10$ SEXHH + $\beta 11$ MODFARM + $\beta 12$ CREDITSEED + $\beta 13$OWNRDIO + $\beta 14$ HHEDUC + ui

$IWVADOPT$= is a dependent variable indicating for probability of improved wheat variety adoption.

Given the above dependent variable (improved wheat variety adoption), to estimate the magnitude of parameters or variables basically to put clearly the %age probability of adoption and marginal effect of variables.

Marginal effect of a variable is the effect of unit change of that variable on the probability of

$P(Y = 1|X = x)$, given that all other variables are constant

From this unobserved or latent model specification, therefore, the utility function depends on household specific attributes X and a disturbance term (u) having a zero mean:

$$Ui1(X) = \beta 1Xi + ui0 \quad \text{for adopters}$$

As utility is random, the ith household will adopt if and only if $Ui1 > Ui0$. Thus, for the household i, the probability of adoption is given by:

$$P_1 = P(Ui1 > Ui0).$$

Where: $P_1 =$ = is the probability of adopting improved wheat varieties.

3.5.2.3. Choice of matching algorithm

After estimation of the propensity scores, seeking an appropriate matching estimator is the major task of a researcher. The choice of matching method involves a trade-off between matching quality and its variance. Various matching estimators have been suggested in the literature. These include the nearest neighbor matching, caliper and radius matching, stratification and interval matching, kernel and local linear matching (Caliendo and Kopeinig, 2008). The discussions of most commonly applied matching estimators are as follows:

Nearest Neighbour (NN) matching: It is the most straightforward matching estimator. In NN matching, an individual from a comparison group is chosen as a matching partner for a treated individual that is closest in terms of propensity score (Caliendo and Kopeinig, 2008).The NN matching can be done with or without replacement options. In the case of the NN matching with replacement, a comparison individual can be matched to more than one treatment individuals, which would result in increased quality of matches and decreased precision of estimates. On the other hand, in the case of NN matching without replacement, a comparison individual can be used only once. Matching without replacement increases bias but it could improve the precision of the estimates. In cases where the treatment and comparison units are very different, finding a satisfactory match by matching without replacement can be very problematic (Dehejia and Wahba, 2002). It means that by matching without replacement, when there are few comparison units similar to the treated units, we may be forced to match treated units to comparison units that are quite different in terms of the estimated propensity score.

Caliper Matching: The above discussion tells that NN matching faces the risk of bad matches, if the closest neighbor is far away. To overcome this problem researchers use the second alternative matching algorism called caliper matching. Caliper matching means that an individual from the comparison group is chosen as a matching partner for a treated individual that lies within a given caliper (propensity score range) and is closest in terms of propensity score (Caliendo and Kopeinig, 2008). If the dimension of the neighborhood is set to be very small, it is possible that some treated units are not matched because the neighborhood does not contain a control unit. On the other hand, the smaller the size of the neighborhood the better is the quality of the matches (Becker and Ichino, 2002). As Smith and Todd (2005) note, a possible drawback of caliper matching is that it is difficult to know a priori what choice for the tolerance level is reasonable.

Kernel Matching: This is another matching method whereby all treated units are matched with a weighted average of all controls with weights which are inversely proportional to the distance between the propensity scores of treated and controls (Venetoklis, 2004). It is a non-parametric matching estimator that use weighted averages of (nearly) all-depending on the choice of the kernel function- individuals in the control group to construct the counterfactual outcome (Caliendo and Kopeinig, 2008). Kernel weights the contribution of each comparison group member so that more importance is attached to those comparators providing a better match. The difference from caliper matching, however, is that those who are included are weighted according to their proximity with respect to the propensity score. The most common approach is to use the normal distribution (with a mean of zero) as a kernel, where the weight attached to a particular comparator is proportional to the frequency of the distribution for the difference in scores observed (Bryson *et al.*, 2002). According to Caliendo and Kopeinig (2008), a drawback of this method is that possibly bad matches are used as the estimator includes comparator observations for all treatment observation. Hence, the proper imposition of the common support condition is of major importance for kernel matching method. A practical objection to its use is that it will often not be obvious how to set the tolerance. The question remains on how and which method to select. Clearly, there is no single answer to this question. The choice of a given matching estimator depends on the nature of the available data set (Bryson *et al.*, 2002).

Radius Matching: is a variant of caliper matching. The basic idea of this variant is to use not only the nearest neighbor and limit itself within each caliper but all of the comparison members or observations within the caliper. The benefit of this approach is that it uses only as many comparison units as available within the caliper and therefore allows for usage of extra (fewer) units when good matches are (not) available (Dehejia and Wahba, 2002).

In other words, it should be clear that there is no winner for all situations and that the choice of a matching estimator crucially depends on the situation at hand. The choice of a specific method depends on the data in question, and in particular on the degree of overlap between the treatment and comparison groups in terms of the propensity score. When there is substantial overlap in the distribution of the propensity score between the comparison and treatment groups, most of the matching algorithms will yield similar results (Dehejia and Wahba, 2002). To give an example, if there are only a few control observations, it makes no sense to match without replacement. On the other hand, if there are a lot of comparable untreated individuals it might be worth using more than one nearest neighbor to gain more precision in estimates (Caliendo and Kopeinig, 2008).

A good matching estimator is that provides low pseudo-R^2 value (Sianesi, 2004) and statistically insignificant likelihood ratio test of all regressors after matching(a matching estimator which balances all explanatory variables between both groups) (Smith and Todd, 2005) and also expected to retain relatively larger observations for evaluating the impact of an involvement (i.e; relatively large matched sample size is preferable) and one that yields statistically identical covariate means for both groups (Caliendo and Kopeinig, 2008). In particular, a rejection of the group means difference test after matching implies a good balancing of the covariates.

3.5.2.4. Checking overlap and region of common support

Imposing a common support condition ensures that any combination of characteristics observed in the treatment group can also be observed among the control group (Bryson *et al*., 2002). No matches can be made to estimate the average treatment effects on the ATT parameter when there is no overlap between the treatment and non-treatment groups. The common support region is the area which contains the minimum and maximum propensity scores of treatment and control group households, respectively. Only the subset of the comparison group that is comparable to the treatment group should be used in the analysis i.e., observations which lie outside this region are discarded from analysis (Caliendo and Kopeinig, 2008). Hence, an important step is to check the overlap and the region of common support between treatment and comparison group. One means to determine the region of common support more precisely is by comparing the minima and maxima of the propensity score in both groups.

3.5.2.5. Testing the matching quality

One important concern that shall be taken care of while doing PSM is balancing test. Since we do not condition on all covariates but on the propensity score, it has to be checked if the matching procedure is able to balance the distribution of the relevant variables in both the control and treatment group. The main purpose of the propensity score matching is not to perfectly predict selection into treatment but to balance all covariates. While differences in covariates are expected before matching, these should be avoided after matching. The primary purpose of the PSM is that it serves as a balancing method for covariates between the two groups. Consequently, the idea behind balancing tests is to check whether the propensity score is adequately balanced.

In other words, a balancing test seeks to examine if at each value of the propensity score, a given characteristic has the same distribution for the treated and comparison groups. The basic idea of all approaches is to compare the situation before and after matching and check if there remain any differences after conditioning on the propensity score (Caliendo and Kopeinig, 2008). Rosenbaum and Rubin, 1983), Dehejia and Wahba, 2002), emphasized that the crucial issue is to ensure whether the balancing condition is satisfied or not because it reduces the influence of confounding variables. The success of propensity score estimation is therefore assessed by the resultant balance rather than by the fit of the models used to create the estimated propensity scores (Lee, 2006).

There are different approaches in applying the method of covariate balancing (i.e., the equality of the means on the scores and all the covariates) between treated and non-treated individuals. Among different procedures the most commonly applied ones are described below.

Standard bias

One suitable indicator to assess the distance in marginal distributions of the $\boldsymbol{X}_{.}$ variables is the standardized bias (SB) suggested by Rosenbaum and Rubin (1985). It is used to quantify the bias between treated and control groups. For each variable and propensity score, the standardized bias is computed before and after matching as:

$$SB(X) = 100.\frac{X_1 - X_0}{\sqrt{0.5(V_1(X) + V_{0(X)}}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.\ldots\ldots(\mathbf{3.7})$$

Where X_1 and X_0 are the sample means for the treatment and control groups $(V_1(X)$ and $V_{0(X)}$ are the corresponding variance (Caliendo and Kopeining, 2008). The bias reduction (BR) can be computed as:

$$\mathrm{BR} = 100(1 - \frac{\mathrm{B(X)after}}{\mathrm{B(X)before}}) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.(\mathbf{3.8})$$

One possible problem with the SB approach is that one does not have a clear indication for the success of the matching procedure.

t -test

A similar approach uses a two-sample t -test to check if there are significant differences in covariate means for both groups (Rosenbaum and Rubin, 1985). Before matching differences are expected, but after matching the covariates should be balanced in both groups and hence no significant differences should be found. The t-test might be preferred if the researcher is concerned with the statistical significance of the results. The shortcoming here is that the bias reduction before and after matching is not clearly visible.

Joint significance and pseudo- R^2

Additionally, Sianesi (2004) suggests to re-estimate the propensity score on the matched sample, i.e. only on participants and matched non-participants, and comparing the pseudo-R^2s before and after matching. The pseudo- R^2 indicates how well the regressors X explain the participation probability. After matching there should be no systematic differences in the distribution of covariates between both groups and therefore the pseudo- R^2 should be fairly low. Furthermore, one can also perform a likelihood ratio test on the joint significance of all covariates in the probit or logit model. The test should not be rejected before, and should be rejected after, matching. In our case, in order to test the matching quality of matching estimators the combinations of the above procedures was applied.

Bootstrapping

Standard errors in psmatch2 are invalid, since they do not take into account the estimation uncertainty involved in the probit/logit regressions (p-score). One way to deal with this problem is to use bootstrapping as suggested by Lechner (2002). This method is a popular way to estimate standard errors in case analytical estimates are biased or unavailable.

Recently it has been widely applied in most of economic literatures in impact estimation procedures. Each bootstrap draw includes the re-estimation of the results, including the first steps of the estimation (propensity score, common support, etc). Bootstrap standard errors attempted to incorporate all sources of error that could influence the estimates.

3.5.2.6. Sensitivity analysis for unobserved biases

Propensity score matching provides an estimate of the effect of a treatment variable on an outcome variable that is largely free of bias arising from an association between treatment status and observable variables. However, matching methods are not robust against hidden bias arising from unobserved variable that simultaneously affect assignment to treatment and the outcome variable. One strategy for addressing this problem is the Rosenbaum bounds (2002) approach, which allows the analyst to determine how strongly an unmeasured confounding variable must affect selection into treatment in order to undermine the conclusions about causal effect from a matching analysis.

If there are unobserved variable that simultaneously affect assignment and the outcome variable, a hidden bias might arise to which matching estimators are not robust (Rosenbaum, 2002). Since estimating the magnitude of selection bias with non- experimental data is not possible, the problem is addressed with the bounding approach proposed by Rosenbaum (2002). The basic question is whether unobserved factors can alter inferences about treatment effect. One wants to determine how strongly an unmeasured variable must influence the selection process to undermine the implications of the matching analysis.

The bounding approach does not test the un-confoundedness assumption itself; because this would amount to testing that there are no (unobserved) variables that influence the selection into treatment. Instead, Rosenbaum bounds provide evidence on the degree to which any significant result hinge on this un- testable assumption. If the results turn out to be sensitive, the researcher might have to think about the validity of his identifying assumption and consider other estimation strategies. DiPrete and Gangl (2004) provide an ado-file (rbounds) that lets the researcher to test sensitivity for continuous variables.

All of the above tests suggest that the matching algorithm we have chosen is relatively the best with the data we have at hand. Thus, we can proceed to estimate ATT for households. Finally, using predicted probabilities those who was involved in the adoption of IWVs' (i.e. propensity score) match pairs was constructed using alternative methods of matching estimators. Then the impact estimation is the difference between simple mean of outcome variable of interest for involved and non-involved households. In this study, the mean stands for the average productivity generated by adoption of improved wheat varieties. In particular, ATT was computed using the following equation.

$$\frac{1}{K}\sum_{i=1}^{K}\left[Yi^{i\in T=1} - Yi^{i\in T=0}\right] \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (\mathbf{3.9})$$

Where k is number of matched pairs.

3.6. Variables Definition and Hypotheses

Dependent variable

Treatment variable: It is involvement in adoption of improved wheat variety. It is a dummy variable which takes on 1 if the household adopted IWVs' and 0 otherwise.

Outcome variable

Wheat productivity: is the kilogram of wheat production obtained from one hectare of land.

Explanatory variables

Different factors are expected to influence involvement in adoption of IWVs' at various degrees of the study areas. Based on economic theories and empirical works the following explanatory variables which are expected to have significant impacts in determining the wheat productivity and involvement in adoption of IWVs' are selected and hypothesized as follows:

Age of household head (AGEHH): It refers to the age of the household head in years and it is a continuous variable. Age is important household related variable that has relationship with adoption. It is also assumed to be a determinant of adoption of new technology. Older farmers are assumed to have gained knowledge and skill over time and are better able to evaluate technology information than younger farmers (Mignouna *et al.,* 2011; Kariyasa and Dewi 2011). On contrary age has been found to have a negative relationship with adoption of technology. This relationship is explained by Adesina & Zinnah (1993) and Mauceri *et al.* (2005) that as farmers grow older, there is an increase in risk aversion and a decreased interest in long term investment in the farm. On the other hand younger farmers are typically less risk-averse and are more willing to try new technologies. For instance, Alexander and Van Mellor (2005) found that adoption of genetically modified maize increased with age for younger farmers but declines with age for those farmers closer to retirement. Hence, the coefficient was not be determined or hypothesized in prior.

Total Operated land (TOPLND): Cultivated land size is a farm size under operation and is continuous variable. It is associated with greater wealth. It will increase farmers' production thereby enhancing market oriented production. In order to be market oriented, however, the farmers need to first adopt new more productive wheat varieties. For example a study carried out by Mwanga *et al.* (1998) in Tanzania has indicated that cultivated land size significantly affected the adoption of improved wheat varieties. Many others, Tesfaye and Alemu (2001), Mulugeta (2000), Million and Belay (2004) and Taha (2007), also reported positive relationship of cultivated land size with adoption. Cultivated land size was therefore expected to increase the likelihood of adoption of IWVs'.

Sex of the households heads (SEXHH): is a dummy variable which indicates whether the household head is male or female. A study by Legesse, (1992); Fitsum, (2003); Namwata *et al.,* (2010) and found that sex of the household head has an impact on the adoption of new improved technologies. These studies revealed that male-headed households have more likelihood to adopt new technologies than their female-headed counterparts. For instance, Namwata *et al.*, (2010) indicated that there is a positive link between male-headed households and adoption of new technologies. Likewise, (Burger *et al.*, 1996) revealed that the likelihood of adoption decision is higher among male headed farm households than female headed ones. In such instances, positive coefficient was expected for IWVs' adoption.

Education of the households heads (HHEDUC): It is a continuous variable measured in number of years of schooling. In almost all of the studies on agriculture, education has been taken as an important explanatory factor that positively affects the decision of the households to participate and practice new innovations. Education basically equips individuals with the necessary knowledge as to how to allocate their scarce resources to achieve optimal output and accordingly is positively associated with adoption. Mwanga *et al. (*1998) carried out a study in Tanzania and found that education level significantly affected the adoption of improved wheat varieties. Similarly, Studies carried out by Asfaw *et al*. (1997), and Tesfaye and Alemu (2001), indicated positive relationship between education and adoption. Education level was therefore expected to increase the probability of adoption of IWVs'.

Access to Credit to buy improved wheat seed (CREDITSEED): It is a categorical variable; representing 1 if household has credit access and 0 otherwise to buy improved wheat seed. Credit access reduces liquidity problems that household could face while intending to purchase agricultural inputs; and hence paves the way for timely application of inputs thereby increase the overall productivity and farm income (Mpawenimana, 2005). Hence, access to credit to by improved seed was expected to increase the probability of adopting IWVs'.

Frequency of Extension Agents' Contact(EXTCONT): It is a continues variable that shows frequency of farmers' visited by extension agents and are believed to be exposed for different, new, updated information used to adopt IWVs' thereby increase and double wheat production and productivity that finally could increase farm income (Wondimagegn *et al.*, 2011). Hence, contact with extension agents (development agents) was expected to increase a farmer's likelihood of adopting improved wheat varieties.

Distance to Main Market (MINMAINMRKET): It is a continuous variable measured in minutes of walking. Afework and Lemma (2015) used probit model to study determinants of improved rice varieties adoption in Fogera district of Ethiopia. According to the result of their study, access to main market affects farmers' participation in the adoption of rice seed technologies. The marginal effect reveals that 1 km decrease in distance to the main market would increase probability of participating in improved rice varieties by 0.07 %. Hence, farmers residing nearest to the main market, get agricultural inputs both adequately and timely. Therefore, distance to the nearest market center was expected to be negatively related to the probability of adoption of improved wheat varieties.

Distance to Nearest Source of Seed (MINSOURSED): It is a continuous variable measured in minutes of walking. Distance to source of improved seed varieties vary among farmers in different places. Some farmers may have short distance of walking than others do due to their proximity to seed dealing agents. Distance to source of seed is also an important socio-economic variable that determines adoption of improved varieties. Distance to the nearest source of seed was hypothesized to lead to less probability of adopting improved varieties.

Number of months to the main road (NUMMONTHS): It is a continuous variable measured in number of months. It refers to the number of months available for farmers' to the main all weather roads. As farmers' gets all weather roads, they can have access to transportation facilities and relatively better support from concerned bodies to their use of improved agricultural technologies which might increase the use of technology. According to study by Solomon *et al*. (2014) on adoption of improved wheat varieties in Robe and Digalu Tijo districts of Arsi Zone in Oromiya Region, Ethiopia, access to all weather roads is found to be positive and significant at a less than 1% significance level, suggesting that farmers who have access to all weather roads are more likely to adopt improved wheat varieties. Therefore, in this study, it was hypothesized that this variable is positively related to participate in improved wheat varieties adoption.

Livestock holding (TLU): It is a continuous variable measured in number; where those who possess a flock of Livestock will be expected to adopt IWVs' better than the have-nots. The presence of Livestock can solve the liquidity problem that farm households could face while intending to purchase and adopt improved wheat varieties. Franklin *et al* (2011) used probit model to assess determinants of agricultural technology adoption. Their result shows that ownership of livestock returned a positive and significant coefficient suggesting that households that own larger amounts of livestock have a higher propensity to adopt improved varieties of pigeon pea than those that do not own livestock. Similarly other evidence shows that household with larger TLU have better economic strength and financial position to purchase sufficient amount of fertilizer (Legesse, 1992; Techane, 2002). Generally, the ownership of livestock is an indicator of the wealth of the household, suggesting that slightly wealthier households have the means to access and use IWVs'. Hence, for IWVs' adoption decision, positive was the coefficients expected from the final probit estimation result.

Household owns a radio (OWNRDIO): information is important to make decisions on accepting new practices and adopting new varieties. Mass media exposure is one of communication variables availing information for farmers. At present in rural areas, a radio is the popular means of mass communication. Many studies reported the positive and significant relationship of mass media with adoption of agricultural technologies. In line with this, Yishak (2005) in his study on determinants of adoption of improved maize technology indicated that ownership of radio had positive influence on adoption of improved maize technologies. Hence, mass media exposure was expected to positively influence adoption of IWVs' and was measured on having of radio or not.

Model farmer (MODFARM): It is a dummy; representing 1 if household is a model farmer and 0 otherwise. A model farmer is the one who always produces the best crop in his/her field, takes up new innovations as quick as possible and is willing to train other farmers. The model farmer is the main contact for project and any technology providing agency. Model farmer approach involves training farmers who in turn train and share their knowledge and skills acquired with other farmers. Improved extension systems have great potential for providing farmers with more and better information and strengthening their capacities to help them improve productivity and well-being (Davis and Suleiman, 2015).Therefore being a model farmer will increase the propensity to adopt improved wheat varieties and positive coefficient was expected.

Distance to nearest farmer cooperative from residence (MINCOOPS (Min)): It is a continues variable that shows minutes of walking of farmers to reach the nearest farmers cooperatives. Supplying agricultural inputs and credit are the most important activities of cooperatives in Ethiopia. Proximity of farmers to such places is essential for timely input delivery and less transport cost of inputs. According to the study by Hassenr *et al.* (2012) on determinants of chemical fertilizer technology adoption in North eastern highlands of Ethiopia: the double hurdle approach, distance from distribution centre for improved seed had

influenced adoption through proximity for farmers. Distance to nearest farmer cooperative was expected to be negatively related to the probability of adoption of improved wheat varieties, since households near cooperative tend to have easier improved wheat seed access to dispose of their production.

Experience in wheat farming (HHEXP): is to be measured in number of years since a respondent started wheat farming on his own. Experience in a particular farming area or with a given crop may not be strictly correlated with age (CIMMYT, 1993). Experience of the farmer is likely to have a range of influences on adoption. Experience will improve the farmer's skill on the production of wheat. Higher skill increases the opportunity cost of not growing the traditional enterprise. A more experienced grower may have a lower level of uncertainty about the innovation's performance (Chilot *et al*, 1996; Abadi *et al*, 1999), as cited in Mulgeta, 2009). Farmers with higher experience appear to have often full information and better knowledge and were able to evaluate the advantage of the technology in question. Hence, experience of the head of the household in wheat farming was hypothesized to affect adoption positively.

Table 1: Variables definition and measurement

Variables	Type and definitions	Measurement	Expected sign
Treatment Adoption of improved wheat varieties	Dummy, household participation in adoption of improved wheat varieties	1 if adopted IWVs' and 0 other wise	
Outcome variable Wheat productivity	Continuous, wheat production obtained from one hectare	Kilogram	
Explanatory variables			
Sex	Dummy, sex of the household head	1 if male and 0 otherwise	+
Age	Continuous, age of the household head	Years	-/+
Education	Continuous, number of years of schooling of the HHH	Years	+
Total operated land	Continuous, number of hectares of operated land of HHH	Hectare	+
Distance to the nearest main market	Continuous , minutes of walking to the nearest main market	Minutes	-
Distance to seed source	Continuous, minutes of walking to seed source	Minutes	-
Distance to cooperative	Continuous, minutes of walking to cooperative office	Minutes	-
Number of months passable for vehicle	Continuous, number of months passable for vehicle	Number of months	+
Credit for seed	Dummy ,use of credit for seed	1 if household has credit for seed, 0 otherwise.	+
Frequency of Extension Agents' Contact	Continuous ,frequency of extension agents' contact with HHH	Frequency of contact in a year	+
Experience	Continuous, experience in wheat growing	Years	+
Livestock ownership	Continuous , Livestock holding	Tropical livestock unit	+
Model farmer	Dummy, HH being model farmer	Number	+
Mass Media	Dummy, having a radio	1 if HHH have a radio,0 otherwise	+

4. RESULTS AND DISCUSSION

This section consists of three sub-sections. The first one is description of sample households' characteristics. The second subsection is estimation of adoption rate by both survey and DNA finger printing data. The third sub-section is estimation results of impact study by DNA finger printing which include propensity score matching, treatment effect and sensitivity analysis results.

4.1. Descriptive statistics

The descriptive statistics gave some insight about the characteristics of sampled units for the present study. Appendix Table 1 reports descriptive statistics disaggregated by their adoption status.

Characteristics of sample respondents

The average age of household head was about 46.29 years for adopters and 48.25 years for non adopters of improved wheat varieties shown in Appendix Table 1. The t-test result indicated there was significant difference between the average age of adopters and non adopters for improved wheat varieties sample farmers at 5% significance level.

The average total operated land size for the sampled households is 1.64 hectare and adopting households have significantly larger holding of operated land1.74 hectare than the non-adopting households 1.56 hectare. As shown in Appendix Table 1 the t-test indicated that, from sample farmers the mean differences for average total operated land size and adoption of improved wheat verities were found to be at 5% significant level suggesting the importance of cultivatable landholding for adoption of the improved wheat varieties as the farmer provide extra land for wheat farming.

The average livestock ownership of adopters of improved wheat varieties was 4.91 and for non adopters 4.22 as shown Appendix Table1.The implication is that adopters have more access to financial capital by selling their livestock to purchase improved seed from suppliers. This result suggests that, those farmers who owned more livestock have better chance to use improved seed technology.

The average number of years of experience in wheat farming is 14.05 years. The mean wheat growing experience of adopter households was 15.23 years and 13.12 years for non-adopter. Experienced farmers have knowledge, skills, and attitudes with farming that enables them to easily understand and be familiar with the benefits of the technology better than less experienced counterpart. As depicted in Appendix Table 1 the t-test result showed that the wheat growing experience mean difference between the two groups is significant at 1% level.

The average distance to the nearest market for the sample household is 112.81 minutes. Adopting households have significantly shorter distances to the village market 107.20 minutes than non adopting households 117.25 minutes. The findings suggest that farmers with access to markets have a higher propensity to adopt improved wheat varieties than those that with limited access to markets. One of the reasons that of improved wheat varieties a technology user in Ethiopia is to be nearer to the main road than the rest farmers that is not used improved wheat varieties. As revealed in Appendix Table 1 the t-test result showed that the near market distance mean difference between the two groups is significant at 5% level.

The sampled households are distinguishable in terms of having of availability of all weather roads whereby adopters own more months in terms of road availability which is on average 8.73 and 7.46 months for non-adopter. As shown in Appendix Table 1) the t-test indicated that, from sample farmers the mean differences for number of month road available were found to be at 1% significant level between adopter and non-adopter of improved wheat varieties

The mean distance travelled to get to the nearest seed dealer was 70.19 minutes, for adopters of improved wheat varieties, while for non adopters of improved wheat varieties they travel 77.01 minutes. As shown in Appendix Table 1 the t-test result showed that the nearest seed dealers distance mean difference between adopter and non-adopter is significant at 5% level

The average frequency of extension contact in a year was 2.47 for adopters and 1.75 for non adopters of improved wheat varieties. Extension access is a necessary catalyst to technology adoption as it is the major source of agricultural information in Ethiopia. As shown in Appendix Table 1 the t-test indicated that, from sample farmers the mean differences for frequency of extension contact were found to be at 1% significant level between adopter and non-adopter of improved wheat varieties. Farmers who have a frequent contact with extension agents have more information that would influence farm household's demand for new technologies.

The average distance travelled to get to the nearest farmers cooperative was 61.99 minutes, for adopters of improved wheat varieties, while for non adopters of improved wheat varieties they travel 70.82 minutes. As shown in Appendix Table 1 the t-test result showed that the farmers' cooperative distance mean difference between the two groups is significant at 5% level.

The education level of the household's head is expressed in terms of years of schooling results indicate that the average number of years of education for the head of households in the sample is 2.03 years. Adopting households have significantly more years of education (2.19years) than non-adopting households (1.89 years) suggesting that there is a positive correlation between adoption and the number of years of formal education. Education is very important for the farmers to understand and interpret the information coming from any direction to them. As shown in Appendix Table 1 the t-test indicated that, from sample farmers the mean differences for a year of schooling were found to be at 5% significant level between adopter and non-adopter of improved wheat varieties.

The sample households were composed of household heads having radio or not having. Of the total, 38.99 % of the sample household heads were under the category of having radio while 61.01% of household heads did not have radio (Table 6). The proportion of the household heads having radio under the adoption category was 18.72 %. On the other hand, the proportion of the household heads that did not have their own radio under the non-adoption category was 35.54 %. The chi-square test of the two groups was run and found to be significant at 5% level. As shown in Table 6, sex, access to credit and model farmer are dummy variables that show no significant difference between adopter and non-adopter of improved wheat varieties.

The existence of differences in covariates between adopters and non adopters could also contribute to the disparities in wheat productivity between the two groups. Results indicate that on average adopters achieved better yields (2079.50 kg/ha) compared to non-adopters (1644.20 kg/ha) using DNA fingerprinting data and 1870kg/ha for adopter and 1795 kg/ha for non-adopters by farmer recall data analysis result (Appendix Table 1).

Table 2 revealed that there is statistically significant difference between adopter and non-adopter in having a radio. However, some of dummy variables described in table below are statistically insignificant (p>0.1) between adopter and non-adopter households. Compared to non-adopters, adopter households has got satisfied with their credit needs for fertilizer and improved seed purchases. In a nut shell, descriptive statistics of the observable variables for the adopter and non-adopter households clearly shows that there are significance differences between the two groups. This indicates that there is possible selection bias in the sample, which necessitates matching of households with similar characteristics from the two groups before computing the adoption effect.

Table 2: Descriptive and inferential statistics of sample HHs (for dummy variables) using DNA finger printing data

Variables		Non-adopter		Adopter		Total		χ^2
		N	%	N	%	N	%	
Sex	Male	676	47.57	524	36.88	1,200	84.45	0.87
	Female	117	8.23	104	7.32	221	15.55	
Need and got credit for seed	No	446	31.39	353	24.84	799	56.23	0.01
	Yes	347	24.42	275	19.35	622	43.77	
Are you model farmer?	No	336	23.65	245	17.24	581	40.89	1.64
	Yes	457	32.16	383	26.95	840	59.11	
Do you have a radio?	No	505	35.54	362	25.48	867	61.01	5.37**
	Yes	288	20.27	266	18.72	554	38.99	

Note: χ^2 = chi-square, ***, ** significance level at 1 % and 5 % respectively. % =%age, Standard deviation, Source: Authors compilation, 2018

Mean productivity of the most popularized wheat varieties

Availability of quality seeds of improved cultivars is considered as crucial for realizing productivity and adoption of cultivars in different agro-climatic conditions. The quality of seed alone is known to account for at least 10-15% increase in the productivity. However, lack of quality seed continues to be one of the greatest impediments to bridging the vast yield gap. Genetic purity is one of the attributes of good quality seed. Varietal purity indicates genetic purity of the seed. This factor is extremely important in obtaining pure stands of a specific variety. Full genetic potential of high–yielding, improved varieties is important to increase production and productivity (Tesfaye *et al*., 2001).

Varietal mixtures can cause uneven maturity, lower yield potential, increased susceptibility to disease and insect pests, and be less adapted to specific environmental conditions (Erker *et al*., 2001).The following tables (3, 4&5) show the mean productivity of the most popularized wheat varieties (Kubsa, Digalu and Kakaba) in Ethiopia according to the varietal level adoption rate estimates. The productivity potential of the varieties was estimated at three genetic purity level scenarios which are (scenario I :(between >= 90% and< 90%), scenario II: (between >= 95% and< 95%), scenario III: (between >= 99% and< 99%), respectively (Tables below). These scenarios are used to show the existence of mean productivity difference and consistence of the productivity of the varieties as their genetic purity increase. Accordingly, maximum yield is obtained at scenario III than scenario I and scenario II which is at high purity level. There is also mean productivity significance difference between user of the seed above and below the scenarios.

Table 3 : Mean Comparison of Kubsa Variety

Cut-off points(N=1421)		n	Adoption rate	Mean(kg/ha)	Std. Dev.	t-test
Scenario I	>=90%	423	95.92	1885.54	797.42	2.10**
	< 90%	18	4.08	1478.82	1142.93	
Scenario II	>=95%	371	84.13	1924.34	803.34	3.32***
	< 95%	70	15.87	1575.31	829.22	
Scenario III	>=99%	220	49.89	2103.00	724.58	6.26***
	< 99%	221	50.1	1635.94	837.67	
Overall				1868.94	816.59	

Note: ***’ ** = significance level at 1 % =%age, Source: DNA finger printing data and own compilation, 2018, where n= number of households found below and above the specified cut of points

Table 4 : Mean Comparison of Digalu Variety

Cut-off points(N=1421)		n	Adoption rate	Mean(kg/ha)	Std. Dev.	t-test
Scenario I	>=90%	155	99.36	1871.98	745.86	
	< 90%	1	0.64	306.25		
Scenario II	>=95%	150	96.15	1868.22	725.12	0.52
	< 95%	6	3.85	1705.21	1386.31	
Scenario III	>=99%	86	55.13	2029.80	652.55	3.2***
	< 99%	70	44.87	1655.73	821.04	
Overall				1861.95	753.94	

Note: *** = significance level at 1 % =%age, Source: DNA finger printing data and own compilation, 2018, where n= number of households found below and above the specified cut of points

Table 5 : Mean Comparison of Kakaba Variety

Cut-off points(N=1421)		n	Adoption rate	Mean(kg/ha)	Std. Dev.	t-test
Scenario I	>=90%	182	96.08	1989.73	726.41	2.46**
	< 90%	6	3.2	1251.042	583.24	
Scenario II	>=95%	177	92.55	1987.143	733.84	1.58
	< 95%	11	7.45	1628.41	653.16	
Scenario III	>=99%	140	74.47	2090.98	701.06	4.16***
	< 99%	48	25.53	1602.08	707.39	
Overall				1966.154	732.654	

Note: ***, ** = significance level at 1 % and 5% =%age, Source: DNA finger printing data and own compilation, 2018, where n= number of households found below and above the specified cut of points

Table 6 below shows, the mean productivity of improved wheat varieties at different categories of purity level of the varieties according to DNA finger printing results. For simplification and better comparison, it was divided into 3 cut of points: Scenario I, Scenario II and Scenario III based on genetic purity level of the varieties. In addition, this classification allows us to understand the status of farmer's wheat productivity as genetic purity of the varieties increases. The results of the study showed that the average of improved wheat productivity has increased for user of high gene pure variety in each category. Accordingly, mean productivity below and above each of the cut of points are positive and statistically significant at 1% level. As compared to the non- user (below the cut of point of the scenarios), user (above the cut of point of the scenarios) of improved wheat varieties have gained 163.92kg/ha (90%), 285.58kg/ha (95%) and 435.3kg/ha (99%) at each of the cut of points.

Table 6 : Mean of comparison by purity level categories (kg/ha)

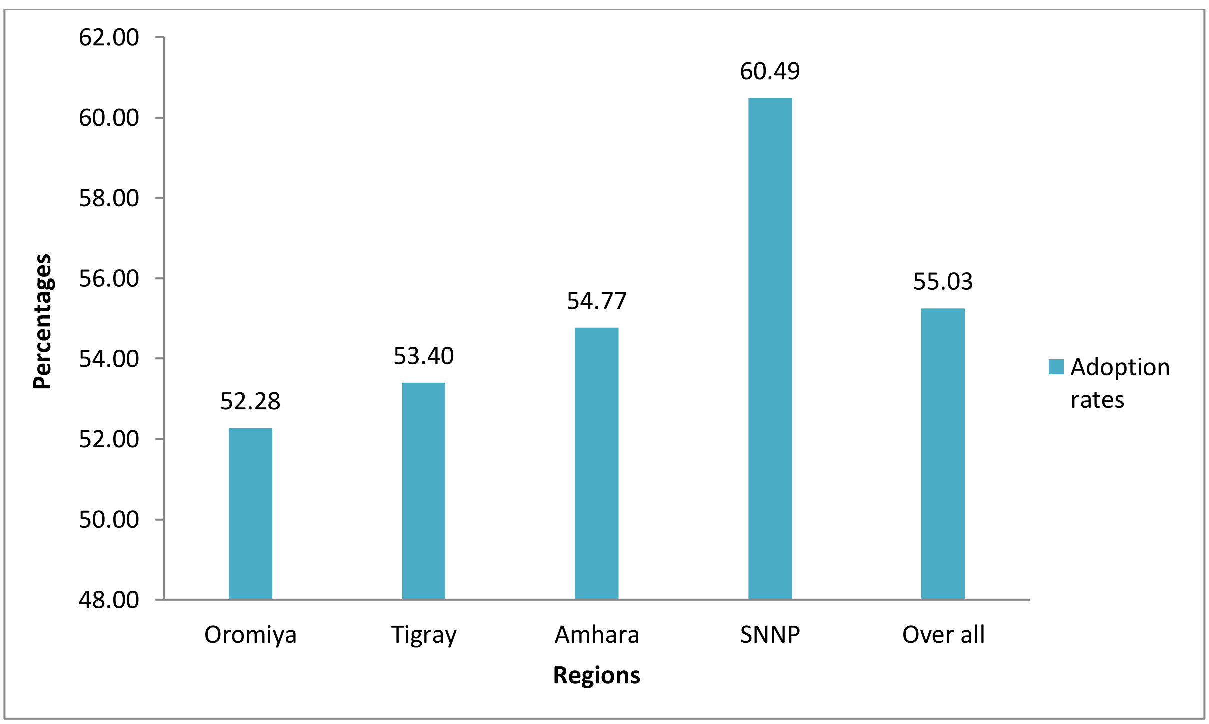
Cut-off points(N=1421)		n	Adoption rate	Mean(kg/ha)	Std. Dev.	t-test
Scenario I	>=90%	1197	84.24	1862.42	820.23	2.77***
	< 90%	224	15.76	1698.50	779.82	
Scenario II	>=95%	1,046	73.61	1911.94	815.87	5.88***
	< 95%	375	26.39	1626.36	779.43	
Scenario III	>=99%	628	44.20	2079.50	739.53	10.35***
	< 99%	793	55.80	1644.20	822.67	
Overall				1836.58	815.92	

Note: *** = significance level at 1 % =%age, Source: DNA finger printing data and own compilation, 2018, where n= number of households found below and above the specified cut of points

4.1.1. Adoption study by household survey and DNA fingerprinting

4.1.1.1. Wheat adoption rate estimates by household survey

Figure (2) presents reported adoption of wheat varieties based on the household survey. The result of the study shows that majority (60.49%) of farmers in the SNNP had adopted the improved wheat varieties. The Amhara regional state had 54.77% of farmers growing the improved varieties. Adoption rates in Oromia and Tigray is 52.28% and 53.40%, respectively. Overall, 55.03% of farmers across the country had adopted improved wheat varieties. This result is very encouraging and pointing to increased dissemination of improved wheat technologies by government and non government organization in Ethiopia in the past years. A result of this study is comparable with previous varietal adoption studies in Ethiopia. For instance, Tesfaye *et al* .(2001) reported improved wheat variety use among smallholder farmers increased from less than 1% in 1981 to 72% in 1998 in selected areas of Northwestern Ethiopia. Further, the study by Mideksa and Tadele (2014) revealed that the adoption rates of improved bread wheat varieties were increased from 10% in 2008 to 67.5% in 2013 at Boji Gebisa Ambo District, Oromia Regional State, Ethiopia.



Source: Household recall data and own compilation, 2018

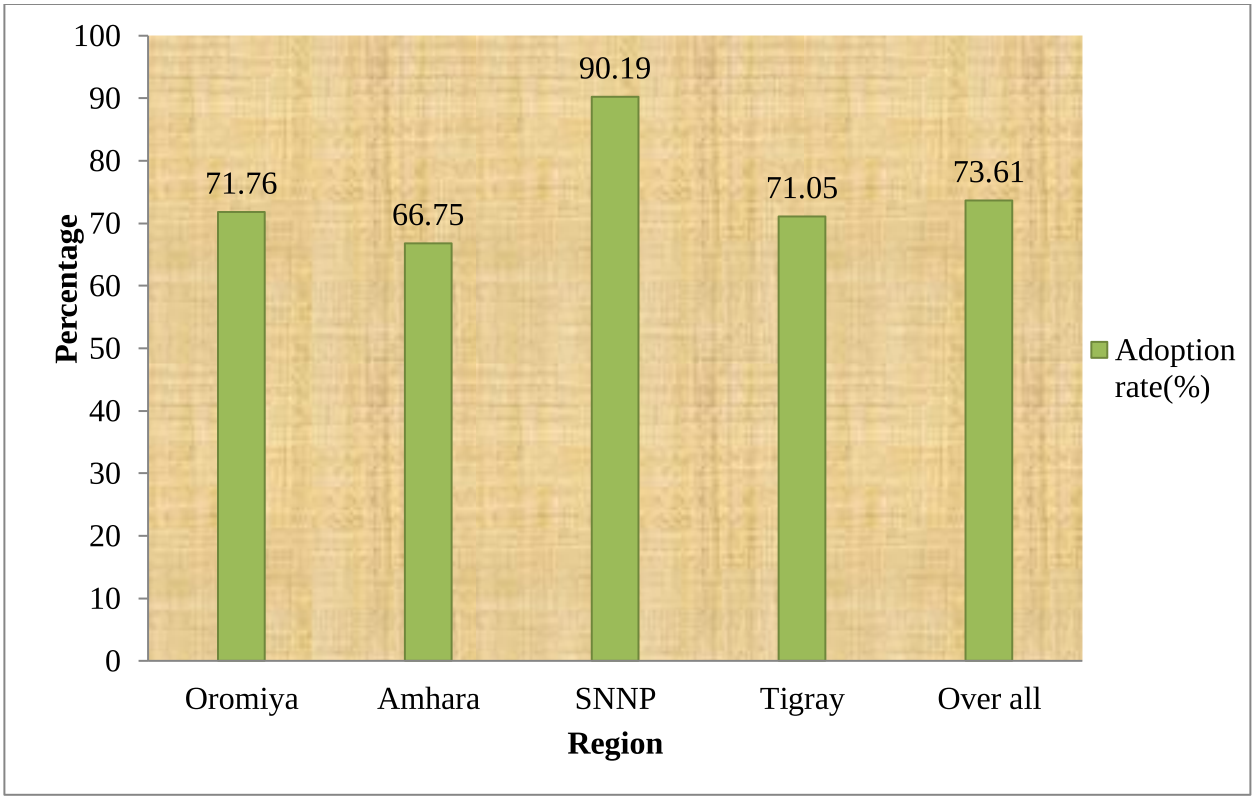
Figure 2 : Wheat adoption rate estimates of IWVs' by household survey

In terms of individual varieties, according to farmer perception of the current study, four leading improved varieties were identified namely Kakaba, Digalu, Kubsa and Dashen, respectively as showed in Appendix Table 2. The study showed that slightly over half of the area under IWVs' (69.17%) is planted to these leading improved varieties namely Kakaba, Digalu Kubsa and Dashen respectively. This result is comparable with pilot study by Chilot *et al.* (2016) on tracking the diffusion of crop varieties using DNA fingerprinting in three purposively selected zones of Oromiya. Their result revealed that Digalu, Kubsa and Dashen (58%) are the three leading improved varieties covered over half of area under improved wheat varieties. The implication of our study result is that farmer's dependence on and adopted limited number of IWVs' in Ethiopia.

4.1.1.2. Wheat adoption rate estimates by DNA finger printing

We adopt a relatively high purity level of 95 % as the minimum threshold for correctly identifying a variety in the present study. The study done by Chilot *et al.* (2016) on tracking the diffusion of maize and wheat varieties using DNA fingerprinting in Ethiopia had used purity level at 70%. Similarly, Leonard *et al*. (2015) had used purity level 70% minimum threshold for correctly identifying maize and rice varieties in Tanzania. They stated that, this threshold can be varied depending on the desired precision levels.

Figure (3) presents reported adoption of wheat varieties based on the DNA finger printing data. The result of the study showed that majority (90.19%) of farmers in the SNNP had adopted the improved wheat varieties. The Oromia regional state had 71.76% of farmers growing the improved varieties. Adoption rates in Tigray and Amhara regional state are 71.05% and 66.75%, respectively. Overall, 73.61% of farmers across the country had adopted improved wheat varieties.



Source: DNA finger printing data and own compilation, 2018

Figure 3: Adoption estimates of IWVs' from DNA finger printing, % of households using IWVs' in each region

In terms of individual varieties, according to DNA finger printing of the study, four leading improved varieties were identified namely Kubsa, Kakaba Digalu, and Galema, respectively. The result from DNA finger printing revealed that over half of the area under IWVs'(78.22%) is planted to these leading improved varieties namely Kubsa, Kakaba Digalu, and Galema respectively as showed in Appendix Table 3.The result is similar with farmer recalls that farmer's dependence on and adopted limited number of IWVs' in Ethiopia.

Table 7 below compares adoption estimates from the DNA fingerprinting analysis with farmer recalls. As noted, according to survey respondents 55.03% of the farmers used IWVs' during the study year. In reality, however, 73.61% of the respondents used IWVs' suggesting the household survey underestimated the economic importance of improved varieties in the wheat sector by 18.58%. This probably due to inability of the farmer to identify and know the name of the varieties. Because the farmers are obtaining seeds from various sources. The study result on source of seed shows that only a small portion of farmers have been bought seeds from certified packages.

Table 7: Comparison of adoption rate estimates of DNA fingerprinting analysis with farmer recalls

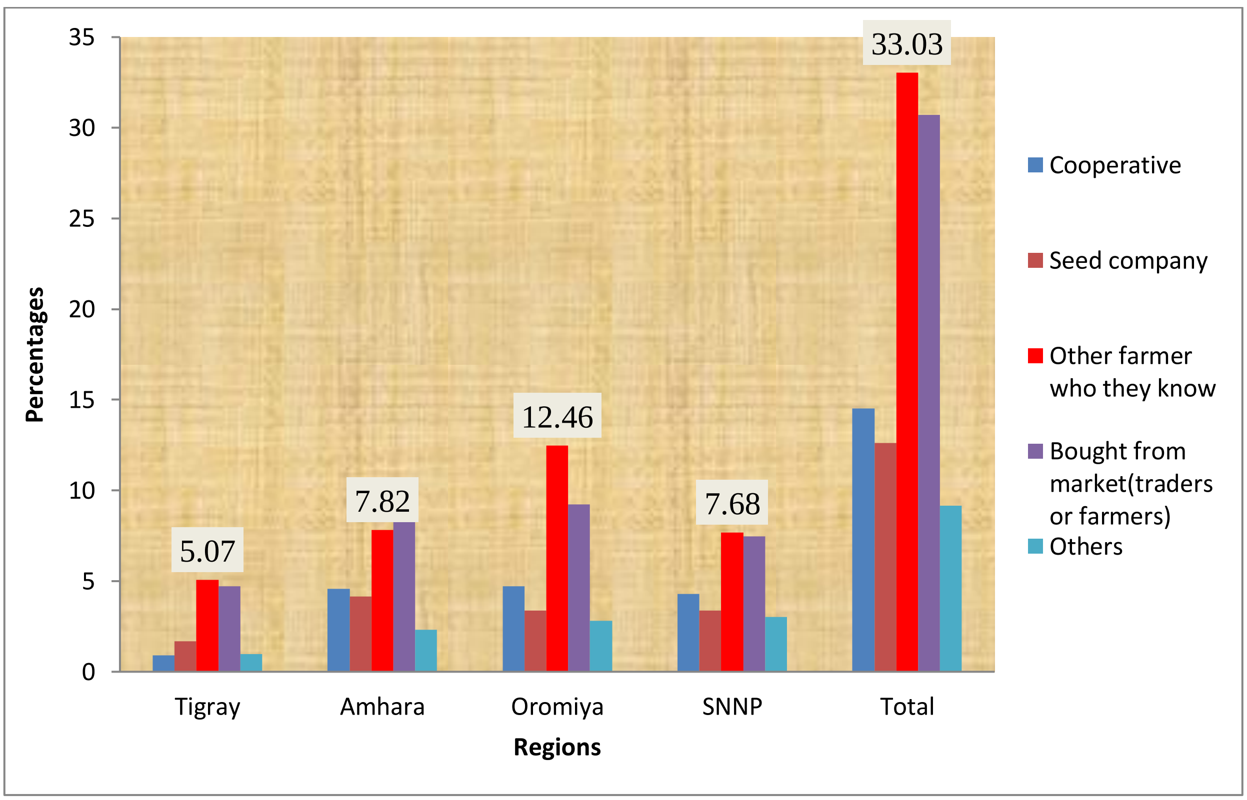
Variety category	Farmer response/perception		DNA Fingerprinting	
	Number	**%**	**Number**	**%**
Improved	782	55.03	1046	73.61
Local or unknown variety	639	44.97	375	26.39
All varieties	1421	100.00	1421	100

Source: DNA finger printing data and own compilation, 2018

The DNA fingerprinting results indicated that Kubsa followed by Kakaba Digalu, and Galema are the most important IWVs' grown during the study year as showed in Appendix Table 4. Farmer perceptions, however, indicate that Kakaba and Digalu are the most popular wheat varieties followed by Kubsa and Dashen. Farmer perception under estimated the importance of Kubsa, Digalu, Galema, and Kakaba. In particular, it severely under estimated the share of area planted to, Kubsa by 1.17 %. It is worth noting that while the household survey failed to show the importance of Kubsa, the DNA fingerprinting revealed that 36.6% of household cultivated the variety on 67.62 % of the wheat area. According to household survey, majority of the farmers had used Kakaba and Digalu, 7.18% each. Kakaba which is rust resistance variety covered 64.31% of area under improved wheat varieties.

However, contradict to farmer recalls, the result of the DNA finger printing showed that Kubsa which is rust susceptible variety was used by 26.11% of the farmers and covered 67.62% of the area under improved wheat varieties. Adoption estimates based on farmer sample survey, therefore, did not only under estimate aggregate levels of adoption but also distorted the relative importance of individual varieties that may have serious implication in seed demand and supply. Besides, the implication of the result is that there is poor performance of supplying of IWVs' by agro-input dealers and lack of awareness for farmers in identifying the varieties in Ethiopia.

Besides, the household survey dealt with source of seeds. Predominant sources of seed in the study areas are other farmers who they know and local market reported by 36.33% and 31.28% of households, respectively. The %age of cooperative and seed company as a source of initial seed is relatively low which 13.37% and 12.63% respectively (Figure 4).This is in line with the pilot study done by Chilot *et al.*(2016) on tracking diffusion of crop varieties using DNA fingerprinting in three purposively selected zones of Oromia. The result of the study revealed that importance of the formal seed sector is limited suggesting the seed market is under developed in Ethiopia. The study result provided evidence to show that seed was not being distributed from seed depots in the way that policymakers believed. This may probably be enforcing the farmers to buy contaminated seed and poor genetic identity of varieties from seed vendors.



Source: household recall data and own compilation, 2018: Figure 4: Source of wheat seed

4.2. Results of Econometrics Model

The probit estimates of the adoption propensity equation are presented in Appendix Table 6. The estimated model appears to perform well for the intended matching exercise. According to the result from the DNA fingerprinting data shows the probit model has a McFadden pseudo R^2 value of 0.0567 and log likelihood value of -920.03. The pseudo- $R2$ value is 0.0567, which is fairly low. The dependent variable is binary wheat adoption. A low pseudo- R^2 value means that households involved in adoption of IWVs' do not have many distinct characteristics over all and as such finding a good match between involvement in adoption of IWVs' and non-involvement in adoption of IWVs' households becomes easier, and the pseudo- R^2 indicates how well the independent variables explain the probability of involvement (Caliendo and Kopeinig, 2008). The various test of goodness- of-fit indicate that the selected covariates provide good estimate of the conditional density of adoption for both household survey data result and DNA fingerprinting. For example, the LR chi^2 test statistic (110.67) indicates that explanatory variables are jointly highly statistically significant (1%) and this confirms that there is a relationship between the dependant and explanatory variables included in the model used.

The results of probit estimates show that the coefficients of most of the variables hypothesized to influence adoption have the expected signs and they include covariates such as the age of the of the head of household, the cultivated land size, tropical livestock unit, number of years of experience in wheat farming , number of months to main road available for vehicle in a year, , distance to cooperative ,sex of the households, household extension contact in a year and , ownership of radio among others in DNA fingerprinting results.

4.2.1. Impact of improved wheat variety adoption on wheat productivity

Farmer recall method can only be fairly accurate in a setting where farmers are mostly planting seeds freshly purchased or acquired from the formal seed system as certified or truthfully labeled seed. In other words, the farm survey method can be effective if the seed system is well-functioning and can effectively monitor the quality and genetic identity of varieties being sold by the seed vendors.

The result of the adoption rate study shows that importance of the formal seed sector is limited suggesting the seed market is under developed in Ethiopia. However, in settings where the formal seed system is non-existent or ineffective, and farmers mostly rely on harvested grain (either from their own farms or acquired from other farmers or purchased from the market) as the main source of planting material, the reliability of estimating varietal adoption using this method is challenging (Yirga *et al*. 2014 as cited in Maredia *et al*., 2015). By implication, it also makes the results of impact assessments based on those survey-based adoption estimates questionable. This result supports the use of DNA finger printing data to assess the accurate result of the impact of IWVs' on wheat productivity. As such, in what follows, the following estimation results and discussions are the direct outcomes of the DNA finger printing data.

4.2.2.1. Decision of Adopting Improved Wheat Variety: Probit Model

Estimation Results of Propensity Scores

Although the unconditional summary statistics and tests in general suggest that IWVs' adoption may have a positive role in improving wheat productivity, these results are only based on observed mean differences in outcomes of interest and may not be solely due to IWVs' adoption. They may instead be due to other factors, such as differences in household characteristics and the endowments discussed earlier. To measure the impact of adoption, it is necessary to take into account the fact that individuals who adopt IWVs' might have achieved a higher level of wheat productivity even if they had not adopted. As a consequence we apply propensity score matching methods that control for these observable characteristics to isolate the intrinsic impact of improved wheat variety adoption on wheat productivity.

The importance of estimation of the propensity score is twofold: first, to estimate the ATT and, second, to obtain matched treated and non-treated observations. The results of the probit model are reported in Appendix Table 6. They indicate that age, wheat growing experience, total cultivated land, number of months available all weather road, extension contact, sex of the households, owning a radio and livestock holding are important variables that determine farmers' propensity to adoption of improved wheat varieties.

Appendix Table 6 shows the model output of DNA fingerprinting data that predicted coefficients for explanatory variables. They are discussed as the following:

Age of the households (AGEHH): The probit model output shows that age of the head of household is negative and significant at 1% suggesting that the probability of adopting at least one improved wheat variety diminishes by 0.21% with old age other variables held constant. The negative effect of age on adoption can be interpreted in terms of the risk-aversion paradigm assuming that farmers consider the new technologies to be riskier than older technologies that they have been growing for a long period of time. In line with the study by, (Morris *et al*., 1998, Fufa and Hassan, 2006, Thomson *et al*., 2014 and Bashir and Wegrary, 2014) found negative influence of age on adoption.

Total operated land (TOPLND): To assess the effect of cultivated land size on the probability of adopting improved wheat varieties, size of the total cultivated land was included in the model. The result is as expected and indicates that as cultivated land area increases by one hectare, the propensity of adopting IWVs' increases by 1.74 %, helding other variables constant, confirming the expectation that owning more cultivated farmland is correlated with higher adoption rates. Consistent with earlier findings (Mendola, 2007; Suri , 2011; Kassie *et al*., 2011; Mariano *et al*., 2012; Asfaw *et al*., 2014), the result likely reflects the importance of large land area among rural farming households for the cultivation of new-generation of crop varieties.

Livestock ownership (TLU): As proposed, the effect of livestock ownership had a significant and positive effect on adoption of improved wheat varieties. Suggesting that the increase in a number of livestock owned increases the likelihood of farm household's choice of IWVs' by 1.45%. This might be due to the fact that livestock are source of additional income which supports farmers in buying the improved varieties and farm inputs. This is in line with the study by Teferi *et al. (*2015) that shows livestock ownership was shown to positively and significantly influence the adoption decision of improved maize varieties in Central Oromiya, Ethiopia.

Household wheat growing experience (HHEXP): As expected, wheat growing experience significantly affected the probability of adoption of improved wheat varieties at 1% significance level. The result is as expected and indicates that as wheat growing experience increases by one year, the likelihood of adopting IWVs' increases by 0.3 %, confirming the expectation that having more wheat growing experience is correlated with higher propensity to adopt improved wheat varieties. This implies that farmers who have longer years of experience in wheat crop production have adopted improved wheat varieties than those who have the lower years of experience in wheat crop production. This may be due to relatively farmers who have longer years of experience may develop the confidence in handling the risk lovers, skills in technology application. This is similar with the study by Abera (2013) that shows farming experience significantly affected the probability of adoption and intensity of use of adoption of improved wheat varieties at 1% significance level.

Availability of all weather passable roads (NUMMONTHS): As expected, the coefficient of availability of number months of all weather roads had the expected positive sign and significant effect at 1% significance level on adoption of improved wheat varieties suggesting that households that have more months of all weather passable road have a higher propensity to adopt improved varieties of wheat by 2.1 % than those that do not have more all weather passable road. It is not only the proximity to local and external markets that influences adoption of improved technologies but all weather passable roads is also significant. Availability and proximity of farmers to all weather passable roads is essential for timely input delivery and output disposal. It also decreases the transport cost of inputs. The result is consistent with the finding of (Berhanu and Swinton, 2003).

Sex of the households (SEXHH): The negative and significant coefficient of sex of the household on the adoption of improved wheat varieties was a surprising finding. Not as proposed, sex of the household returned a negative and significant coefficient at 10% significance level, suggesting that, female-headed farmers are more likely to adopt improved wheat varieties by 6.5 % than male-headed farmers. The possible explanation for this is that if female farmers are provided with equal access to technology, resources and information with their counterparts, they will be the higher level of technology users. This finding is consistent with the result of (Croppenstedt and Demeke, 1996).Besides the result by Solomon *et al*. (2014) on adoption of improved wheat varieties in Robe and Digalu Tijo districts of Arsi Zone in Oromiya Regional state, Ethiopia shows negative significant coefficient of household head sex on the intensity of use of improved wheat varieties.

Household ownership of a radio (OWNRDIO): As expected, ownership of a radio returned a positive and significant coefficient at 10% significance level, suggesting that households that own a radio have a higher propensity to adopt improved varieties of wheat by 4.85 % than those that do not own a radio. The ownership of a radio may enhance technology adoption through improved access to information about new varieties released and seed sources.

Frequency of extension contact in a year (EXTCONT): As expected, frequency of extension contact was found to be positively and significantly affects the propensity to adopt of improved wheat varieties. From the result obtained as frequency of contact with development agent increases by a unit, adoption of IWVs' would be increase by 2.98 per cent units. This implies when farmers have regular contact with extension agent, probability of using production enhancing inputs would increase through increased awareness from the extension organization. This finding is in harmony with the observations of (Kidane, 2001; Techane, 2002; Asfaw *et al*., 2012; Mariano *et al*., 2012) those underlines the importance of extension in promoting adoption.

Choice of matching algorithm

Alternative most commonly used matching estimators like Nearest Neighbor (NN), Kernel Matching (KM) Caliper Matching (CM), and Radius Matching were tried in matching the treatment and control households in the common support region and performed several tests to select a preferred estimator. The question remains on how and which method to select. Clearly, there is no single answer to this question. The choice of a given matching estimator depends on the nature of the available data set (Bryson *et al.*, 2002).In other words, it should be clear that there is no winner for all situations and that the choice of a matching estimator crucially depends on the situation at hand. The choice of a specific method depends on the data in question, and in particular on the degree of overlap between the treatment and comparison groups in terms of the propensity score. When there is substantial overlap in the distribution of the propensity score between the comparison and treatment groups, most of the matching algorithms will yield similar results (Dehejia and Wahba, 2002).

Table 8 below shows after looking into the results, guided by the indicators; it was found that kernel (0.08) was the best estimator for the data at hand. Therefore, the following estimation results and discussion are the direct outcomes of the kernel matching algorithm based on a band width of (0.08). As such, in what follows, estimation results and discussions are the direct outcomes of the kernel matching algorithm.

Table 8: Performance of matching estimators

Source: DNA finger printing data and own compilation, * Number of explanatory variables with no statistically significant mean differences between the matched groups of user and non-user households after matching.

Matching estimators	Balancing test*	Pseudo-R^2 after matching	Matched sample size
Nearest Neighbor (NN)			
Neighbor(1)	13	0.007	1,417
Neighbor (2)	14	0.004	1,417
Neighbor r(3)	14	0.004	1,417
Neighbor (4)	14	0.004	1,417
Neighbor (5)	14	0.004	1,417
Caliper Matching(CM)			
0.01	13	0.007	1,414
0.05	13	0.007	1,417
0.1	13	0.007	1,417
0.5	13	0.007	1,417
Kernel Matching (KM)			
With band width of (0.08)	14	0.001	1,417
With band width of (0.1)	14	0.002	1,417
With band width of (0.25)	11	0.016	1,417
With band width of(0.5)	4	0.046	1,417
Radius Matching			
With band width of (0.01)	7	0.053	1,417
With band width of (0.1)	7	0.053	1,417
With band width of (0.25)	7	0.053	1,417
With band width of (0.5)	7	0.053	1,417

Verifying the Common Support Condition

Figure 5 below gives the histogram of the estimated propensity scores for adopter and non-adopters of DNA fingerprinting data estimates. A visual inspection of the density distributions of the estimated propensity scores for the two groups indicates that the common support condition is satisfied: there is substantial overlap in the distribution of the propensity scores of both adopter and non-adopter groups. The bottom half of the graph shows the propensity scores distribution for the non-adopters and the upper half refers to the adopters. The densities of the scores are on the y-axis.

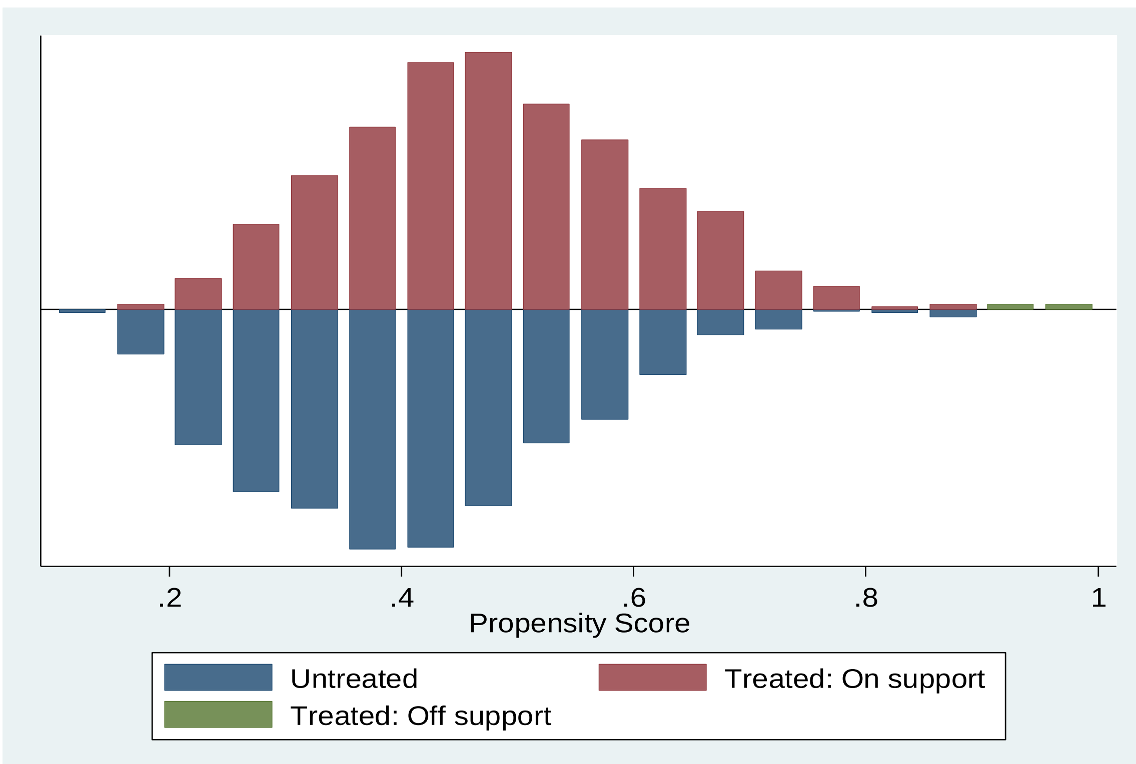


Figure 5: Propensity score distribution and common support for propensity score estimation. Note: ‘‘Treated/untreated: on support’’ indicates the observations in the adoption group that have a suitable comparison and off support indicates the observations in the adoption group that have no suitable comparison.

Matching involved and non-involved households

The estimated propensity scores vary between 0.1852 and 0.9720, with a mean of 0.4828, for treatment households and between 0.1099 and 0.8856, with a mean of 0.40790, for control households (Table 9). The common support region would then lie between 0.1852 and 0.8856 that is the minimum and maximum value of treated and control households, respectively. This ensures that any combinations of characteristics observed in the treatment group can also be observed among the control group. In other words, households whose estimated propensity scores are less than 0.1852 and larger than 0.8856 are not considered for the matching exercise. This is because no matches can be made to estimate the average treatment effects on the ATT parameter when there is no overlap between the treatment and non-treatment groups (Bryson *et al.,* 2002). As a result of this restriction, 4 households all from adopter were discarded. This shows that the study does not have to drop many adopter households from the sample in computing the impact estimator.

Table 9: Distribution of estimated propensity scores

Group	Obs	Mean	Std.Dev	Minimum	Maximum
Total households	1,421	0.4410	0.1354	0.1099	0.9720
Treatment households	628	0.4828	0.1310	0.1852	0.9720
Control households	793	0.40790	0.1296	0.1099	0.8856

Obs= observation, Std.Dev= standard deviation, Source: DNA finger printing data and own compilation, 2018

Testing the balance of propensity score and covariates

After choosing the best performing matching algorithm and common support condition, the next step is checking the balancing of propensity score and covariate using different procedures by applying the selected matching algorithm. The main purpose of the propensity score estimation is not to obtain a precise prediction of selection into treatment, but rather to balance the distributions of relevant variables in both groups. The balancing powers of the estimations are determined by considering different test methods such as the reduction in the mean standardized bias between the matched and unmatched households, equality of means using t-test and chi-square test for joint significance for the variables used.

The mean standardized bias before and after matching are shown in the fifth columns of table 10, while column six reports the total bias reduction obtained by the matching procedure. In the present matching models, the standardized difference in Z before matching is in the range of 0.5 % and 35.5% in absolute value. After matching, the remaining standardized difference of Z for all covariates lies between 0.1 % and 13.2 % which is below the critical level of 20% suggested by Rosenbaum and Rubin (1985). In all cases, it is evident that sample differences in the unmatched data significantly exceed those in the samples of matched cases. The process of matching thus creates a high degree of covariate balance between the treatment and control samples that are ready to use in the estimation procedure.

Table 10: Propensity score and covariate balance

Variables	Sample	Mean			%reduct	t-test	
		Treated	Control	%bias	bias	t	p>t
_pscore	Unmatched	0.4767	0.4127	52.7		9.85	0.000
	Matched	0.47531	0.4754	-0.1	99.9	-0.01	0.991
AGEHH	Unmatched	46.293	48.253	-13.2		-2.48	0.013
	Matched	46.373	46.475	-0.7	94.8	-0.12	0.902
TOPLND	Unmatched	1.7364	1.5574	10.4		1.95	0.051
	Matched	1.7396	1.6599	4.6	55.5	0.77	0.441
TLU	Unmatched	4.9087	4.2237	19.5		3.68	0.000
	Matched	4.8197	4.8992	-2.3	88.4	-0.40	0.688
EXPNEW	Unmatched	15.232	13.117	17.7		3.32	0.001
	Matched	15.24	14.887	3	83.3	0.50	0.620
MINMAINMRKET	Unmatched	107.2	117.25	-13.2		-2.47	0.014
	Matched	107.36	107.18	0.2	98.3	0.04	0.967
NUMMONTHS	Unmatched	8.7341	7.4628	35.5		6.60	0.000
	Matched	8.7244	8.7058	0.5	98.5	0.10	0.923
MINSOURSED	Unmatched	70.194	77.014	-11.2		-2.11	0.035
	Matched	70.003	70.075	-0.1	98.9	-0.02	0.983
MINCOOPS	Unmatched	61.999	70.82	-12.4		-2.35	0.019
	Matched	61.743	62.853	-1.6	87.4	-0.29	0.775
EXTCONT	Unmatched	2.4745	1.7516	31		5.81	0.000
	Matched	2.3846	2.2672	5	83.8	0.89	0.373
SEXHH	Unmatched	0.8344	0.8525	-5.0		-0.93	0.351
	Matched	0.8333	0.8308	0.7	86.2	0.12	0.906
MODFARM	Unmatched	0.60987	0.57629	6.8		1.28	0.201
	Matched	0.61218	0.60455	1.6	77.3	0.28	0.783

CREDITSEED	Unmatched	0.4379	0.43758	0.1		0.01	0.990
	Matched	0.4375	0.44084	-0.7	-945.1	-0.12	0.906
OWNRDIO	Unmatched	0.38854	0.32535	13.2		2.48	0.013
	Matched	0.38622	0.38841	-0.5	96.5	-0.08	0.937
HHEDUC	Unmatched	2.1927	1.8941	9.7		1.81	0.070
	Matched	2.1859	2.1493	1.2	87.7	0.20	0.841

Table 11 below presents results from covariate balancing tests before and after matching using DNA fingerprinting data. The standardized mean difference (Caliendo and Kopeinig, 2008) for overall covariates used in the propensity score (around 14.2% before matching) is reduced to about 1.6% after matching. The bias substantially reduced, in the range of 30 to 40% through matching. The p-values of the likelihood ratio tests indicate that the joint significance of covariates was always rejected after matching; whereas it was never rejected before matching. The pseudo- R2 also dropped significantly from 5.7% before matching to about 0.1% after matching. The low pseudo-R2, low mean standardized bias, high total bias reduction, and the insignificant p-values of the likelihood ratio test after matching suggest that the proposed specification of the propensity score is fairly successful in terms of balancing the distribution of covariates between the two groups.

Table 11: Propensity score matching: quality test.

Sample	Ps R^2	LR chi^2	$p>chi^2$	MeanBias	MedBias	B	R	%Var
Unmatched	0.057	110.67	0.000	14.2	12.8	57.1*	1.04	30
Matched	0.001	2.37	1.000	1.6	0.9	8.7	0.85	40

Source: DNA finger printing data and own compilation, 2018

4.2.2.2. Treatment effect on the treated (ATT)

Impact analysis and its recommendations in this study was focused on purity level at scenario III for better comparison and where maximum mean productivity was obtained(see descriptive statistics in Table 6). Table 12 provides the mean wheat productivity of adopters and non-adopters as well as the average treatment effect on the treated for kernel matching algorithm. This sub-section provides evidence as to whether or not the adoption of IWVs' has brought significant changes on wheat productivity. The kernel matching algorithm estimator used as the matching estimator for the data at hand and was used to compute the average impact of the adoption of IWVs' among involved households.

The impact estimation result presented in Table 12 scenario (III) provides a supportive evidence of statistically significant effect of the involvement in adoption of IWVs' on wheat productivity. After controlling for differences in socio-economic characteristics of the adopter and non-adopter households, it has been found that, on average, involvement in adoption of IWVs' has impact on wheat productivity of the participating households in adoption of IWVs' by 418.51 Kg/ha. On the other hand, households who actually adopted would have wheat productivity of about 418.51 Kg/ha hectare less had they not adopted. That implies on average adopter households get 20.12% more wheat productivity than non-adopter households due to involvement in adoption of improved wheat varieties. This result is also statistically significant at 1% probability levels. Besides, the impact estimation presented in Table 13 scenarios (II) below shows a supportive evidence of statistically significant effect of the involvement in adoption of IWVs' on wheat productivity.

On average, involvement in adoption of IWVs' at purity level (95%) has impact on wheat productivity of the participating households in adoption of IWVs' by 266.20Kg/ha which is less than mean productivity obtained at scenario (III). On average adopter households get 13.93% more wheat productivity than non-adopter households due to involvement in adoption of improved wheat varieties at scenario II. The implication is that as high gene purity of improved wheat varieties maintained and adopted, productivity to be obtained from a hectare of land is high.

Table 12: Treatment effect on the treated **(**scenario III**)**

Outcome variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Mean wheat productivity(Kg/ha)	Unmatched	2079.494	1644.203	435.2912	42.04014	10.35
	ATT	2080.094	1661.584	418.5106	44.54525	9.4***

Note: *** = significance level at 1 % and S.E is calculated using bootstrap with 100 repetitions Source: DNA finger printing data and own compilation, 2018

Table 13 : Treatment effect on the treated (scenario II)

Outcome variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Mean wheat productivity(kg/ha)	Unmatched	1911.943	1626.355	285.5881	48.53788	5.88
	ATT	1911.613	1645.411	266.2023	51.31444	5.19***

Note: *** = significance level at 1 % and S.E is calculated using bootstrap with 100 repetitions Source: DNA finger printing data and own compilation, 2018

4.2.2.3. Sensitivity analysis

Results on appendix Table 12 show that the inference for the effect of the adoption of improved wheat varieties is not changing though the adopter and non-adopter households has been allowed to differ in their odds of being treated up to gamma =3.45 (100%) in terms of unobserved covariates**.** That means for outcome variable estimated, at various level of critical value of gamma, the p-critical values are significant (i.e., there is no hidden bias due to unobserved confounder) which further indicate that we have considered important covariates that affected both involvement in adoption of improved wheat varieties and outcome variable, wheat productivity. In the analysis it set the maximum value for gamma = 3.45 (100%) with increment of 0.05. These values are a good starting place for many data sets in social sciences. Thus, we can conclude that our impact estimates (ATT) are not sensitive to unobserved selection bias and is a pure effect of adoption of improved wheat variety.

5. SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.1. Summary

This study was conducted in four major wheat producing regions (Oromiya, Amhara, SNNP and Tigray) of Ethiopia on impact of adoption of improved wheat variety on smallholder wheat productivity. The ultimate goal of any rural or agricultural development strategy or program is to improve the welfare of rural households. This goal is achieved among other things by increasing productivity at farm level and by raising farmer's income and by improving their welfare. This is possible if improved agricultural technologies are properly transferred and disseminated to farmers so as to deepen and intensify their production.

The empirical analysis utilizes cross-sectional farm household level data collected from a randomly selected sample of 1421 households in selected EA,s of four major wheat producing regions of Ethiopia using crop cut(for DNA finger printing data) and structured questionnaire(for survey data). The study employed descriptive statistics to estimate adoption rate of IWVs' using both DNA finger printing and household survey data. Besides, to estimate the impact of adopting IWVs' on smallholder farmers' wheat productivity, the study has used DNA fingerprinting data and applied average treatment effect regression based on the propensity score matching and matching algorithms in a non-random involvement setup and absence of baseline data.

The results from the descriptive statistics show that the mean differences between the adopters and non-adopters were significantly differ in terms of total operated land, Tropical livestock unit of the households, wheat growing experience, number of months available in all weather road, minutes to walk to main market, frequency of extension contact in a year, age and number of schooling year of the households and owning of a radio.

The study result shows the average of improved wheat productivity has increased and statistically significant for user of high gene pure wheat variety in each scenario specified. These scenarios show the existence of mean productivity difference of the varieties as their genetic purity increase.

A number of interesting findings were emerged from the adoption rate estimates of the study. Overall, according to household survey, 55.26% of farmers across the country had adopted improved wheat varieties. This result is very encouraging and pointing to increased dissemination of improved wheat technologies by government and non government organization in Ethiopia in the past years. In terms of individual varieties, according to farmer perception of the current study, four leading improved varieties were identified namely Kakaba, Digalu, Kubsa and Dashen, respectively. Besides, the study showed that slightly over half of the area under IWVs' (69.17%) is planted to these leading improved varieties namely Kakaba, Digalu, Kubsa and Dashen respectively.

On the other hand, the result from DNA finger printing shows that overall, 73.61% of farmers across the country had adopted IWVs' according to DNA fingerprinting results. In terms of individual varieties, according to DNA finger printing result, four leading improved varieties were identified namely Kubsa, Kakaba, Digalu, and Galema, respectively. The result from DNA finger printing revealed that over half of the area under IWVs' 78.22% is planted to these leading improved varieties namely Kubsa, Kakaba, Digalu, and Galema respectively.

Besides, adoption rate of improved wheat varieties, the household survey dealt with source of seeds. Predominant sources of seed in the study areas are other farmers who the farmers know and local market reported by 36.33% and 31.28% of households, respectively

The results of probit estimates show that the coefficients of most of the variables hypothesized to influence adoption have the expected signs and they include covariates such as the age of the of the head of household, the Cultivated land size, tropical livestock unit, number of years of experience in wheat farming , number of months to main road available for vehicle in a year, , distance to cooperative ,sex of the households, household extension contact in a year and , ownership of radio among others .

Finding a reliable estimate of the adoption of improved wheat varieties' impact thus necessitates controlling for all explanatory factors adequately. In doing so, propensity score matching has resulted in 628 involved households in (4 households were discarded) to be matched with 793 non-involved households from original sample of 1421 households (628 adopter and 793 non-adopter households). In other words, a matched comparison of total wheat productivity was performed on these households who shared similar characteristics. The resulting matches passed a variety of matching quality tests such as t-test, reduction in standard bias and chi-square test. Moreover, the computed parametric standard error was bootstrapped in order to capture all sources of errors in the estimates and finally sensitivity analyses was made and were fit for answering the study's main objective.

After controlling for differences in socio-economic, institutional and demographic characteristics of the adopter and non-adopter households, it has been found that, on average, involvement in adoption of IWVs' has impact on wheat productivity of the participating households in adoption of IWVs' by 418.51 kg/ha. On the other hand, households who actually adopted would have wheat productivity of about 418.51 kg/ha less had they not adopted. This implies on average adopter households get 20.12% more wheat productivity than non-adopter households due to involvement in adoption of improved wheat varieties. This result is also statistically significant at 1% probability level.

The result of Rosenbaum bounding procedure to check the hidden bias due to unobservable selection shows that the estimated ATT of significant outcome variable is insensitive which clearly indicates its robustness.

5.2. Conclusions

Agricultural technology development is an essential strategy for increasing agricultural productivity, achieving food security and alleviating poverty among smallholder farmers in sub-Saharan Africa. Increasing agricultural productivity and improving the sustainable livelihoods of rural farmers are among Ethiopian's policy priorities. In this effort, adoption of improved agricultural technologies is expected to play a vital role. This study's contribution is to examine the adoption rate of IWVs' and their potential impact on wheat productivity among rural farm households in Ethiopia using farmers' recall and DNA finger printing approach. This study considered both adoption rate and impact of receiving improved wheat varieties. The accurate identification of crop varieties provides a stepping-stone for impact assessment studies to verify the effectiveness and robustness of the result. The results obtained from both household recall and DNA finger printing showed that farmer's dependence on and adopted limited number of IWVs' in Ethiopia. According to survey respondents 55.03% of the farmers used IWVs' during the study year. In reality, however, 74.91% of the respondents used IWVs' suggesting the household survey underestimated the economic importance of improved varieties in the wheat sector by 19.88%.

The DNA fingerprinting results indicated that Kubsa followed by Kakaba, Digalu, and Galema are the IWVs' mostly grown during the study year. Farmer perceptions, however, indicate that Kakaba and Digalu are the most popular wheat varieties followed by Kubsa and Dashen grown during the study year. Farmer perception under estimated the importance of Kubsa, Digalu, Galema. It is worth noting that while the household survey failed to show the importance of Kubsa, the DNA fingerprinting revealed that 26.11% of household cultivated the variety on 67.62% of the wheat area. According to household survey, majority of the farmers had used Kakaba, and Digalu, 7.18% each. Kakaba, which is rust resistance variety, covered 64.31% of area under improved wheat varieties.

However, contradict to farmer recalls, the result of the DNA finger printing showed that Kubsa which is rust susceptible variety was used by 26.11% of the farmers and covered 67.62% of the area under improved wheat varieties. Adoption estimates based on farmer sample survey, therefore, did not only under estimate aggregate levels of adoption but also distorted the relative importance of individual varieties that may have serious implication in seed demand and supply. Besides, the implication of the result is that there is poor performance of supplying of IWVs' by agro-input dealers and lack of awareness for farmers in identifying improved varieties in Ethiopia.

The result obtained shows the mean productivity of the user of high genetically pure varieties is higher and statistically significant. Genetic purity is one of the attributes of good quality seed. Varietal mixtures can cause uneven maturity, lower yield potential, increased susceptibility to disease and insect pests, and be less adapted to specific environmental conditions

The impact study result reveals that on average, involvement in adoption of IWVs' has impact on wheat productivity of the participating households by 418.51 kg/ha than no-involved households.

5.3. Recommendations

As noted, increasing agricultural productivity and improving the sustainable livelihoods of rural farmers are among Ethiopian's policy priorities; this is possible if improved agricultural technologies are properly transferred and disseminated to farmers so as to deepen and intensify their production. In view of the major findings and the above conclusions, the following recommendations are drawn:

The results obtained from both household recall and DNA finger printing showed that farmer's dependence on and adopted limited number of IWVs' in Ethiopia. Creating knowledge and demand for new high yielding wheat varieties quickly after their release is vital for varietal popularization. So the national extension system should be strengthened in popularizing the shelved many of IWVs' to the farmers. .

Alternate system of having access of farmers to quality seeds of new wheat varieties, improve wheat productivity and enhance food security at the household level. Therefore, agricultural policy makers should empower formal seed sector to deliver quality and certified of improved wheat seed.

Policy makers need to encourage and assist private seed companies and community seed producer associations by improving access to agri-business development services and empowering cooperatives and village agro-dealers.

Failure to replace out-dated and rust susceptible varieties with modern and rust resistance cultivars in Ethiopia would need a remedy. This situation will have substantial negative impacts on wheat production and productivity.

Global food production now faces greater challenges than ever before. There is no simple solution to delivering increased crop productivity while improving resource use efficiency. In this view, the focus has been on science and technology, but a broad range of options including social and economic factors such as technology extension and access to technologies by farmers also needs to be pursued. The path from the application of existing technologies should be changed to the delivery of improved wheat seeds particularly genetically pure (true to type) seed of wheat varieties must be provided for the farmers for enhancement of productivity.

As the national seed system is developing and the role of diverse actors increasing, building national capacity in addressing disputes from release-to-distribution through accurate methods like DNA fingerprinting will be crucial.

It is recommended that, varietal adoption estimates and impact study in all crop need to apply DNA finger printing approach as it provides more accurate and dependable results in Ethiopia.

The policy implication of the findings is that agricultural technology innovations need to be generated and promoted continuously to replace older technologies that have reached their saturation point in terms of their yields' performance potential.

Above all, future work will require a mult-disciplinary approach that involves not just plant breeders, soil scientists, agronomists, and farmers, but also ecologists, policy-makers, and social scientists. Our strong view is that government of the Ethiopia must allocate more funds to both fundamental plant science and applied crop research. However, global co-operation is also needed to ensure faster progress in increasing modern high yielding crop varieties.

6. REFERENCES

Abera Abebe, 2013. A determinants of Adoption of Improved wheat varieties by Smallholder Farmers: the Case of Angacha Woreda, Kembata Tembaro Zone, Southern Nations, Nationalities and Peoples Region, Ethiopia. M.Sc. Thesis, Haramaya, Ethiopia.

Abrahaley, G., 2006. Farmers' perception and adoption of integrated striga management technology in Tahtay Adiabo Woreda, Tigray, Ethiopia. Dissertation for Award of MSc Degree at Haramaya University. Haramaya, Ethiopia. pp.20.

Abreham Kebedom and Tewodros Ayalew, 2012. Analyzing Adoption and Intensity of Use of Coffee Technology Package in Yergacheffe District, Gedeo Zone, SNNP Regional State, Ethiopia. *International Journal of Science and Research (IJSR)* ISSN (Online): 2319-7064

Adesina, A. A. and Chianu, J., 2002. Determinants of farmers' adoption and adaptation of alley farming technology in Nigeria. *Agroforestry System*, **55**: 255-265.

Adesina, A. A. and Seidi, S., 1995. "Farmers' Perceptions and Adoption of New Agricultural Technology: Analysis of Modern Mangrove Rice Varieties in Guinea Bissau." *Journal of International Agriculture*, **34** (**4**): 358-385.

Adesina, A.A. and Zinnah, M.M., 1993. Technology characteristics, farmers' perceptions and adoption decisions: A Tobit model application in Sierra Leone. *Agricultural economics*, 9(**4**) :297-311.

Afework Hagos and Lemma Zemedu, 2015. Determinants of Improved Rice Varieties Adoption in Fogera District of Ethiopia. *Science, Technology and Arts Research Journal*, **4**(**1**) : 221-228.

Alan de Brauw, G.T.A. and Minot, N., 2016. The Impact of the Use of New Technologies on Farmers' Wheat Yield in Ethiopia: Evidence from a Randomized Control Trial. In 2016 Annual Meeting, July 31-August 2, 2016, Boston, Massachusetts (No. 235651). Agricultural and Applied Economics Association.

Alene, A.D., Menkir, A., Ajala, S.O., Badu-Apraku, B., Olanrewaju, A.S., Manyong, V.M. and Ndiaye, A., 2009. The economic and poverty impacts of maize research in West and Central Africa. *Agricultural Economics*, **40(5)**: 535-550.

Alexander, C., & Van Mellor, T., 2005. Determinants of corn rootworm resistant corn adoption in Indiana. *AgBioForum*, **8(4):** 197-204

Amare Mulubrhan, Asfaw Solomon, Shiferaw Bekele, 2012. Welfare impacts of maize-pigeon pea intensification in Tanzania. *Agricultural Economics*, **43**: 27–43.

Andersson, C.,Alemu Mekonnen, A. and Stage, J., 2011. Impacts of the Productive Safety Net Program in Ethiopia on livestock and tree holdings of rural households. *Journal of Development Economics*, **94**(**1**): 119-126.

Asnake Fikire., Gowda, C. L., Demissie, Mitiku., Legesse, Dadi., Bantiln, M., Gaur, P. M. and Senait R., 2005. Adoption of improved chickpea varieties in Ethiopia. Ethiopian Agricultural Research organization, Addis Ababa, Ethiopia. 1-32.pp

Awotide, B.A., Alene, A.D., Abdoulaye, T. and Manyong, V.M., 2015. Impact of agricultural technology adoption on asset ownership: the case of improved cassava varieties in Nigeria. Food Security, **7(6):**1239-1258.

Aytekin, I., 2012. Technology and Technique: An Educational Perspective. Turkish Online *Journal of Educational Technology*-TOJET, **11(2) :** 207-213.

Bahadur, K. and Siegfried, B., 2004. Technology Adoption and Household Food Security. Analyzing Factors Determining Technology Adoption and Impact of Project Intervention: A Case of Smallholder Peasants in Nepal. In *Proceedings of Deutscher Tropentag Workshop* (5-7).

Baker, J., 2000. Evaluating the Impact of Development Projects on Poverty. A Handbook for Practitioners. Washington D.C. World Bank.

Becker, S. and A. Ichino, 2002. Estimation of average treatment effects based on propensity scores. *The Stata Journal* **2(4):** 358 -377.

Bekele Hundie., K., Verkuijl, H., Mwangi, W. and Tanner, D., 2000. Adoption of improved wheat technologies in Adaba and Dodola Woredas of the Bale Highlands, Ethiopia. Mexico, D.F.: International Maize and Wheat Improvement Center (CIMMYT) and Ethiopian Agricultural Research Organization (EARO).

Bekele Shifera, Menale Kassie, Moti Jaleta &Chilot Yirga, 2014. Adoption of Improved wheat varieties and impacts on household food security in Ethiopia. *Journal of Food Policy*, **44**: 272-284.

Berhanu Gebremedhin and M Swinton , 2003. Investment in soil conservation in northern Ethiopia: The role of land tenure security and public programme. *Agricultural Economics*, **29**: 69-84

Berihun Kassa Hailu, Bihon Kassa Abrha. and Kibrom Aregawi Weldegiorgis, 2014. Adoption and impact of agricultural technologies on farm income: Evidence from southern Tigray, northern Ethiopia. *International Journal of Food and Agricultural Economics*, **2(4**):91-106

Bezabih Emana, 2001. Determinants of Multiple Technology Adoption: Defining Adopters and Empirical analysis. *Ethiopian. Journal of Agricultural Economics,* **5(1 and 2):** 23-39.

Bryson, A., Dorsett, R. and Purdon, S., 2002. The Use of Propensity Score Matching in the Evaluation of Labour Market Policies. Working Paper No. 4, Department for Work and Pensions

Caliendo, M. and Kopeinig, S., 2008. Some Practical Guidance for the Implementation of Propensity Score Matching. *Journal of Economic Surveys,* **22(1):** 31–72.

Carter, D.W., Milon, J.W., 2005. Price Knowledge in Household Demand for Utility Services. *Land Economics*, **81**: 265–283.

Yirga, C., Alemu, D., Oruko, L., Negisho, K. and Taxler, G., 2016. Tracking the Diffusion of Crop Varieties Using DNA Fingerprinting. Research Report 112. EIAR, Addis Ababa, Ethiopia.

CIMMYT Economics Program, 1993. *The Adoption of Agricultural Technology: A Guide for Survey Design.* Mexico, D.F.: CIMMYT

Croppenstedt, A. and Demeke, M., 1996. Determinants of adoption and levels of demand for fertiliser for cereal growing farmers in Ethiopia (pp. 96-3). University of Oxford, Institute of Economics and Statistics, Centre for the Study of African Economies.

CSA (Central Statistical Agency), 2011. Report on Area and Production of Major Cereals (Private Peasant Holdings, Meher Season). Agricultural Sample Survey *2110/11 (2003 E.C.)*, Volume 1. Addis Ababa, Ethiopia

CSA (Central Statistical Agency), 2017. The Federal Democratic Republic of Ethiopia Central Statistical Agency Agricultural Sample Survey. Report on area and Production of Major Crops. Addis Ababa: Ethiopia

Dallas, J.F., 1988. Detection of DNA" fingerprints" of cultivated rice by hybridization with a human minisatellite DNA probe. Proceedings of the National Academy of Sciences, **85(18)**: 6831-6835.

Danso-Abbeam, G., Bosiako, J.A., Ehiakpor, D.S. and Mabe, F.N., 2017. Adoption of improved maize variety among farm households in the northern region of Ghana. Cogent Economics & Finance, **5(1):**1416896.

Davis,. V.R and Suleiman, K.E., 2015. The new extensionist: Roles and capacities to strengthen extension and advisory services.

Deepa, R., Bandyopadhyay, A. K., & Mandal, M., 2015. Factors related to adoption of maize production technology in cooch behar district of West Bengal. *Agriculture,* **5(2)**:775–777

Degye G., Belay K. and Mengistu K., 2013. Is food security enhanced by agricultural technologies in rural Ethiopia? *African Journal of Agricultural and Resource Economics*, **8 (1)**: 58 – 68.

Dehejia, R. and Wahba, S., 2002. Propensity Score Matching Methods for Non- Experimental Causal Studies. *The Review of Economics and Statistics*, **84(1**):151–161.

Di Zeng, Jeffrey. A., George W. N., Bekele Shifaraw., Moti Jelata. and Chilot Yirga, 2014. Agricultural Technology Adoption and Child Nutrition: Improved Maize Varieties in Rural Ethiopia. *Selected Paper prepared for presentation at the Agricultural and Applied Economics Association' s* 2014 AAEA Annual Meeting, Minneapolis, MN, July 27-29, 2014.

Diagne, A., 2006. Diffusion and adoption of NERICA rice varieties in Cote d'Ivoire. *The Development Economics*, **44(2)**: 208-231

DiPrete, T.A. and Gangl, M., 2004 Assessing Bias in the Estimation of Causal Effects: Rosenbaum Bounds on Matching Estimators and Instrumental Variables Estimation with Imperfect Instruments. *Sociological methodology*, **34(1)**: 271-310.

Dontsop Nguezet, P.M., Okoruwa, V.O., Adeoti, A.I. and Adenegan, K.O., 2012. Productivity Impact Differential of Improved Rice Technology Adoption among Rice Farming Households in Nigeria. *Journal of crop improvement*, **26(1**):1-21.

Doss, C. R., 2003. Understanding farm level technology adoption: lessons learned from CIMMYT's micro surveys in Eastern Africa. *CIMMYT Economics Working Paper* 03-07. Mexico, D.F., CIMMYT.

Dorosh, P.A. and Rashid, S., 2012. Bangladesh rice trade and price stabilization (No. 1209). IFPRI Discussion Paper.

Dunn, D. W., 1984. Applied Decision Analysis. McGraw-Hill Book Company, New York.

Düvel , G.H., 1991. Towards a model for the promotion of complex innovations through programmed extension. S. Afr. J. Agric. Extension. **20**: 70-86.

Ebrahim Jamal., 2006. Adoption of Diary Innovation: Its Income and Sex Implication in Adami Tulu Woreda, Ethiopia. Dissertation for Award of MSc Degree at Haramaya University. Haramaya, Ethiopia, 113pp.

Elias Asres.,Nohmi M., Yasunobu K. & Ishida A., 2013. Effect of Agricultural Extension Program on Smallholders' Farm Productivity: Evidence from Three Peasant Associations in the Highlands of Ethiopia. *Journal of Agricultural Science, Vol.* ***5****, No. 8, 2013.*

Erker, B. and Brick, M.A., 2001. Improve yield with high quality seed. Service in action; no. 0.303.

Evenson, R.E. and D. Gollin (Eds), 2003. Crop Variety Improvement and its Effect on Productivity: The Impact of International Agricultural Research. Oxon, UK: CABI.

Ezemenari, K., Rudqvist, A. and Subbarao, K., 1999. Impact evaluation: A note on concepts and methods. *World Bank Poverty Reduction and Economic Management Network, procesado. Washington, DC: Banco Mundial*, (pp. 1-28).

FAO (Food and Agriculture Organization of the United Nations), 2004. Seed Multiplication by resource poor farmers. Food and Agricultural Organization of the United Nations, Rome

FAO (Food and Agriculture Organization of the United Nations), 2014. "Crop Production Data." Rome, Italy.

FAOSTAT., 2011. FAO Agricultural Database. Rome, FAO.

Feder, G., Just, R.E. and Zilberman, D., 1985. Adoption of agricultural innovations in developing countries: A survey. *Economic development and cultural change*, ***33*****(2)**:255-298.

Fitsum Hagos, 2003. Poverty, Institution, Peasant Behavior and Conservation Investment in Northern Ethiopia. Department of economics and social sciences. Agricultural University of Norway. PhD Dissertation.

Floro, IV, O. Victorino, Ricardo A. Labarta, Luis A. Becerra López-Lavalle, Jose M. Martinez, and Tatiana M. Ovalle, 2016. Household Determinants of the Adoption of Improved Cassava Varieties using DNA Fingerprinting to Identify Varieties in Farmer Fields: A Case Study in Colombia. Draft paper.

Franklin S., Menale Kassie., Aliou D**.,** Solomon Abate, Bekele Shifera and Said S., 2011. Determinants of Agricultural Technology Adoption: The Case of Improved Pigeonpea Varieties in Tanzania. *Quarterly Journal of International Agriculture,* **50(4):** 325-345

GebreEyesus Afework, 2015. A Study on Human Resource Management, Staff Turnover and Incentives in the National Agricultural Research System (NARS). Ethiopian Development Research Institute (EDRI), Research Report 27.

Gebre-Mariam, Y. K., 2012. Holistic Analysis of Household Decision-Making.

Lanham, George W. Norton, Chair, Jeffrey R. Alwang, Bradford F. Mills, Daniel B. Taylor, Edwin G.and Rajotte., 2014. Three Essays on Adoption and Impact of Agricultural Technology in Bangladesh.

Getahun Degu, 2003. Assessment of Factors Affecting Adoption of Wheat Technologies and Its Impact: The Case of Hula Woreda, Ethiopia. MSc. Thesis Presented To School of Graduate Studies of Alemaya University.

Gezahagn Walelign, 2008. Determinants and Role of Farmers' Seed and Seedling Multiplication in the Snnp Region Seed System. An M. Sc. Thesis Presented to the School of Graduate Studies of Haramaya University

Guerrem, E. and Moon H. R., 2004. A Study of Semi-Parametric Binary Choice Model with Integrated Covariates. LSTA, Universite Paris 6 and CREST.

Gujarati, D. and Porter, D. C., 2009. Basic Econometrics. Fifth Edition. McGraw-Hill Companies

Gujirati, D., 2004. Basic Econometrics, 4rd Edition, MacGraw, Hill, New York

Hall, B. and Khan, B., 2002. Adoption of new technology. New Economy Handbook

Hassen Beshir , Bezabhi Emana,Belay Kassa, and Jema Haji,2012. Determinants of chemical fertilizer technology adoption in North eastern highlands of Ethiopia: the double hurdle approach. *Journal of Research in Economics and International Finance*, **1**(**2**):39-49.

Heinrich, C., Maffioli, A. and Vazquez, G., 2010. *A primer for applying propensity-score matching*. Inter-American Development Bank.

Hosmer, D. and Lemeshew,S., 1989. Applied Logistic Regression. *A Wiley-Inter-Science Publication, New York*

Hyman, D., 1989. Modern Microeconomics. Analysis and Application. 2nd edition. Boston, Richard D.Irwin Inc.,U.S.A

Jalan, J. and Ravallion, M., 2003. Estimating the Benefit Incidence of an Antipoverty Program by Propensity-Score Matching. *Journal of Business and Economics Statistics,* **21(1):** 19-30.

Jaleta Moti., Kassie Menale. and Marenya, P., 2015. Impact of improved maize variety adoption on household food security in Ethiopia: an endogenous switching regression approach. In 2015 Conference, August (pp. 9-14).

James Stevenson, 2018. Scaling up DNA Fingerprinting for Crop Variety Identification. Independent science and partnership council.

Jeffreys, A.J., Wilson, V. and Thein, S.L., 1985. Hypervariable 'minisatellite'regions in human DNA. *Nature*, 314(6006), p.67.

Kariyasa, K., Dewi, A., 2011.Analysis of Factors Affecting Adoption of Integrated Crop Management Farmer Field School (Icm-Ffs) in Swampy Areas. *International Journal of Food and Agricultural Economics* ,**1(2):** 29-38

Kassie Menale, Jaleta Moti, Shiferaw, B.A, Mmbando, F. and De Groote, H., 2012, July. Improved maize technologies and welfare outcomes in smallholder systems: evidence from application of parametric and non-parametric approaches. In *2012 Conference, August 18-24, 2012, Foz do Iguacu, Brazil* (No. 128004). International Association of Agricultural Economists.

Kassie Menale, Shiferaw Bekele, & Muricho, G., 2011. Agricultural technology, crop income, and poverty alleviation in Uganda. World Development, **39(10):** 1784–1795

Kebede Degefe, Ketema Mengistu, Dechassa, Nigussie and Hundessa, Feyisa, 2017. Determinants of Adoption of Wheat Production Technology Package by Smallholder Farmers: Evidences from Eastern Ethiopia. *Turkish Journal of Agriculture-Food Science and Technology*, **5(3):**267-274.

Kebede Wuletaw & Tadesse Daniel, 2015. Factors affecting adoption of malt-barley technology: Evidence from North Gondar Ethiopia. *Journal of Food Security*, **3(3):** 75–81

Kebede, M., 2006. Farmers' Perception and determinants of land management practices in Ofla Woreda, Southern Tigray, Ethiopia. Dissertation for Award of MSc Degree at Haramaya University. Haramaya, Ethiopia. 98pp.

Kerr, J., Pangare, G., Pangare, V.L. and George, P.J., 2000. An Evaluation of Dryland Watershed Development Projects in India. *EPTD Discussion Paper-Environment and Production Technology Division, International Food Policy Research Institute*, (68).Food Policy Research Institute, Washington, U.S.A.

Khonje, M., Manda, J., Alene, A.D. and Kassie, M., 2015. Analysis of Adoption and Impacts of Improved Maize Varieties in Eastern Zambia. *World Development*, ***66***: 695-706.

Kidane Gebremariam, 2001. Factors Influencing the Adoption of New Wheat and Maize Varieties in Tigray, Ethiopia: The case in Hawzien Woreda. M.Sc. Thesis (Unpublished) Presented to School of Graduate Studies of Haramaya University, Ethiopia, 140p.

Kijima, Y., Otsuka, K. and Sserunkuuma, D, 2008. Assessing the Impact of NERICA on Income and Poverty in Central and Western Uganda. *Agricultural Economics*, ***38*****(3):** 327-337.

Kosmowski, F., Aragaw, A., Kilian, A., Ambel, A.A., Ilukor, J. and Yigezu, B., 2016. Varietal Identification in Household Surveys: Results from an Experiment Using DNA Fingerprinting Of Sweet Potato Leaves in Southern Ethiopia.

Kosmowski, Frederic, Abiyo Aragaw, Andrzej Kilian, Alemayehu Ambel, John Ilukor, Biratu Yigezu, and James Stevenson, 2016. Varietal Identification in Household Surveys: Results from an Experiment Using DNA Fingerprinting of Sweet Potato Leaves in Southern Ethiopia. Policy Research Working Paper No. 7812. Washington, DC.

Kudi, T. M.1, Bolaji, M.1, Akinola M. O.1 and Nasa'I D. H., 2011. Analysis of Adoption of Improved Maize Varieties among Farmers in Kwara State, Nigeria. *International Journal of Peace and Development Studies*, **1(3):** 8-12.

Labarta, R., Martinez, J.M., Lopera, D., Gonzalez, C., Quintero, C., Gallego, G., Viruez, J. and Taboada, R., 2015. Assessing Impacts of the Adoption of Modern Rice Varieties Using DNA Fingerprinting To Identify Varieties in Farmer Fields: A Case Study In Bolivia. In Paper Accepted For Presentation In The Triennial Meeting Of The International Association of Agricultural Economics (IAAE), Milan.

Le, D.P., Labarta, R.A. and Maredia, M.K., 2014. Analysis of cassava varietal adoption in Vietnam using DNA fingerprinting approach.

Lechner, M., 2002. Program Heterogeneity and Propensity Score Matching: An Application to the Evaluation of Active Labor Market Policies. *The review of economics and statistics*, ***84*****(2):**205-220.

Lee, W.S., 2006. Propensity Score Matching and Variations on the Balancing Test: Melbourne Institute of Applied Economic and Social Research, the University of Melbourne.

Legesse Dadi., Mulugeta, Enki. and Belay Kassa, 2001. Determinants Of Adoption Of Physical Soil Conservation Measures in Central Highlands of Ethiopia The Case of Three Districts of North Shewa. agrekon, **40(3):**293-315.

Leonard Oruko, Diiro Gracious, Fred Tairo and Sam Amanquah, 2015. Diffusion and Adoption of Improved Rice and Maize Varieties in Tanzania: Application of Genetic Fingerprinting Technique Final Technical Report.

Liebenehm, S., Affognon, H. and Waibel, H., 2009. Impact Assessment of Agricultural Maryland: University Press of America. Madagascar. World Development **36 (5),** 797–822.

Morris, M.L., Byerlee, D., 1993. Narrowing the wheat gap in Sub-Saharan Africa: a review of consumption and production. Economic Development and Cultural Change **41** (**4**):737–761.

Martin, M.J. 1989. Innovation Diffusion Models of New Product Acceptance.

Makokha, M., Odera, H., Maritim, H.K., Okalebo, J.R. and Iruria, D.M., 1999. Farmers' Perceptions and Adoption of Soil Management Technologies in Western Kenya. *African Crop Science Journal*, **7(4**):549-558.

Maredia, M. and Reyes, B., 2015. Improving the methods of measuring varietal adoption by farmers in developing countries: Recent experience with the use of DNA fingerprinting and impiactions for tracking adoption and assessing impacts. In 2015 Conference, August 9-14, 2015, Milan, Italy (No. 212226). *International Association of Agricultural Economists.*

Maredia, M.K., Reyes, B.A., Manu-Aduening, J., Dankyi, A., Hamazakaza, P., Muimui, K., Rabbi, I., Kulakow, P., Parkes, E., Abdoulaye, T. and Katungi, E., 2016. Testing Alternative Methods of Varietal Identification Using DNA Fingerprinting: Results of Pilot Studies in Ghana and Zambia.

Mariano, M. J., Villano, R., & Fleming, E., 2012. Factors Influencing Farmers' Adoption of Modern Rice Technologies and Good Management Practices in the Philippines. Agricultural Systems, **110**:41–53.

Mauceri, M., Alwang, J., Norton, G. Barrera, V., 2005. Adoption of Integrated Pest Management Technologies: A Case Study of Potato Farmers in Carchi, Ecuador; Selected Paper prepared for presentation at the American Agricultural Economics Association Annual Meeting, Providence, Rhode Island, July 24-27.

Mekonnen Sime, 2007. Assessment of Factors Influencing Adoption of Integrated Striga Management Technologies of Sorghum in Habro and Fedis Woredas,Oromia region. Dissertation for Award of MSc Degree at Haramaya University. Haramaya, Ethiopia. 120pp.

Melaku Gorfu, 2005. Adoption and Profitability of Kenyan Top Bar Hive Beekeeping Technology. Study in Ambasel District of Ethiopia. An M.Sc. Thesis Submitted to School of Graduate Studies of Haramaya University

Mendola, M., 2007. Agricultural Technology Adoption and Poverty Reduction: A Propensity Score Matching Analysis for Rural Bangladesh. *Food Policy* **32**: 372– 393.

Mideksa Bekele and Tadele Shiberu, 2014. Adoption of Improved Bread Wheat Varieties on Small-Scale Farmers: The Case of Boji Gebisa Ambo District, Oromia Regional State, Ethiopia. *American Journal of Food Science and Technology*. **2(3**), 103-108.

Mignouna, D.B., Manyong, V.M., Mutabazi, K.D.S. and Senkondo, E.M., 2011. (a) Determinants of Adopting Imazapyr-Resistant Maize for Striga Control in Western Kenya: A Double-Hurdle Approach. *Journal of development and agricultural economics*, **3(11),** 572-580.

Mignouna, B., Manyong, M., Rusike, J., Mutabazi, S., & Senkondo, M., 2011. (b) Determinants of Adopting Imazapyr-Resistant Maize Technology and its Impact on Household Income in Western Kenya: *AgBioforum*, 14(**3**):158-163.

Minten, B. and Barrett, C.B., 2008. Agricultural Technology, Productivity, and Poverty in Madagascar. World Development, **36(5):**797-822.

Minyahel, F., 2008. Analysis of Factors Influencing Intensity of Adoption of Improved Bread Wheat Production Package In Jama Woreda,South Wollo,Ethiopia. Dissertation for Award of MSc Degree at Haramaya University. Haramaya, Ethiopia. pp120.

MoFED (Ministry of finance and Economic development), 2006. Ethiopia: Building on progress: A Plan for Accelerated and Sustained Development to End Poverty (2005/06-2009/10, Addis Ababa, Ethiopia: Ministry of Finance and Economic Development

Morris, M.L., Byerlee, D., 1993. Narrowing the Wheat Gap in Sub-Saharan Africa: A Review of Consumption and Production. Economic Development and Cultural Change, **41(4)**:737–761.

Morris, M.L., Tripp, R.B. and Dankyi, A.A., 1999. Adoption And Impacts Of Improved Maize Production Technology: A case study of the Ghana Grains Development Project.

Mulgeta Arega, 2009. Determinants Of Intensity of Adoption of Old Coffee Stumping Technology in Dale Wereda, SNNPRS, Ethiopia. Doctoral dissertation, Haramaya University.

Musa Ahmed, 2015. Adoption of Multiple Agricultural Technologies in Maize Production of the Central Rift Valley of Ethiopia. Studies in Agricultural Economics, **117(3):**162-168.

Musa Hasen, Kassahun Mamo , Aemro Tazeze & Eden Andualem, 2017. The Impact of improved maize varieties on farm productivity and wellbeing: evidence from the East Hararghe Zone of Ethiopia. Development Studies Research, **4(1):**9-21.

Mwanga, J., A. Mussie,W. Mwangi and H. Verkuijl, 1998. Adoption of improved wheat technologies by small-scale farmers in Mbeya district of southern highlands, Tanzania." In the tenth regional wheat workshop for eastern, centeral and southern Africa. University of Stellenbosch, South Africa.

Mwanga, J.R., Mugashe, C.L., Magnussen, P., Gabone, R.M. and Aagaard-Hansen, J., 1998. Experience from video-recorded focus group discussion on Schistosomiases in Magu, Tanzania. *Qualitative Health Research*, ***8*(5):**707-717.

Olayide, S.O., 1980. Agricultural technology and Nigerian small farmers. Nigerian Small Farmers: Problems and Prospects in Integrated Rural Development. Centre for Agricultural Research and Development (CARD). University of Ibadan, Nigeria.

Rabbi, Ismail, Peter Kulakow, Joseph Manu-Aduening, Ansong Dankyi, James Asibuo, Elizabeth Parkes, Tahirou Abdoulaye, Gezahegn Girma, Melaku Gedil, Punna Ramu, Byron Reyes, and Mywish Maredia, 2015. Tracking Crop Varieties Using Genotyping-By-Sequencing Markers: A Case Study Using Cassava (Manihot esculenta Crantz). BMC Genetics 16: 115.

Ravallion, M., 2005. Evaluating Anti-Poverty Programs. Policy Research Working Paper 3625, World Bank, Washington DC.

Rogers, E.M., 1962. Diffusion of innovation. New York Free Press, New York. pp.376.

Rosenbaum, P. and Rubin, D., 1983. The Central Role of the Propensity Score in Observational Studies for Causal effects. Biometrika, **70(1):** 41-55.

Sall, S., Norman, D. and Featherstone, A. M., 2000. Quantitative Assessment of Improved Rice Varieties Adoption in Senegal: Farmers' Perspective." Agricultural systems. **66** (**2**):129-144

Schneider, K. and Anderson, L., 2010. Yield gap and productivity potential in Ethiopian agriculture: Staple grains & pulses. EPAR Brief, 98.

Setotaw Ferede, Gezahegn Ayele and Hailemariam Teklewold, 2003. *Impact of Technology on* Households Food Security in Teff and Wheat Farming Systems of Moretna-Jiru woreda. Ethiopian Agricultural Research Organization (EARO)(No. 48). Research Report.

Shahidur, R. K, Koolwal, G.B. and Samad, H.A., 2010. Handbook on Impact Evaluation Quantitative Methods and Practices. The World Bank. Washington, D.C.

Shiferaw Bekele, Kebede Tewodros, You, Z., 2008. Technology adoption under seed access constraints and the economic impacts of improved pigeonpea varieties in Tanzania. Agricultural Economics.**39**:1–15.

Shiferaw Bekele., Negassa, A Koo, J., Wood, J., Sonder, K., Braun, J-A., Payne, T., 2011. Future of Wheat Production in Sub-Saharan Africa: Analyses of the Expanding Gap between Supply and Demand and Economic Profitability of Domestic Production. Paper presented at the Agricultural Productivity-Africa Conference 1–3 November 2011, Africa Hall, UNECA, Addis Ababa, Ethiopia.

Shiferaw Feleke and Tesfaye Zegeye, 2005. Adoption of improved maize varieties in Southern Ethiopia: Factors and strategy options. *Food Policy* **31**: 442–457.

Sianesi, B., 2004. An Evaluation of the Active Labor Market Programmes in Sweden. *The Review of Economics and Statistics*, **86(1)**: 133-155.

Simon, H.A., Dantzig, G.B., Hogarth, R., Plott, C.R., Raiffa, H., Schelling, T.C., Shepsle, K.A., Thaler, R., Tversky, A. and winter, S., 1987. Decision making and problem solving. Interfaces, **17(5)**:11-31.

Smith, J. and Todd, P., 2005. Does Matching Overcome LaLonde's Critique of Non experimental Estimators? *Journal of Econometrics*, 125(**1–2**): 305–353.

Solomon Asfaw, Shiferaw Bekele, Simtowe, F. and Messia Hagos, 2011. Agricultural technology adoption, seed access constraints and commercialization in Ethiopia. *Journal of Development and Agricultural Economics **3(9)***: 436-447.

Solomon Asfaw., Bekele Shiferaw., Simtowe, F., & Lipper, L., 2012. Impact of modern agricultural technologies on smallholder welfare: Evidence from Tanzania and Ethiopia," *Food Policy* **37 (3)**: 283–295

Solomon, Tesfaye., Tessema, Ayele. and Bekele, Adam, 2014. Adoption of improved wheat varieties in Robe and DigeluTijo Districts of Arsi Zone in Oromia Region, Ethiopia: A double-hurdle approach. *African Journal of Agricultural Research*, **9(51**):3692-3703.

Stork.H,Bezabih Emana, Birhanu Adenew, A.Borowiecki AND Shemelis W/Hawariate, 1991.Farming systems and farm management practices of small holders in the Hararghe Highlands. Farming system practices of resource economics in the tropics.Vol.11, Wissenschaftsverlag, Vauk , Keil KG, Germany.

Suri, T., 2011. Selection and comparative advantage in technology adoption," *Econometrica*. **79(1)**: 159-209.

Taher Salam, 1996. Factors influencing smallholder cocoa production: a management analysis of behavioral decision-making processes of technology adoption and application. *Dissertation for Award of PhD Degree at Wageningen University, Wageningen, Holland*. pp 250.

Techane, A., 2002. Determinants of Fertilizer Adoption in Ethiopia: The Case of Major Cereal Producing Areas. *Dissertation for Award of MSc Degree at Haramay University. Haramaya, Ethiopia*. 120pp.

Teferi, A., Philip, D. and Jaleta Moti, 2015. Factors that affect the adoption of improved maize varieties by smallholder farmers in Central Oromia, Ethiopia. Developing Country Studies, 5, p.15.

Teferi, W., 2003. Trends in and determinants of fertilizer use in Gozamin Woreda, Amhara Region. Dissertation for Award of MSc Degree at Haramaya University. Haramaya, Ethiopia. pp132.

Tesfaye Haregewoin, Baye Belay, Eyob Bezabeh , Kaleb Kelemu, Daniel Hailu and Fitsum Daniel, 2018. Impact of Improved Wheat Variety on Productivity in Oromia Regional State, Ethiopia.

Tesfaye Worku, 2006. Analyzing factors affecting adoption of rainwater harvesting technology in Dugda Bora Woreda, Ethiopia. Dissertation for Award of MSc Degree at Haramaya University. Haramaya, Ethiopia. pp127.

Tesfaye Zegeye. and Alemu Haileye, 2001. Adoption of improved maize technologies and inorganic fertilizer in Northwestern Ethiopia. Ethiopian Agricultural Research Organization (EARO). Research report No.40, Addis Ababa, Ethiopia. pp51.

Tesfaye, S., B. Bedada , 2016. Impact of improved wheat technology adoption on productivity and income in Ethiopia. *African Crop Science Journal* **24(1):** 127-135.

Tesfaye Zegeye, Girma Taye, Douglas, T., Hugo, V., Aklilu., A., Wilfred M., 2001. Adoption of Improved Bread Wheat Varieties and Inorganic Fertilizer by Small-scale Farmers in Yelmana Densa, and Farta Districts of Northwestern Ethiopia. CIMMYT.

UNDP (United Nations Development Programme), 2014. Ethiopia: Quarterly Economic Brief.

USAID (United States Agency for International Development), 2010. Staple Foods Value Chain Analysis. Country Report, Ethiopia. Addis Ababa.

Venetoklis, T., 2004. An Evaluation of Wage Subsidy Programs to SMEs Utilising Propensity Score Matching. Government Institute of Economic Research, Helsinki.

Wageningen, F.S.C.,2016. Multi-Level Mapping and Exploration of Wheat Production and Consumption and Their Potential Contribution to Alleviation of Poverty, Malnutrition and Sex Inequality. Final Report WHEAT Competitive Grant. Wageningen University Food Security Center Study, the Netherlands.

Walker, T.S. and Alwang, J. eds., 2015. Crop improvement, adoption and impact of improved varieties in food crops in Sub-Saharan Africa. CABI.

World Bank, 2013. World Development Report. World Bank, Washington, D.C, USA.

World Bank.2016. Over view of the World Bank in Ethiopia.

Wooldridge, J.M., 2002. Econometric Analysis of Cross Section and Panel

Wu, H., Ding, S., Pandey, S. and Tao, D., 2010. Assessing the Impact of Agricultural Technology Adoption on Farmers' Well-Being in Rural China. *Asian Economic Journal* **24 (2):** 141–160.

Yealembirhan Molla, 2006. Integrating the Formal and Informal Wheat varieties Supply Systems to Improve Farmers' Access to Modern Cultivars in the North Shewa Zone of the Amhara Region. A M.Sc. Thesis Presented To the School of Graduate Studies of Haramaya University

Yirga Chilot, Traxler G, Kim, M. and Alemu Dawit, 2015. Using DNA Fingerprinting to Estimate the Bias of Farm Survey Identification of the Diffusion of Improved Crop Varieties in Ethiopia. In International Conference of Agricultural Economists (pp. 9-14).

Yirga chilot, 2015. Ex Post Impacts of Improved Maize Varieties on Poverty in Rural Ethiopia. *Agricultural Economics* **46 (4)**: 55-526.

Yitbarek Tegegne, 2017. Factors affecting adoption of legume technology and its impact on income of farmers: the case of Sinana and Ginir woredas of Bale Zone. M.Sc. Thesis, Haramaya, Ethiopia.

Zeng, D., Alwang, J., Norton, G.W., Shiferaw, B., Jaleta, M. and Yirga, C., 2015. Ex post impacts of improved maize varieties on poverty in rural Ethiopia. Agricultural Economics, **46(4)**:515-526.

7. APPENDICES

Appendix Table 1 Description of outcome, treatment and household characteristics (for continuous variables) using DNA fingerprinting data

Variables	Over all		Adopter(>=99 , Purity level)		Non-adopter(< 99,Purity level)		
	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	t-test
Treatment variable(Binary adoption)	0.44	0.50					
Outcome variable							
Wheat productivity(Kg/ha)***	1836.58	815.92	2079.49	739.53	1644.20	822.67	10.35
Explanatory variables							
AGEHH (years)**	47.39	14.83	46.29	14.75	48.25	14.85	2.48
TOPLND (ha)**	1.64	1.72	1.74	1.75	1.56	1.68	1.95
TLU***	4.53	3.50	4.91	3.70	4.22	3.32	3.70
HHEXP(years)***	14.05	11.97	15.23	12.27	13.12	11.65	3.32
MINMAINMRKET**	112.81	76.37	107.20	75.74	117.25	76.63	2.47
NUMMONTHS***	8.02	3.66	8.73	3.37	7.46	3.78	6.60
MINSOURSED(Min)**	74	60.64	70.19	62.82	77.01	58.72	2.11
MINCOOPS (Min)**	66.92	70.46	61.99	76.01	70.82	65.53	2.35
EXTCONT (Frequency)***	2.07	2.36	2.47	2.34	1.75	2.32	5.81
HHEDUC (year of schooling)**	2.03	3.10	2.19	3.16	1.89	3.03	1.81

**, ** * shows significant level at 5%, and 1% respectively. Std. Dev = standard deviation, source: author compilation, 2018

Appendix Table 2 Wheat variety knowledge and adoption based on farmer perceptions, % households reporting

Variety	Households		Area	
	Number	%	Ha	%
DIGALU	102	7.18	23.60	2.76
KAKABA	102	7.18	550.09	64.31
KUBSA	55	3.87	9.97	1.17
DASHEN	48	3.38	7.97	0.93
BATU	8	0.56	2.65	0.31
FIRFIR	7	0.49	2.25	0.26
KINKINA	6	0.42	0.52	0.06
CHIKUZ	5	0.35	0.72	0.08
HAWI	5	0.35	2.02	0.24
KEBEN	5	0.35	0.52	0.06
SHEHAN	5	0.35	0.81	0.10
WARKAYE	5	0.35	1.22	0.14
AWALID	4	0.28	0.87	0.10
DANFAME	4	0.28	0.50	0.06
K6290BULK	4	0.28	0.76	0.09
TIRTIKAL	4	0.28	0.62	0.07
C1	3	0.21	0.16	0.02
KUCHO	3	0.21	0.53	0.06
LOGAW SHIBO	3	0.21	0.08	0.01
SEMON	3	0.21	0.17	0.02
WABE	3	0.21	0.07	0.01
CHEFERO	2	0.14	0.52	0.06
DANDA'AA	2	0.14	0.10	0.01
DERESELIGN	2	0.14	0.19	0.02
DULDUL	2	0.14	0.30	0.04
GALEMA	2	0.14	0.09	0.01
JIRU	2	0.14	0.23	0.03
KEMEDI PERA	2	0.14	0.25	0.03

MADA-WALABU	2	0.14	0.48	0.06
MENENE	2	0.14	0.08	0.01
TEKUZ	2	0.14	0.08	0.01
TIGERE SINDE KUCHO	1	0.14	0.20	0.02
DEGEMO	1	0.07	0.10	0.01
ENGLIZ	1	0.07	0.09	0.01
FALKET	1	0.07	0.32	0.04
GOFIRO	1	0.07	0.02	0.00
KENIW SHIBO	1	0.07	0.03	0.00
KOCHONA TIGRE	1	0.07	0.22	0.03
NECH SINDE ABABOT	1	0.07	0.07	0.01
PEBEL	1	0.07	0.50	0.06
SENDAY ADI	1	0.07	0.05	0.01
SERIGE	1	0.07	0.19	0.02
SHALA	1	0.07	1.08	0.13
SHEMETE SINDE	1	0.07	0.06	0.01
TRKRNCHER	1	0.07	0.05	0.01
WEDAME	1	0.07	0.25	0.03
YEDEBO SINDE	1	0.07	0.14	0.02
BOKE	11	0.77	1.76	0.21
FUABEL	12	0.84	61.19	7.15
PAVON-76	10	0.70	1.62	0.19
UNKNOWN IMPROVED	328	23.08	46.04	5.38
UNKNOWN/LOCAL	639	44.97	129.89	15.19
Total	1,421	100.00	852.29	100.00

Source: Authors' compilation, 2018, % = %ages

Appendix Table 3 Adoption estimates by variety level using DNA finger printing (95%)

Varieties	N	%	Ha	%
KUBSA	371	26.11	578.22	67.620
KAKABA	177	12.46	39.66	4.638
DIGALU	150	10.56	21.31	2.493
GALEMA	112	7.88	29.64	3.466
PAVON-76_TOSSA	61	4.29	9.67	1.131
DANDA'AA	59	4.15	8.61	1.007
SIMBA	26	1.83	6.83	0.799
HAWI	22	1.55	4.88	0.571
BOLO	13	0.91	1.68	0.196
LASTA	11	0.77	1.32	0.154
GAMBO	6	0.42	1.3	0.152
TUSIE	5	0.35	0.52	0.060
DASHEN	4	0.28	0.58	0.068
ET-13	4	0.28	0.76	0.089
BIQA	3	0.21	0.39	0.045
MADA WALABU	3	0.21	0.64	0.075
RW1202017	3	0.21	0.09	0.010
ABOLA	2	0.14	0.26	0.030
K6294A	2	0.14	0.12	0.014
MERARO	2	0.14	0.08	0.009
ARENDETO	1	0.07	0.50	0.058
AMIBERA	1	0.07	0.09	0.010
DODOTA	1	0.07	0.05	0.006
ENKOY	1	0.07	0.07	0.008
HULLUKA	1	0.07	0.02	0.003
K6295-4A	1	0.07	0.02	0.002

MITIKE	1	0.07	0.11	0.012
SIRBO	1	0.07	0.02	0.002
SOFUMAR	1	0.07	0.24	0.028
SULLA	1	0.07	0.18	0.021
NOT IMPROVED	375	26.39	147.92	17.30
ALL VARIETIES	1421	100	855.10	100

Source: Authors' compilation, 2018%, = %ages

Appendix Table 4 Comparison of adoption estimates from farmer responses and DNA finger printing

Variety	DNA Fingerprinting(N=1421)		Farmers' Recall(N=1421)		Difference(N=1421)	
	Number	%	Number	%	Number	%
KUBSA	371	26.11	55	3.87	316	22.24
DIGALU	150	10.56	102	7.18	48	3.38
KAKABA	177	12.46	102	7.18	75	5.30
GALEMA	112	7.88	2	0.14	110	7.74
PAVON-76_TOSSA	61	4.29	10	0.70	51	3.59
DANDA'AA	59	4.15	2	0.14	57	4.01
SIMBA	26	1.83	0	0.00	26	1.83
HAWI	22	1.55	5	0.35	17	1.20
LASTA	11	0.77	0	0.00	11	0.77
BOLO	13	0.91	0	0.00	13	0.91
GAMBO	6	0.42	0	0.00	6	0.42
TUSIE	5	0.35	0	0.00	5	0.35
DASHEN	4	0.28	48	3.38	-44	-3.10
ET-13	4	0.28	0	0.00	4	0.28
BIQA	3	0.21	0	0.00	3	0.21
MADA WALABU	3	0.21	2	0.14	1	0.07
RW1202017	3	0.21	0	0.00	3	0.21

ABOLA	2	0.14	0	0.00	2	0.14
ENKOY	1	0.07	0	0.00	1	0.14
K6294A	2	0.14	0	0.00	2	0.14
MERARO	2	0.14	0	0.00	2	0.14
AMIBERA	1	0.07	0	0.00	1	0.07
ARENDETO	1	0.07	0	0.00	1	0.07
DODOTA	1	0.07	0	0.00	1	0.07
HULLUKA	1	0.07	0	0.00	1	0.07
K6295-4A	1	0.07	0	0.00	1	0.07
MITIKE	1	0.07	0	0.00	1	0.07
SIRBO	1	0.07	0	0.00	1	0.07
SOFUMAR	1	0.07	0	0.00	1	0.07
SULLA	1	0.07	0	0.00	1	0.07
All varieties	1,046	73.61	328	23.08	718	50.58

Source: Authors' compilation, 2018, % = %ages

Appendix Table 5 Results of Probit estimation of propensity scores using DNA fingerprinting data (scenario **II)**

Variables	Coef.	Std. Err.	P>z	Marginal effects
AGEHH	-0.0037	0.0026	0.16	-0.0012
TOPLND	0.0397*	0.0220	0.071	0.0126
TLU	0.0173	0.0110	0.115	0.0055
EXPNEW	0.0049	0.0032	0.125	0.0016
MINMAINMRKET	0.0007	0.0006	0.231	0.0002
NUMMONTHS	0.0468***	0.0103	0.000	0.0149
MINSOURSED	-0.0009	0.0008	0.268	-0.0003
MINCOOPS	0.0002	0.0007	0.791	0.0001
EXTCONT	0.0939***	0.0202	0.000	0.0299
SEXHH	-0.1294	0.1045	0.215	-0.0399
MODFARM	-0.0453	0.0752	0.547	-0.0144
CREDITSEED	-0.0423	0.0755	0.576	-0.0135
OWNRDIO	0.1998**	0.0810	0.014	0.0623
HHEDUC	0.0225	0.0137	0.100	0.0072
_cons	0.0810	0.2129	0.704	
Model diagnosis				
Number of Obs	1421			
LR chi2(14)	81.94			
Prob > chi2	0.0000			
Log likelihood	-779.08			
Pseudo R2	0.0500			

Note: ***, ** and * is significant at 1%, 5% and 10% level of statistical error, Source: Authors compilation, 2018

Appendix Table 6 Results of Probit estimation of propensity scores using DNA fingerprinting data (scenario III)

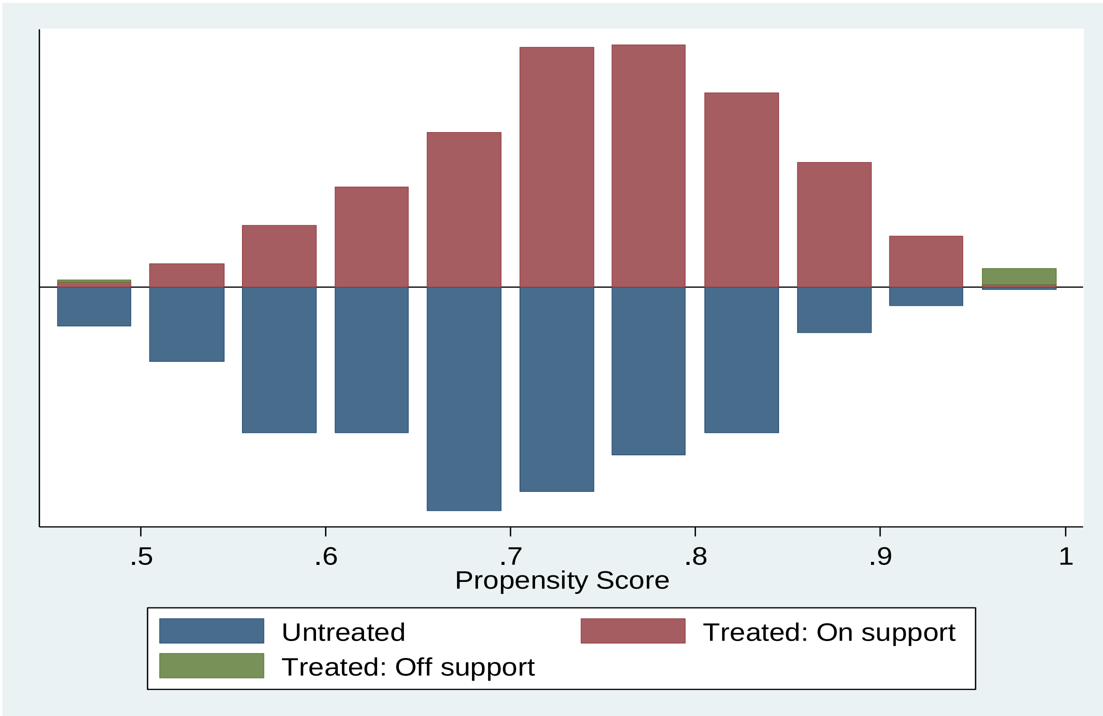
Variables	Coef.	Std. Err.	P>z	Marginal effects
AGEHH	-0.0054**	0.0025	0.03	-0.0021
TOPLND	0.0442**	0.0198	0.026	0.0174
TLU	0.0367***	0.0106	0.001	0.0145
HHEXP(years)	0.0076***	0.0029	0.008	0.0030
MINMAINMRKET	-0.0003	0.0005	0.559	-0.0001
NUMMONTHS	0.0532***	0.0099	0.000	0.0210
MINSOURSED	0.0002	0.0007	0.734	0.0001
MINCOOPS	-0.0005	0.0006	0.373	-0.0002
EXTCONT	0.0755***	0.0156	0.000	0.0298
SEXHH	-0.1640*	0.0970	0.091	-0.0650
MODFARM	0.0541	0.0700	0.44	0.0213
CREDITSEED	-0.0646	0.0703	0.358	-0.0255
OWNRDIO	0.1227*	0.0740	0.097	0.0485
HHEDUC	0.0078	0.0123	0.525	0.0031
_cons	-0.7012	0.1998	0.000	
Model diagnosis				
Number of Obs	1,421			
LR chi2(14)	110.67			
Prob > chi2	0.0000			
Log likelihood	-920.03			
Pseudo R2	0.0567			

***, ** and * is significant at 1%, 5% and 10% level of statistical error, Source: Authors compilation, 2018

Appendix Table 7 Performance of matching estimators (scenario II)

Matching estimators	Balancing test*	Pseudo-R^2 after matching	Matched sample size
Nearest Neighbor (NN)			
Neighbor(1)	12	0.008	1,405
Neighbor (2)	12	0.006	1,405
Neighbor r(3)	12	0.005	1,405
Neighbor (4)	13	0.004	1,405
Neighbor (5)	13	0.004	1,405
Caliper Matching(CM)			
0.01	12	0.008	1,405
0.05	12	0.008	1,405
0.1	12	0.008	1,405
0.5	12	0.008	1,405
Kernel Matching (KM)			
With band width of (0.08)	13	0.003	1,405
With band width of (0.1)	12	0.005	1,405
With band width of (0.25)	7	0.023	1,405
With band width of(0.5)	5	0.043	1,405
Radius Matching			
With band width of (0.01)	9	0.047	1,405
With band width of (0.1)	9	0.047	1,405
With band width of (0.25)	9	0.047	1,405
With band width of (0.5)	9	0.047	1,405

Source: Authors compilation, 2018, * Number of explanatory variables with no statistically significant mean differences between the matched groups of user and non-user households after matching



Appendix Figure 1 Propensity score distribution and common support for propensity score estimation. Note: ‘‘Treated/untreated: on support’’ indicates the observations in the adoption group that have a suitable comparison and off support indicates the observations in the adoption group that have no suitable comparison

Appendix Table 8 Distribution of estimated propensity scores (scenario II)

Group	Obs	Mean	Std.Dev	Minimum	Maximum
Total households	1,421	0.7358	0.1026	0.4565	0.9991
Treatment households	1,046	0.7507	0.0982	0.4565	0.9991
Control households	375	0.6943	0.1033	0.4612	0.9584

Source: Authors compilation, 2018

Appendix Table 9 Propensity score and covariate balance (scenario II)

Variable	Sample	Mean		%reduct		t-test	
		Treated	Control	%bias	bias	t	p>t
AGEHH	Unmatched	46.924	48.677	-11.9		-1.97	0.050
	Matched	47.012	47.31	-2	83	-0.46	0.644
TOPLND	Unmatched	1.6881	1.4927	11.2		1.89	0.059
	Matched	1.6942	1.5479	8.4	25.1	1.85	0.065
TLU	Unmatched	4.6296	4.2387	10.9		1.86	0.064
	Matched	4.5846	4.664	-2.2	79.7	-0.50	0.617
EXPNEW	Unmatched	14.463	12.907	13.1		2.16	0.031
	Matched	14.447	14.003	3.7	71.5	0.83	0.406
MINMAINMRKET	Unmatched	112.09	114.81	-3.6		-0.59	0.555
	Matched	112.56	112.44	0.2	95.8	0.03	0.973
NUMMONTHS	Unmatched	8.3413	7.1413	32.4		5.50	0.000
	Matched	8.3252	8.2719	1.4	95.6	0.34	0.735
MINSOURSED	Unmatched	71.802	80.131	-13.7		-2.29	0.022
	Matched	71.755	71.843	-0.1	98.9	-0.03	0.973
MINCOOPS	Unmatched	65.488	70.921	-8		-1.28	0.200
	Matched	65.644	66.474	-1.2	84.7	-0.28	0.780

EXTCONT	Unmatched	2.2591	1.5467	32		5.06	0.000
	Matched	2.0854	1.9909	4.2	86.7	1.05	0.294
SEXHH	Unmatched	0.84321	0.848	-1.3		-0.22	0.826
	Matched	0.84272	0.84625	-1	26.2	-0.22	0.825
MODFARM	Unmatched	0.59082	0.592	-0.2		-0.04	0.968
	Matched	0.59223	0.58831	0.8	-233.2	0.18	0.856
CREDITSEED	Unmatched	0.44264	0.424	3.8		0.62	0.533
	Matched	0.44272	0.43708	1.1	69.7	0.26	0.797
OWNRDIO	Unmatched	0.37763	0.28533	19.7		3.22	0.001
	Matched	0.37573	0.36676	1.9	90.3	0.42	0.674
HHEDUC	Unmatched	2.1577	1.6587	16.7		2.69	0.007
	Matched	2.1388	2.0756	2.1	87.3	0.45	0.653

Source: Authors compilation, 2018

Appendix Table 10 Propensity score matching: quality test (scenario II)

Sample	Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
Unmatched	0.05	81.94	0.000	12.7	11.5	54.7*	1.29	70
Matched	0.002	6.71	0.945	2.2	1.7	11.5	0.93	50

Source: Authors compilation, 2018

Appendix Table 11 Result of sensitivity analysis using Rosenbaum bounding approach

Rbounds delta, gamma (1(0.05)4)

Rosenbaum bounds for delta (N = 624 matched pairs)

Gamma(e^{γ})	p-critical		Hodges-Lehmann point estimate			
	sig+	sig-	t-hat+	t-hat-	CI+	CI-
1	0	0	386.013	386.013	329.807	453.452
1.05	0	0	368.727	405.569	314.216	479.586
1.1	0	0	356.719	421.486	301.199	498.488
1.15	0	0	342.595	436.124	291.141	517.554
1.2	0	0	329.655	453.789	279.413	535.166
1.25	0	0	317.082	475.299	265.689	547.002
1.3	0	0	305.489	491.722	254.242	558.059
1.35	0	0	295.816	509.098	244.352	569.981
1.4	0	0	288.283	522.469	234.659	581.74
1.45	0	0	277.511	536.713	224.372	596.591
1.5	0	0	266.449	546.191	213.836	611.09
1.55	0	0	257.015	555.352	206.754	621.504
1.6	0	0	248.365	565.1	200.149	634.152
1.65	5.60E-16	0	240.758	574.529	193.183	646.348
1.7	5.40E-15	0	232.646	584.648	182.179	661.861
1.75	4.50E-14	0	224.361	596.625	173.079	673.082
1.8	3.20E-13	0	215.809	608.492	160.275	685.384
1.85	2.00E-12	0	209.395	617.814	148.525	697.087
1.9	1.10E-11	0	204.174	626.004	140.836	707.7
1.95	5.60E-11	0	198.981	636.929	133.541	722.972
2	2.50E-10	0	193.001	646.652	124.624	736.274

2.05	1.00E-09	0	184.256	659.343	116.89	750.807
2.1	3.90E-09	0	176.648	669.572	110.03	762.05
2.15	1.40E-08	0	168.38	677.015	103.896	773.348
2.2	4.40E-08	0	157.429	688.43	97.9056	786.291
2.25	1.30E-07	0	148.566	697.025	91.1292	799.755
2.3	3.70E-07	0	142.429	705.433	83.0237	809.848
2.35	9.80E-07	0	136.852	715.959	77.7717	814.848
2.4	2.40E-06	0	130.56	727.83	73.1001	817.055
2.45	5.80E-06	0	123.424	738.546	68.1942	819.125
2.5	0.000013	0	117.325	750.004	62.245	820.235
2.55	0.000028	0	111.813	758.621	56.4912	821.292
2.6	0.000057	0	106.747	767.773	51.5081	822.6
2.65	0.000112	0	102.018	776.119	46.8968	823.664
2.7	0.000211	0	97.5233	787.375	42.4164	824.701
2.75	0.000383	0	92.2534	797.411	38.2397	825.423
2.8	0.000671	0	85.7076	806.283	33.8332	826.091
2.85	0.001137	0	81.1164	811.895	29.7478	826.782
2.9	0.001868	0	76.937	815.277	25.2082	827.848
2.95	0.002978	0	73.5225	816.845	20.5902	828.886
3	0.004613	0	69.7277	818.551	16.439	829.707
3.05	0.006956	0	65.3384	819.686	12.8552	830.449
3.1	0.010225	0	60.8353	820.472	9.35414	831.163
3.15	0.014672	0	56.5132	821.29	5.76506	832.328
3.2	0.020574	0	52.6908	822.402	2.3533	833.86
3.25	0.02823	0	49.3446	823.217	-1.52176	835.588
3.3	0.037943	0	45.3948	823.991	-5.43208	836.799
3.35	0.050008	0	42.1403	824.761	-9.0632	839.588
3.4	0.064697	0	39.1089	825.289	-13.7652	843.306
3.45	0.082239	0	35.5517	825.799	-18.0633	845.918

Source: Authors compilation, 2018

Gamma - log odds of differential assignment due to unobserved factors

sig+ - upper bound significance level

sig- - lower bound significance level

t-hat+ - upper bound Hodges-Lehmann point estimate

t-hat- - lower bound Hodges-Lehmann point estimate

CI+ - upper bound confidence interval (a= .95)

CI- - lower bound confidence interval (a= .95)

```
. vif
```

Variable	VIF	1/VIF
MINSOURSED	1.64	0.608981
MINCOOPS	1.59	0.629973
MINMAINMRKET	1.24	0.804634
AGEHH	1.15	0.870305
HHEDUC	1.15	0.870853
NUMMONTHS	1.08	0.928645
EXTCONT	1.05	0.954220
Expnew	1.02	0.979512
TOPLND	1.02	0.984779
Mean VIF	1.21	

Appendix Figure 2 VIF for all continues explanatory variables included in the probit model

```
. correlate SEXHH MODFARM CREDITSEED OWNRDIO
(obs=1421)
```

	SEXHH	MODFARM	CREDIT~D	OWNRDIO
SEXHH	1.0000			
MODFARM	-0.0251	1.0000		
CREDITSEED	0.0068	0.0500	1.0000	
OWNRDIO	0.1506	0.0337	0.0423	1.0000

Appendix Figure 3 Contingency coefficient for dummy variables

Appendix Table 1: Conversion factors used to compute tropical livestock units

Animal Category	Tropical Livestock Unit
Oxen	1.1
Cow	1
Heifer	0.5
Bull	0.6
Calves	0.2
Sheep	0.01
Goat	0.09
Donkey	0.5
Horse	0.8
Mule	0.7
Poultry	0.01

Source: Stork *et al*., 1991