Impact of technology Adoption legume producing on Farmers' Income:

A Case study of Guraghe Zone

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A Thesis submitted as partial fulfillment of the requirements for the award of MSc degree in Economics (Major in Development Economics)

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Examiners Approval Sheet

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We, the undersigned, members of the Board of Examiners of the final open defense by Sahlu Badishe have read and evaluated his thesis entitled "Impact of Legumes Technology Adoption on Farmers income: The Case of Guraghe Zone, SNNP of Ethiopia", and examined the candidate. This is, therefore, to certify that the thesis has been accepted in partial fulfillment of the requirements for the Degree of Master of Science in Developmental Economics.

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This is to certify that the thesis prepared by Sahlu Badishe , entitled: "Impact of legumes Technology Adoption on Farmer's Income" A case study in Guraghe Zone" Ethiopia is submitted in partial fulfillment of the requirements for Master Degree of Development Economics complies with the regulation for the University and meets the accepted standards with respect to originality & quality.

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DECLARATION

This research is my original work and has not been presented for a Degree program in any other university and that all source of materials used for the study have been properly acknowledged.

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Date ---04/06/19.-------------------------------

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Table of Contents

Table of List---viii

List of Figure

ACRONYMS AND ABBREVIATIONS

CSA	Central Statistics Agency
EATA	Ethiopian Agricultural Transformation Agency
EEPA	Ethiopia Export Promotion Agency
GDP	Gross Domestic Product
GPS	Generalized Propensity Score
GZANRDD	Guraghe Zone Agricultural & Natural Resource Development Department
GZFEDD	Guraghe Zone Finance and Economics Development Department
Ha	Hectare
ICARDA	International Center for Agricultural Research in the Dry Areas
ICRISAT	International Crops Research Institute for the Semi-Arid Tropics
IFPRI	International Food Preparation Research Institution
MOARD	Ministry of Agriculture and Rural Development
NBE	National Bank of Ethiopia
NERICA	New Rice for Africa
OPHI	Oxford Poverty and Human Development Initiative
PSM	Propensity Score Matching
SNNPRS	Southern Nation Nationality Peoples Regional State
USAID	United States Agency for International Development
USD	United States Dollar
WB	World Bank
WDR	World Development Report

Abstract

*The importance of agricultural technology in enhancing production and productivity can be realized when yield increasing technologies are widely been used and diffused. Standing from this logical ground, this paper aimed to evaluate the impact of legumes technologies adoption on farm income on Guraghe Zone in Ethiopia. This study used cross sectional data that acquired from total of 204 households which were randomly and proportionately sample from 9 major legumes producer kebeles in three district of Guraghe zone stratifies sampling techniques. Logit model was used to estimate to identify underlying factor that determine adoption of legume technologies (improve legume seed, fertilizers, chemicals, inoculants and farming techniques). PSM model was used to estimate to evaluate the impact of legume technologies adoption of farmers' income. Descriptive statistics and econometric models were used to analyze the data. The results from logit model indicate that educational level of household, the household headed, member of cooperative association***,** *to advices to agricultural extension services, size of cultivated land for crop, credit access, off-farm participation and tropical livestock unit positively significant adopt of legume technologies adoption. If female of household headed and plot size for legumes crop cultivated purpose negatively significant influence of legume technologies adoption. Impact assessment of the marginal effect showed that farmers who had adopted legume technologies could enhance their annual total income level by 46.6% and the crop income particularly from grain legume has been increased by 88%. What about the impact based on the findings, the study suggests that strengthening the promotion of full package technology adoption will have crucial role towards improving the livelihood of households in the study area. In doing so, managing the possible influencing factors that affect adoption of legume technology should be a prerequisite.*

Key words: Legumes Technology, technology adoption, Logit , PSM Model, Guraghe, Ethiopia

CHAPTER ONE
INTRODUCTION

1.1. Background of the study

Globally, agricultural development is expected to have the potential of helping in trimming down poverty for 75% of the world's poor, who lives in rural areas and work mainly in farming. It can also contribute in raising incomes, improving food security and benefitting the environment. Agriculture accounts for one-third of GDP and three-quarters of employment in Sub-Saharan Africa (WB, 2013).

Ethiopian economy is fundamentally agrarian where the performance of the agriculture sector dictates the entire economic performance of the country. Despite the reportedly growing importance of the manufacturing and the industry sectors, agriculture continues to account for nearly 36.7% of the gross-domestic product (GDP), more than 72% of labor employment and 80.84% of foreign export earnings (NBE , 2015/16).

Principal crops of Ethiopian agriculture include coffee, legumes, oilseeds, cereals, potatoes, sugarcane, and vegetables. The major staple foods in Ethiopia are grains (e.g. teff, wheat, barley, corn, sorghum, and millet), legumes, oils, ensete, fruits and vegetables. Grains are the most important field crops and the chief element in the diet of most Ethiopians. Exports are almost entirely from agricultural commodities, and coffee is the largest foreign exchange earner, the next sesame and legumes are estimated to be the third most important export crop in Ethiopia just next to sesame (MOARD, 2008).

Pulses/Legumes are the second most important element in the national diet and a principal protein source. They are boiled, roasted, or included in a stew-like dish known as wot, which is sometimes a main dish and sometimes a supplementary food. Pulses, grown widely at all altitudes from sea level to about 3,000 meters, are more prevalent in the Northern and Central highlands. Pulses were a particularly important export item before the revolution. Major pulse crops grown in the country are chickpea, haricot beans, lentils, faba bean and peas. Legumes in Ethiopia cover 12.42% of the total cultivated land and provide 11.89% of the total crop production of the country, which is 2.67 million tons (CSA, 2015).

According to Legese (2004), feeding the rapidly growing population of Ethiopia by means of extensive farming is becoming unachievable due to limited opportunities for area expansion. Rather, the option that looks more likely is increasing yield through intensification, which involves adoption of different improved agricultural practices (Million and Belay, 2004). Despite the significant contribution of adoption of agricultural innovations for increasing production and income, adoption rate of modern agricultural technologies in the country is very low (Di Zeng *et al*., 2014 and Berihun *et al.,* 2014). In order to raise the agricultural production and productivity, raise income, reduce poverty and to enhance the food security and children nutrition, on a sustainable basis in the developing countries like Ethiopia, large-scale adoption and diffusion of new technologies is very essential (Tsegaye and Bekele, 2012; Degye *et al.,*2013 and Di Zeng *et al.,*2014).

Despite the crucial role of legumes for poverty reduction and improving food security in Ethiopia, lack of technological change and market imperfections have often locked small producers into subsistence production and contributed to stagnation of the sector (Shiferaw and Teklewold, 2007). Even if several research and development efforts have attempted to facilitate productivity growth for small farmers, some of these efforts did not stimulate large-scale technology uptake and diffusion. This is mainly because of the limited understanding of farm level constraints, farmer preferences and the challenges related to better coordination of input supply and delivery of new technologies and market linkages for small producers. Therefore, this study aimed at filling the gap on identification of determinants behind lower adoption of legume technologies and evaluating the impacts of adoption on the farmer′s incomes of household.

The general motivations of this paper is that eight main legumes widely grown in Ethiopia are: faba bean, chickpea, field pea, grass pea, and lentil for the cooler highlands and on haricot bean, groundnut and soybean, for the warmer mid and low altitudes of the country. Overall, faba bean is the largest leguminous crop in Ethiopia followed by haricot bean and chickpea. Field pea and grass pea serve as an important food security crop in many areas and still account for more than

300,000 tons each. In total, Ethiopian legume production accounts for almost 3 million tons. At present, virtually all legume production in Ethiopia is undertaken by smallholder farmers with limited external inputs on plot sizes of up to 1.5 ha (CSA, 2013).

Legumes grown in Ethiopia 2016/17 (2009 E.C.) covered 12.92% (1,624,773.23 hectares) of the grain crop area and 10.13% (about 29,442,665.89 quintals) of the grain production was drawn from the same crops. Faba beans, haricot beans (white), haricot beans (red), chick peas, lentils, grass pea, soya bean and groundnut were planted to 3.40% (about 427,696.80 hectares), 0.63% (about 78,910.13 hectares), 1.68% (about 211,292.30 hectares), 1.79% (about 225,607.53 hectares), 0.9%(about 113,684.63 hectares), 1.2%(about 151,268.58 hectares), 0.29%(about 36,635.79 hectares) and 0.59%(about 74,861.23 hectares) of the grain crop area

According to (IFPRI, 2010) report pulses are grown throughout the country. However, the lion share production is concentrated in the Amhara and Oromiya regions, which together account for 92 percent of chickpea production, 85 percent of faba bean production, 79 percent of haricot bean production, and 79 percent of field pea production. The SNNPRG stands third in overall production of pulses by producing 10% of the faba bean, 18% of the filed pea, 3% of chickpea and 15% of haricot bean. Guraghe Zone in 2017/2018 productive season annual achievement report the main crop on average area of land "belg" & "meher" 175,505.5 hectares cultivated, of which legumes 25,428.75 hectares sow under legumes crop about 6% of the total sow different variety of certified legumes seed used.

1.2. Statement of the Problem

Based on the Multidimensional Poverty Index, Ethiopia ranks the second poorest country in the world just ahead of Niger (OPHI, 2015). Ethiopian economy is highly agriculture-dependent and it is characterized as subsistence-oriented. Use of improved seed holds the key to sustainable food crop production across the globe because seed is the basic agricultural inputs that brought improvement of agricultural productivity (Pelmer, 2005). Likewise, chemical fertilizer is regarded as a crucial component of farm inputs by small-scale farmers. In ideal farming condition, farmers should use fertilizer and improved seed together in order to achieve the optimal return of crop production (Nigussie et al., 2012).

The development in cropping system helps for the improvement of standard of living of smallholder farmers who took the major part of the nations of Ethiopia. Despite the fact that farming technologies such as improved seed and chemical fertilizer is considered as contributing determinants for development of the worldwide agriculture, Ethiopia has chronicle poverty and food insecurity problem for a sustained period of time. One of the reasons for the prevalence of food insecurity is low rate of adoption of improved farm inputs. In fact different agricultural technologies have been released to improve productivity of smallholder farmers in the country (Hailu, 2008). But the national adoption rate could not exceeded 11% in major farming inputs such as improved seed and chemical fertilizers. As a result, low crop production and household income remained to be endemic problems in the country (Paul and Shahidur, 2012).

The study area was conducted in 73.2% of residents are severe poor in the region (OPHI, 2017) of Ethiopia, SNNPRG regional state specifically in Gurage Zone. Even if so much has been done in developing improved technologies of legumes and in disseminating them in different parts of Ethiopia, understanding the drivers of adoption and the structure of the diffusion process is an essential component of any research aimed at tackling the challenges faced by resource poor households. There are in fact many studies on the adoption and impact of agricultural technologies (Asfaw *et al.,* 2011; 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 wellbeing by considering adoption as a binary treatment (Asfaw *et al.,* 2011; Tsegaye and Bekele, 2012). But there are prospects to predict the factors affecting adoption level via constructing semi-experimental scenarios. This study is designed to impact of technologies adoption of legumes producing on farmers' income.

Leguminous crops are the second crops both in production and consumption in Ethiopian farming system next to cereals. It has also the big market share in the export market and generating foreign currency for the national economy. Leguminous are the ultimate source of protein in diet complements of these substance-farming communities but are rarely the major focus of attention. Predominantly legume farming is carried out traditionally without the relief of agricultural technology. In recent years, the adoption of agricultural technologies such as improved seed, fertilizer, and farming equipments being utilized by the farming community but still the rate of adoption is in its lower level. More importantly, Gurage zone where this study conducted, dominantly known in cereal production and most of the adoption studies associated with cereal crops while legumes are disregarded. Therefore, this study initiated to choose the study area to fill the mentioned knowledge gap. Furthermore, as technology has a dynamic nature, its effect varies along with time and hence continuous updating adoption effect is required then technologies adoption means as a full package form. In this regard, it is fundamental to researchers to measure the outcome of agricultural technology along with time and as a full package form.

Variations in level of adoption of technology can be a result of generalization of farmers by decision makers. Farmers' initiative towards responding a technology varied due to not only on agro ecological determinants but also socioeconomic characteristics and technologies adoption is including appropriate improve seed varieties, appropriate chemical fertilizers, row planting, inoculants and integrated pest management use as a package form but not separately use. Drawing key characterization elements among farmers will have an indispensable importance towards customizing technology adoption. Thus, it is better to develop a typology of legume farmers based on their current status in technology adoption.

1.3. Research Questions

The study addresses the following major research questions:

1. What are the factors that determine adoption of legume technologies?
2. What is the impact of adoption of haricot bean, chickpea, faba bean and field pea varieties on households' income?

1.4. Objectives of the Study

The main objective of this study was to evaluate the impact of legumes technology adoption on farmers' income in Guraghe zone of Ethiopia.

The specific objectives of the study are to:

- ✓ Identify the determinants of adoption of haricot bean, chickpea, faba bean and field pea technologies.

- ✓ Evaluate the impact of adoption of haricot bean, chickpea, faba bean and field pea varieties on households' income.
- ✓ To identify the typology of farmers based on haricot bean, chickpea, faba bean and field pea producing their current technologies adoption status.

1.5. Significance of the study

Development of agricultural technology by itself is not enough to bring growth of farmers' and improvement in livelihood. There should be an enabling policy environment which creates the condition where farmers have access to improved technologies and also to increase their production and productivity (Sitotaw, 2006). Dealing on adoption of agricultural technology from farmers' livelihood perspective has a significance to draw the clear picture for policy makers involved in development and dissemination of new technologies.

The result of this study could help stakeholders (agriculture offices, development partners, research institutions) to identify the pivotal issue to address the technologies in attaining the ultimate objectives. In addition, identifying determinants which determine success or failure of technology adoption has importance to guide future research. This study expected to point out the main determinants that influence the adoption level.

Technologies to be recommended for adoption should insure the livelihood of farmers. And hence, impact studies enables researcher to identify their end towards the most pressing issues. With this respect, the study shows to what extent adoption of technology influence their livelihood. Once knowing the impact of technology, designing appropriate policy and extension service that is directed towards fostering the adoption level by identifying the potential factors is important. Besides, it is expected that this study would serve as introductory to undertake detailed and comprehensive studies in related scenario.

Therefore, the study of adoption impact and determinants impeding the adoption of legume technology would provide useful insight to policy makers, strategic planners, and administrators in the formulation of appropriate agricultural policy. This study also serves as a springboard for further detail research in legume grain farming.

1.6. Scope of the study

This study was in three district of Guraghe zone, which found in the SNNPR State. Farmers' preference for of legume technology adoption packages is influenced by many factors. During this analysis, factors influencing adoption of legumes technologies with relevancy chemical fertilizer and pesticide by legumes producer of in Gurage Zone were the subject of the study. The study tried to assess that factors adoption of the technology, the intensity of use of the technology within the study area and to look at whether or not technology adoption led to higher financial gain to legume crops growers in Gurage Zone. And here specific issues connected with land use, socio-economic condition of home farms, and therefore the practice of legumes production with reference to the adoption of chemicals like fertilizer and pesticide; and opportunities of using those technologies in enhancing production have assessed. However, since this study is limited to technology adoption, it cannot provide detailed information about other related problems related to rural agriculture of the study area. Lack of adequate historical data is also another problem in this study. The available information also varies in many ways from year to year. In addition to this local problem, lack of related literature about legumes technologies adoption within Gurage Zone agriculture in general and within legumes producers in particular is one of the significant limitations for this study. Therefore, the study has undertaken to fulfill its objectives inside the mentioned constraints.

1.7 Limitations of the study

The study was limited to three districts in Gurage Zone. It was designed in such a way that the sample was representative of the food legumes production potential of the area and yet it can hardly have sufficient external validity given the size of Gurage Zone both agro ecologies heterogeneity of the farming communities within. The study was prepared based on cross-sectional data and hence does not look into the temporal dynamics of adoption of the technologies and the impact thereof. In addition, the impact assessments were limited to improved varieties despite the fact that the remaining technologies are usually recommended as a package.

1.8 Organization of the study

The rest of this thesis is organized in five sections. Section two, dealt with review of literature that includes definitions of concepts of legumes crops, adoption, agricultural technologies adoption, stage of adoption, and theoretical and empirical reviews. Section three has presented methodology with a brief description of the study area, sampling method, and methods of data analysis. The results and discussion more detail in section four. Section five has presented conclusions and recommendation.

CHAPTER TWO

LITERATURE REVIEW

2.1. Definition of Basic Concepts

2.1.1. Definition of leguminous crops

Leguminous crops are sources of protein for humans and animals, vegetable oil for human consumption, for human health, and resources for industries and bio-fuels. They are important forage crops, groundcovers, and timber resources. Legume plants are notable for their ability to fix atmospheric nitrogen, due to a mutualistic symbiotic relationship with bacteria (rhizobia) found in root nodules of these plants. Legumes' nitrogen fixation ability resupplies depleted soil with nitrogen. Usage example: "The use of a leguminous crop, such as alfalfa, can provide a significant amount of nitrogen to subsequent crops in rotation and can replace the application of synthetic nitrogen fertilizer. This means reduced fertilizer cost and reduced fossil fuel consumption to produce the fertilizer". Grain legumes, also called pulses, are plants belonging to the family leguminosae (alternatively Fabaceae) which are grown primarily for their edible seeds. These seeds are harvested mature and marketed dry to be used as food or feed or processed into various products. Being legumes, these plants have the advantage of fixing atmospheric nitrogen for their own needs and for soil enrichment, thereby reducing the cost of fertilizer inputs in crop farming. Crops that are harvested green for forage and for vegetables are excluded, as well as those grown for grazing or green manure. Also excluded are the leguminous crops with seeds which are used exclusively for sowing, such as alfalfa and clover (FAO, 2010).

2.1.2. Impact of Legume

There are several factors that can help explain why the uptake and impact of legume technology is less well documented than is the case for some other major staples. Some are related to the relative importance of legumes and hence the absolute contribution of changes in legume technology and the importance that farmers may accord to opportunities for innovation. A second set of factors is related to the mechanisms for promoting legume technology and particularly the limitations of national seed systems for diffusing new varieties. A third set of factors relates to the way that statistics are collected about legume technology use (Robert Tripp, 2011).

2.1.3. Importance of legumes

Legumes are known to perform multiple functions. Grain legumes provide food and feed, and facilitate soil nutrient management and mitigating climate change. Herbaceous and tree legumes can restore soil fertility and prevent land degradation while improving crop and livestock productivity on a more sustainable basis. Thus cultivation of such dual-purpose legumes, which enhance agricultural productivity while conserving the natural resource base, may be instrumental for achieving income and food security, and for reversing land degradation. Ethiopian farmers' produce different legume crops mainly for food and feed, to fetch cash, and more importantly to restore the fertility of the crop land. Farmers' participation on pulses cultivation in the country has been increased nearly by double from 4.5 to 8.5 million farmers for the last nearly 20 years. Legumes contribute to smallholder income, as a higher-value crop than cereals, and to diet, as a cost- effective source of protein that accounts for approximately 15 percent of protein intake. Moreover, pulses offer natural soil maintenance benefits through nitrogen-fixing, which improves yields of cereals through crop rotation, and can also result in savings for smallholder farmers from less fertilizer use. It also contributes significantly to Ethiopia's balance of payments.

2.1.4. Definition of Adoption

The adoption of an innovation within a social system takes place through its adoption by individuals or groups. According to Feder*et al*. (1985), adoption may be defined as the integration of an innovation into farmers‟ normal farming activities over an extended period of time. Dasgupta (1989) noted that adoption, however, is not a permanent behavior. This implies that an individual may decide to discontinue the use of an innovation for a variety of personal, institutional, and social reasons one of which might be the availability of another practice that is better in satisfying farmers' needs.

Feder *et al*. (1985) classified adoption as an individual (farm level) adoption and aggregate adoption. Adoption at the individual farmers' level is defined as the degree of use of new technology in long run equilibrium when the farmer has full information about the new technology and its potential. In the context of aggregate adoption behavior they defined diffusion process as the spread of new technology within a region. This implies that aggregate adoption is measured by the aggregate level of specific new technology with a given geographical area or within the given population.

Rogers (1983) defines the adoption process as the mental process through which individual passes from first hearing about an innovation or technology to final adoption. This indicates that adoption is not a sudden event but a process. Farmers do not accept innovations immediately; they need time to think over things before reaching a decision. The rate of adoption is defined as the percentage of farmers who have adopted a given technology. The intensity of adoption is defined as the level of adoption of a given technology. The number of hectares planted with improved seed (also tested as the percentage of each farm planted to improved seed) or the amount of input applied per hectare will be referred to as the intensity of adoption of the respective technologies (Nkonya *et al*. 1997).

2.1.5. Agricultural Technology Adoption

The concept of technology adoption could be better conceptualized through understanding the difference between technology adoption and diffusion, which are highly interrelated but distinct concepts. Adoption is related to private utility mechanisms (Feder*et al.,* 1985; Feder and Umali, 1993) and can be defined as "the choice to acquire and use a new invention or innovation" (Hall and Kahn, 2002), whereas "diffusion is the process by which an innovation is communicated through certain channels over time among the members of a social system" (Rogers, 1983).Technology adoption is measured at one point in time while technology diffusion is the spread of a new technology across population over time (Thirtle and Ruttan, 1987).

Rogers (1962) summarized the above definition of technology diffusion using the following four core elements: (1) the technology that represents the new idea, practice, or object being defused, (2) communication channels which represent the way information about the new technology flows from change agents suppliers (extension, technology suppliers) to final users or farmer, (3) the time period over which a social system adopts a technology and (4) the social system. Overall, the technology diffusion process essentially encompasses the adoption process of several individuals or farmers over time. Further, another study by Rogers (1995), defined the rate of adoption (speed of adoption) of a given technology. It is the relative speed with which farmers adopt technology; in this definition consideration is given to the element of a given technology to the farmers. According to Feder *et al*. (1985), adoption can be categorized into individual or aggregate adoption. They defined individual adoption as the degree of use of a new technology in a long-run equilibrium when the farmer has full information about the new technology and its potential, whereas aggregate adoption is defined as the process of spread of a technology within a region. Further, their studies distinguished technologies that are divisible and non-divisible. Divisible technology in terms of resource allocation requires the decision process to involve area allocations as well as levels of use of the rate of application (for instance, improved seed, chemical fertilizer, and herbicide and pesticide). Whereas, technologies that are not divisible in term of resource allocation require how much resource to be allocated to the new and old technologies (for instance: mechanization, irrigation and better farm management practices such as uses of recommended agronomic practices). The application of the concept of adoption in empirical studies, therefore, requires making distinction between technologies which are divisible and non-divisible. This is because often times the nature of the technology dictates the terms on which adoption is conceptualized and analyzed. Therefore, adoption of improved agricultural technologies such as improved variety and/or chemical fertilizer can therefore be categorized as divisible technology, defined as farmers who planted at least one improved maize variety and/or use chemical fertilizer for maize, and non-adopters are those who did not grow any of the improved maize variety and/or used chemical fertilizer in maize farming. Adoption of recommended agronomic practices such as the use of timely planting, cropping system and seed spacing are categorized as a non-divisible technology, measured in terms of the status of use by smallholder farmers for planting.

Rogers (1962) developed a technology adoption model, generalized the use of it in his book entitled as "*Diffusion of Innovations*". He used the model to describe how technology spread in the social system. The technology adoption model describes the adoption or acceptance of a new product or technology. The process of adoption over time is typically illustrated as a classical normal distribution or bell-curve and use the mean and standard deviation to divide the normal adopter distribution categories. The model indicates that the first group of people to use a new product or technology is called innovators, followed by early adopters. Next come the early and late majority, and the last group to eventually adopt a product are called laggards. While explaining each of the categories the study by Rogers (1962) defined as:

Innovators: These are the first individuals to adopt a given technology and hence they are willing to take risks, youngest in age, have the highest social class, have great financial liquidity, are very social and have closest contact with scientific sources and interacting with other innovators.

Early adopters: These are those groups of individuals who are typically younger in age, have a higher social status, have more financial liquidity, advanced education, and are more socially forward than late adopters, which means more discrete in adoption choices than innovators.

Early majority: Individuals in this category adopt technology after a varying degree of time. This time of adoption is significantly longer than the innovators and early adopters. Early majority tend to be slower in the adoption process, have above average social status, contact with early adopters, and seldom hold positions of opinion leadership in a system.

Late majority: Individuals in this category will adopt technology after the average member of the society. These individuals approach technology with a high degree of skepticism, and after the majority of society has adopted the technology. Late majority is typically skeptical about technology, have below average social status, very little financial lucidity, in contact with others in late majority and the early majority, very little opinion leadership.

Laggards: Individuals in this category are the last to adopt a technology. Unlike some of the previous categories, individuals in this category show little to no opinion leadership. These individuals typically have an aversion to change-agents and tend to be advanced in age. Laggards typically tend to be focused on "traditions", likely to have lower social status, lowest financial fluidity, older of all other adopters, in contact with only family and close friends.

2. 2. Theoretical Reviews

Impact assessment is a process of systematic and objective identification of the short and long term effects of intervention on economic, social, institutional and environments. Such effects may be anticipated or unanticipated and positive or negative, at the level of individuals, households, or the organization caused by ongoing or completed development activities such as a project or program (Rover and Dixon, 2007, Omoto, 2003). Impact assessment evaluation is the extent to which a project has caused desired or undesired changes in the intended users. It is concerned with the net impact of intervention on individuals, households, or institutions attributable only and exclusively to that intervention (Baker, 2000). Impact on income is a reward that the owners of fixed factors of production receive as a result of allowing their land, capital, and labor to take part in production.

The very focus of impact analysis was the contrast of adopters to the counter factual non adopters. Therefore, measuring the marginal effect of the adoptions of the new technology over the traditional practice is essential. According to FAO (2000), impact assessment is done for several practical reasons: (1) accountability – to evaluate how well we have done in the past, to report to stakeholders on the return to their investment, and to strengthen political support for continued investment; (2) improving project design and implementation - to learn lessons from past that can be applied in improving efficiency of research projects; and (3) planning and prioritizing - to assess likely future impacts of institutional actions and investment of resources, with results being used in resource allocation and prioritizing future projects and activities, and designing policies.

Technological change is very important in cases where there is limited scope for increasing agricultural production through increased use of input of factors like land (Solow, 1957). There are serious complexities associated with understanding the impact pathway through which agricultural technology adoption might affect household welfare. This is due to the fact that crop production can affect household welfare directly or indirectly. Crop production affects poverty directly by raising the welfare of poor farmers who adopt technological innovation though increased production, lowering cost of production, and improving natural resource management (Janvry et al., 2001).

Impact studies essentially have the same process as technology development itself. It typically does this by comparing outcomes between beneficiaries and control groups (AIEI, 2010).

Since the data for this study was obtained from survey, non experimental impact evaluation design is preferred using propensity score matching method of analysis. According to Rosenbaum and Rubin (1983) and, Heckman et al., (1998), Propensity Score Matching is a non experimental method for estimating the average effect on social programs. The method compares average outcomes of participants and non participants conditioning on the propensity score values. In order to make causal inferences, random selection of subjects and random allocation of treatments to subjects was required. In observational studies, random limitations of an observational study are that there may be random selection of subjects but not random allocation of treatments to subjects. When there is lack of randomization, causal inferences can't be made because it is not possible to determine whether the difference in outcome between treated and control (untreated) subjects is due to treatment difference between subjects on other characteristics.

Programs might appear potentially promising before implementation yet fail to generate expected impacts or benefits. The obvious need for impact evaluation is to help policy makers decide whether programs are generating intended effects; to promote accountability in the allocation of resources across public programs; and to fill gaps in understanding what works, what does not, and how measured changes in well-being are attributable to a particular project or policy intervention (Shahidur et al., 2010).

Estimating the impact of the participation – in this case adoption of legume technologies - requires separating its effect from participating factors, which may be correlated with the outcomes. This task of "netting out" the effect of the program from other factors is facilitating if control groups are introduced. "Control group" consists of a comparable group of individuals or households who did not involve in the program, but have similar characteristics as those participating in the program, called the "treatment group". 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.

2.3. Experimental method and Non-Experimental methods

Experimental method is randomized method, where 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 do not involve in the program. This allows the researcher to determine the participation impact by comparing means of outcome variable for the two groups. In the contrary, non experimental approach is used in cases where program placement is intentionally located. Non experimental methods are frequently used in practice either because program administrators are not too keen to randomly exclude certain parts of the population from an intervention or because a randomized approach is out of context for a rapid-action project with no times to conduct an experiment.

Generally, randomized evaluations seek to identify a program's effect by identifying a group of subjects sharing similar observed characteristics (say, across incomes and earning opportunities) and assigning the treatment randomly to a subset of this group. The non-treated subjects then act as a comparison group to mimic counterfactual outcomes. This method avoids the problem of selection bias from unobserved characteristics. However, the quality of impact analysis depends ultimately on how it is designed and implemented. Often the problems of compliance, spillovers, and unobserved sample bias hamper clean identification of program effects from randomization. In such cases, researchers then turn to non-experimental methods. The basic problem with a non experimental design is that for the most part individuals are not randomly assigned to programs, and as a result, selection bias occurs in assessing the program impact (Shahidur et al., 2010).

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.

A quasi-experimental method is the only alternative when neither a baseline survey nor randomizations are feasible options (Jalan and Ravallion, 2003). The main benefit of quasi experimental designs are that they can draw on existing data sources and are thus often quicker and cheaper to implement, and they can be performed after a project has been implemented, given sufficient existing data. The principal disadvantages of quasi-experimental techniques are that the reliability of the results is often reduced as the methodology is less robust statistically;

the methods can be statistically complex and data demanding; and there is a problem of selection bias.

2.4. Propensity Score Matching

Propensity score matching (PSM) is one of the quasi-experimental methods, which constructs a statistical comparison group that is based on a model of the probability of participating in the treatment, using observed characteristics. Participants are then matched on the basis of this probability, or propensity score, to nonparticipants. The average treatment effect of the program

is then calculated as the mean difference in outcomes across these two groups. The validity of PSM depends on two conditions: (a) conditional independence (namely, that unobserved factors do not affect participation) and (b) sizable common support or overlap in propensity scores across the participant and nonparticipant samples. Different approaches are used to match participants and nonparticipants on the basis of the propensity score. They include nearest neighbor (NN) matching, caliper and radius matching, stratification and interval matching, kernel matching and local linear matching (LLM). Regression-based methods on the sample of participants and nonparticipants, using the propensity score as weights, can lead to more efficient estimates.

PSM is not without its potentially problematic assumptions and implementation challenges. First, PSM requires large amounts of data both on the universe of variables that could potentially confound the relationship between outcome and intervention, and on large numbers of observations to maximize efficiency (Bernard et al., 2010). Second, related to the previous point one can never be entirely sure that it has actually included all relevant covariates in the first stage of the matching model and effectively satisfied the conditional independence assumption (CIA). Furthermore, PSM is non-parametric: that does not make any functional form assumptions regarding the average differences in the outcome. Although the first stage involves specification choices - e.g., functional form like logit and probit, empirical analyses tend to find impact estimates that are reasonably robust to different functional forms. Moreover, if unobservable characteristics also affect the outcomes, PSM approach is unable to address this bias (Ravallion, 2005).

Irrespective of its shortcomings, PSM model was employed to evaluate the impact of adoption (as a binary treatment variable) on the income of household because it is very appealing to evaluators with time constraints and working without the baseline data that it can be used with a single cross-section of data.

2.5. Generalized propensity score matching:

Currently, propensity score matching methods are extended to be applied in settings with continuous treatments, where the focus is on assessing the heterogeneity of treatment effects arising from different treatment levels, that is, different amount of intensity of adoption of improved legume varieties. Generalized Propensity Score (GPS) or Dose Response Function is a continuous treatment estimator developed by Hirano and Imbens (2004).The GPS method relies on the assumption that selection into different levels of adoption of legume technologies is random, conditional on observable characteristics (unconfoundedness) which could be important determinants of intensity of adoption. In this study, generalized propensity score matching was employed to assess the impact of intensity of adoption legume varieties (adoption as continues treatment variable) on the adopter households by discarding non-adopter from the model.

After this study to shows that the difference between adoption of legumes technologies adopters and none adopters based on annual income & income from legumes crops. According to this the number of legumes technologies adopter increase then after agricultural production & productivity increases.

2.6. Empirical Review literature

As is the case in many developing countries with an agrarian economy, agricultural technology adoption has got a number of processes. It has both spatial and temporal dimension. It is argued that technology adoption is not a one of static decision rather it involves a dynamic process in which information gathering, learning and experience play pivotal roles particularly in the early stage of adoption and diffusion (Assefa and Gezaghegn, 2010).

Technology can be adopted when it is found to be beneficial while dropped over time if loss is entertained due to increasing cost of inputs, falling of yields or shift to other more profitable technology (Dinar and Yaron, 1992). There are various reasons that brought agricultural technologies to be adopted or brought for failed to do adoption. Quite much of the studies have been generated on determinants of technology adoption both domestically and internationally. Farmers move from learning to adoption to continuous or discontinuous use over time. The characteristics of both the user and the technology are important in explaining adoption behavior and the pathway for adoption. The lag between learning and adoption, and the possibility of discontinuation imply that a longer period will be required for the majority of farmers to use the technology than if adoption was a one off decision leading to continuous use. This picture has been clearly demonstrated by the adoption process of the technology in the four regions of Ethiopia considered in this study.

The study conducted in Ethiopia and western Kenya using probit analytical model shows that gender, agro-climate zone, manure use, hired labor and extension service has a significant effect towards adoption of improved seed and fertilizer (Salasya et al., 1998, Cropenstedt et al., 2003). On the other hand a study conducted in the coastal low lands of Kenya shows that non availability and high cost of seed, unfavorable climate conditions, perception, and insufficient soil fertility has a negative and significant effect on adoption of technology.

The study conducted in Morena district of India, on wheat production, found that knowledge of farmers which may be acquired through education, training, and availability of information and the credit facility has a significance positive contribution to the adoption of improved technology (Kansana et al., 1996). Nkonya et al.,(1997), analysis factors affecting adoption of improved maize seed and fertilizer in Northern Tanzania indicated that farm size, education and frequency of visits by extension agents significantly and positively influenced maize seed adoption where as the factors such as farmers' age, family labor and yield variability have not significantly influenced improved maize seed adoption. Batz et al., (1999) a study conducted in Meru district of Kenya to find out factors affecting rate and speed of adoption of technology, less risky technology is preferable and easily adopted.

Misfin (2005), on his study carried out to determine factors influencing adoption of triticale in Farta wereda of Amhara region using Logistic regression model, maximum likelihood estimation procedure, traced that distance to market center, distance to all weather road, access to leased-in land, perception about superiority of yield of triticale, livestock holding, off/non farm income and input price were found to influence farmers adoption decision of triticale (wheat crop). According to Yanggen et al., (1998), in Africa fertilizer application is determined by human capital (basic education, extension and health); financial capital (income, credit and assets); yield response (bio-physical technology and extension), basic services (infrastructure and quality control) and input output price (structure conduct and performance of subsector, competition and equity).

Foyed et al., (1999), in a study of adoption and associated impact of technology; conducted in the western hill of Nepal draw that a balanced investment in research and extension is needed to ensure adoption at the household level. The study found that the typical reason for failing of adoption is either lack of know how or supply of the technological inputs. So, in conditions where official sources are not available, farmer to farmer interaction is important. Farmer to farmer information flow can be built on by extending by the involvement of farmers in technology development and by developing methods that enables to enhance their current roles in technology dissemination.

Yu et al., (2011), in a study conducted on cereal technology adoption in Ethiopia, to examine the extent of adoption of fertilizer seed technology package and factors affecting the adoption of same using nationally representative secondary data, found that variables affecting the adoption of the new technology, like access to extension service, the level of adoption at the district level, and the experience of farmers using fertilizer in other crops, have a significant effect on the probability of accessing fertilizer and improved seed by farmers. Specialization, together with wealth and risk aversion, also plays a major role in explaining crop area under fertilizer, which should be related to better access to technology-related knowledge.

According to Feder et al., (1982) the conventional explanations for the sequential adoption process are: lack of credit, limited access to information, aversion to risk, inadequate farm size, and inadequate incentive associated with farm tenure arrangements, insufficient human capital, absence of equipment to relieve labor shortage, and inappropriate transportation infrastructure. Hailu (2008) used the probit and Tobit models to examine factors influencing adoption and intensity of teff technologies in Ethiopia. The study revealed that farmers education level, frequency of DA officer visits, credit availability and knowledge of farmers have positive influence towards technology adoption and adoption intensity whereas variables like age of farmers, number of family labor, frequency of risk were inhibiting adoption of technology.

Saha et al., (1994) divide the adoption process into three stages: information collection, decision on whether or not to adopt, and decision on how much to adopt. Filho (1997) applied both probit and logit models and duration analysis to explain the maize growers' behavior in the adoption of new technologies. He found that both economic (such as yield level, income, and cost of adoption) and non-economic (such as behavior of adopters' factors influences a farmer's decision to adopt the new technologies of maize. It shows that decision to adopt the sustainable technologies for maize is positively related to his/her contact with government/non-government organizations, the farmer's understanding of the negative effect of chemicals, the available labor force in the family and the soil fertility. Filho (1997) further concludes that the adoption is negatively related to farm size. According to Foster and Rosenzweig (1996), agricultural technology adoption decision was seriously been determined by imperfect information, risk, uncertainty of institutional constraints, human capital, input availability and infrastructural problems.

The study by Degye (2013) in Eastern and Central highlands of Ethiopia identified the determinants of adoption of chemical fertilizer, high yielding crop varieties and improved livestock breeds and their interdependence by using multivariate probit model. The results verify that adoptions of these three agricultural technologies were significantly interdependent of each other. Uses of chemical fertilizer were positively affected by use of irrigation water, gross agricultural income, distance to research institution and farming system. Whereas the adoption of high yielding variety were positively determined by land allocated to cash crops, gross agricultural income, distance to research institution and farming system; where adoption of improved livestock breeds were positively affected by amount of cultivated land and distance to research institution while it negatively affected by farming experience of household and distance to nearest road.

Similar studies were also done on factors affecting the adoption and intensity of use of improved forages in South Wollo, north east highlands of Ethiopia by Hassen (2014), using the double hurdle model. The finding of this study suggests that the likelihood of adoption were enhanced by age of household head, ownership of livestock, and access to credit and extension service. Where farm size, off/non-farm income, distance to all weather roads and markets, distance to input and credit offices were found to adversely affecting the likelihood of adoption of improved forages. The intensity of adoption of improved forages was enhanced by sex of household head [being male], labor availability, and farm size where it is adversely affected by household size, off/non-farm income, distance to all weather roads and markets and distance from development agent office. Similarly, the study by Abreham and Tewodros (2014) identified level of education, social participation, access to credit, labor availability, farm size, achievement motivation and market distance as the major socio economic factors that affect the intensity of adoption of coffee in Yerga Cheffe District in Gedeo Zone of SNNP Regional State of Ethiopia by using Tobit model.

Using Logit model, Debelo (2015) assessed factors influencing adoption of Quncho tef in Wayu Tuqa district of Ethiopia. Results revealed that family labor availability, participation of farmers in agricultural trainings, education level of the household head, livestock holding (TLU), farmer's ability of meeting family food consumption and frequency of extension contact were enhancing the decision to adopt Quncho teff. In this study, age of household head, owning oxen and distance from household residence to market center was found to influence adoption of Quncho tef negatively.

Similarly, Berihun et al. (2014) examined the determinants of adoption of chemical fertilizer and high yielding varieties in Southern Tigray Ethiopia by using Probit model. Sex of household head, land ownership, use irrigation, access to credit, contact with extension worker and participation in off farm activities were found to be positively affecting the adoption of chemical fertilizer, whereas plot distance, distance to the nearest market and livestock holding affected the adoption negatively. The adoption of high yielding varieties was positively affected by land ownership, access to credit, use of irrigation and livestock holding where as it is negatively affected by age of household head and distance to the nearest market.

As discussed above, the empirical evidence on the adoption and its determinant in Ethiopia generally indicate that the adoption rate of agricultural technologies was relatively low with considerable personal and spatial heterogeneities. They suggest that the rate and intensity of adoption of agricultural technologies is notably influenced by socioeconomic factors such as livestock holding, farm size, active family member and so on and other organizational factors such as access to credit, input and output market, agricultural extension services etc. Even though there are many adoption studies throughout Ethiopia, there is a clear bias towards major cereal crops or key cash crops within the geographic scope of the crops' ideal agro-ecologies. Unlike previous studies, this study focuses on estimating the determinants of adoption of legume technologies on farmer's income in Guraghe Zone of Ethiopia where legumes are not the dominant crops. In addition, most of the studies above were in locations with entirely different socioeconomic and biophysical features compared to Guraghe Zone.

In general, the above reviewed study shows that most of the researchers focused on improved seed and chemical fertilizers, improved seed varieties based on agro climates it depends on these variables positively and negatively significantly influence. These researchers the study of technology adoption more focus improve seed varieties & chemical fertilizers or improve seed varieties and other technologies were separately used. Technologies mean dynamics to change over times. The best of my special attention technology adoption as a full package means, improve appropriate seed varieties, appropriate chemical fertilizer application, row planting based on spacing , integrated pest management (IPM), proper agronomy management to be done from site selection up to storing on time used on each household level, both agricultural practices incorporate as packaging form but not separately use . Those practices always to be done appropriate time because one of miss the technologies component fails the new technologies.

2.7. Conceptual Framework

The conceptual framework of adoption and impact of legumes technologies on the welfare of farm households starts with identification of the driving factors for adopting improved agricultural technologies. These factors include external dynamics (environmental factor, for example, like unfavorable weather condition, land degradation, erratic rainfall, and low fertility status of land), demographic characteristics of the household (e.g. age, education level etc.) and other social and institutional factors (availability of new information, availability of new technology, availability of credit etc.).

Then after, adoption of legume technologies is expected to have considerable economic advantage in terms of increase in yield, increase in marketable surplus of farm households and ultimately in reducing food security and poverty.

Diagram on conceptual framework

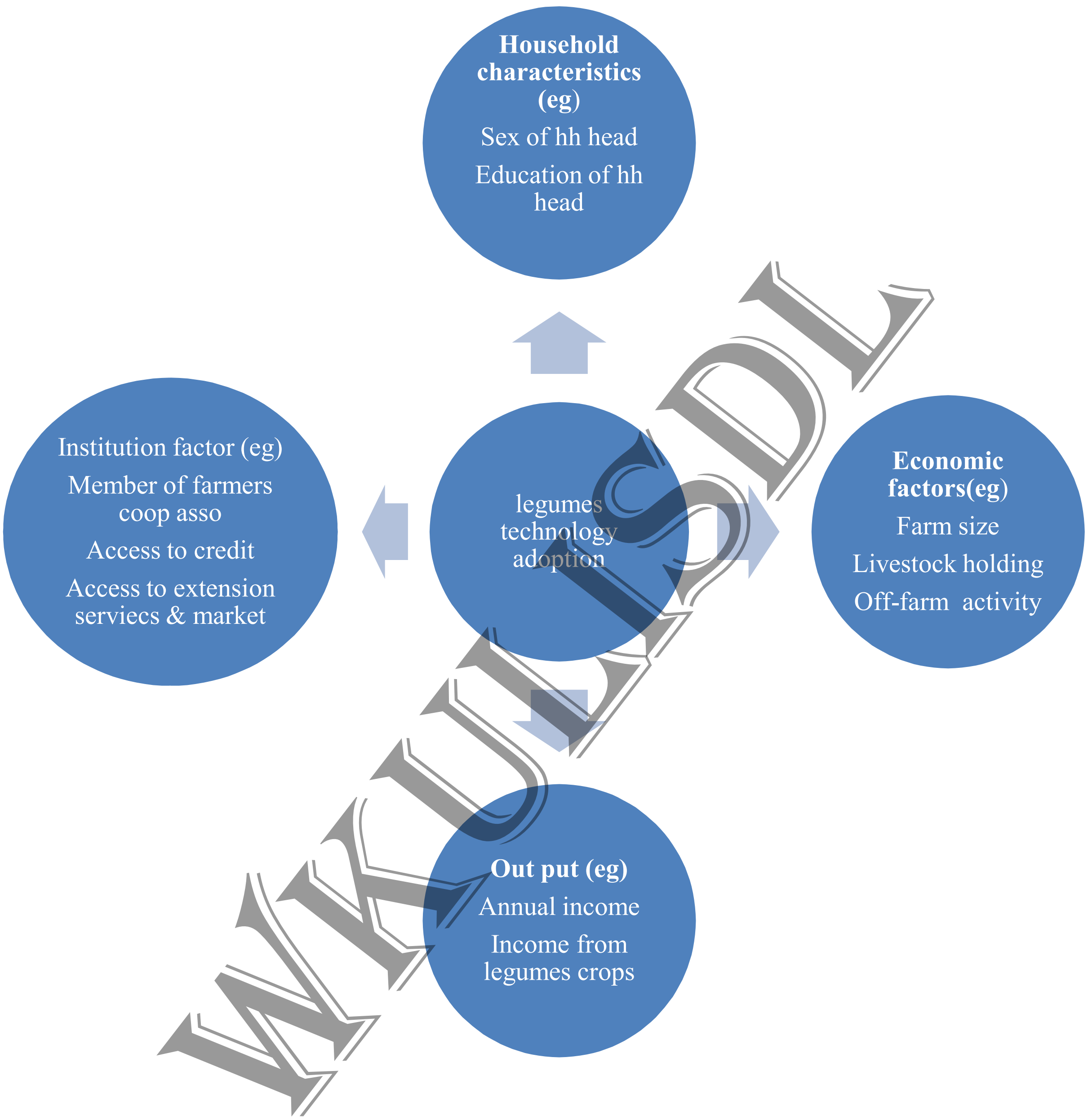


Figure 2.1 Diagram on conceptual framework

Source own computation survey data 2019

CHAPTER THREE

RESEARCH METHODOLOGY

3.1. Description of the Study Area

Gurage Zone is one of the 15 administrative Zone including Hawassa city and 4 special woreda in Southern Nations, Nationalities, and Peoples' Region (SNNPR) state in south- Western Ethiopia situated at 8˚10N 38˚15E. It has 13 districts and two towns. Guraghe is bordered on the Southeast by Hadiya and Yem special woreda, on the West, North and East by the Oromia Region, and on the South east by Silt'e CSA (2009).

The altitude in Guraghe zone ranges from 1000 to 3600 m.a.s.l. The Zone has four agro-ecological zones essentially based on altitude, namely extreme highlands (above 3000 m.a.s.l), highland (2300 to 3000m.a.s.l), midland (1800 to 2300 m.a.s.l), and lowland (below 1800 m.a.s.l) covering 4.1%, 27.5%, 65.3%, and 3.1% of the zone, respectively. The natures of topography in the zone exhibit, broadly speaking, three categories: The mountainous highland represented by the Guraghe mountain chain, dividing the zone east to west, having an elevation of 3600Mts. The plateau flat lands, the area covered by "Amora and Ambusa meda". The low stretching area, the western fringe of the rift valley and the Wabe Gibe valley having an elevation of 1000Mts.The area receives an average annual rainfall of 700-1600mm and minimum and maximum temperature of 7.5^{o}C and 32^{o}C, respectively GZFEDD, annually socio economic report (2017).

Total area of Guraghe zone is about 5893 square kilometers accounting for 5.6 % of SNNPRG. Only about 73.64 % of the zone is arable land under crop production, whereas 11.85% is grazing land, 11.74% covered with forest, and the remaining 3.77% of the zone is under other land use forms (GZANRDD, 2017). The districts in the Guraghe zone are known for their bimodal rainfall pattern and hence highly suitable for agriculture. They have two distinct seasons; i.e, Belg (from March to June) and Meher (from July to January).

According to GZFEDD report (2017) the zone has estimated total populations of about 1,724,324 out of which about 836,896 are male and 887,428 are female. Out of total population of the zone, more than 93.76% is dependent on agriculture and 87.76% lives in rural areas. Major crops grown in the zone are wheat, maize, teff, barley, faba bean (Vicia faba), field pea (Pisum sativum), chickpea, haricot bean, sorghum and Enset (Ensetumventricosum), Peper, coffee and are also grown in the zone the location of map shows (Appendix I.13) .

3.2 Sampling Techniques and Procedures

In this study, three stage sampling technique was employed. First, major legume producing districts in Gurage zone based on legumes production potential and suitable agro ecologies for legumes growers were identified with the help of as key informants to use in Gurage Zone Agricultural and Natural Resource Development Departments through many times experienced. At this stage, three major legume producing districts were selected purposively. The districts were Abeshge, Gumer and Sodo based on relative importance of legumes in the crop production system. Then, three kebeles were randomly selected from each district. Accordingly, Mida Tedele, Bido Tedele, and Abiko Kebles were selected from Abeshge district. Abesuja, Esen, Dirbo and Sunen Kebeles were selected from Gumer district. Similarly, Sewaty geda, Wudget and Wacho kebeles were randomly selected from Sodo district. Finally, out of total 9 kebles a sample of 102 household headed legumes technologies adopter and 102 non adopter random selected based on each kebele agriculture development agent through past time recorded data 204 farm households in total 78, 88 and 38 sample households from Abeshge, Gumer and Sodo, respectively- were selected proportionately across kebeles based on their total households. Ordinarily multi-stage sampling is applied in big inquires extending to a considerable large geographical area, say, the entire Gurage Zone. There are two advantages of this sampling design viz., (a) It is easier to administer than most single stage designs mainly because of the fact that sampling frame under multi-stage sampling is developed in partial units. (b) A large number of units can be sampled for a given cost under multistage sampling because of sequential clustering, whereas this is not possible in most of the simple designs. This sample size represent in the target populations, Research methodology methods and techniques C.R.KOTHARI (1990). Table3.1 shows the distribution of the sample households across the three Kebeles in each of the districts.

Table.3.1 Sample distribution

District	Kebele	Number of household	Adopter	Non adopter	Number of sample household	Total (%)
Sodo			**19**	**19**	**38**	**18.63**
	Sewaty geda	311	5	6	11	5.392
	Wudget	366	6	6	12	5.882
	Wacho	451	8	7	15	7.353
Abeshge			**39**	**39**	**78**	**38.24**
	Mida tedele	1160	20	20	40	19.61
	Bido tedele	810	14	14	28	13.73
	Abiko	300	5	5	10	4.9
Gumer			**44**	**44**	**88**	**43.13**
	Abesuja	862	14	15	29	14.21
	Esen	1200	21	20	41	20.1
	Dirbo & sunen	534	9	9	18	8.82
			102	**102**	**204**	**100**

3.3 Types and method of data collection

Both qualitative and quantitative types of data were collected from primary and secondary sources. The study was started with a series of short visits to the study sites for rapport development with the key actors in the legumes development continuum. Then a reconnaissance survey was conducted with a brief checklist to identify and document the key socioeconomic and biophysical features of the study area and major challenges and opportunities of improved legume production and marketing. The visits and the preliminary surveys were used, among others, to develop the instrument for the formal survey of the study.

The primary data were obtained by the use of semi-structured questionnaires by interviews with the farm households. The adoption and impact survey was carried out from first week of December to January 30 of 2018. The data were collected by enumerators (Agricultural staff experts and development agents under supervision of the researcher. In order to facilitate data collection, the enumerators were trained regarding the objectives of the study, content of the questionnaire, and data collection procedure.

Data were collected on several issues including households' demographic characteristics, asset endowments, importance of legumes, access and adoption of legume technologies, household income and its source, access to market, access to credit and membership in different rural institutions.

3.4 Pre-Testing (Validity and reliability)

To ensure validity and reliability of the research instrument, the researcher will ensure that the Questions that are asked are in conformity with the research objectives of the study and a pilot test of the research instrument will be conducted and a calculation using office Microsoft excel will be computed for question reliability and validity assessment

3.5 Method of Data Analysis

The data collected was analyzed using both descriptive statistics and econometric model. Descriptive statistics includes mean, standard deviation (SD), frequency, percentage, graph and tabular representation, which has been mostly used to examine the socio economic and farming characteristics of households.

3.6 Econometric model

The legumes technology adoption being used, a farmer's was taken as an adopter if he or she sows certified improved seed use, chemical fertilizer application, IPM and row planting; either independently or both with their indigenous seeds and manure. The dependent variable, technology adoption, has the value of 1 for adopters and 0 for non-adopters. In this regard an econometric model employed while examining probability of farm households' agricultural technology adoption decision was the logit model. Often, logit model is imperative when an individual is to choose one from two alternative choices, in this case, either to adopt or not to adopt. Hence, an individual i makes a decision to adopt legumes technologies if the utility associated with that adoption choice (V_{1i}) is higher than the utility associated with decision not to adopt (V_{0i}). Hence, in this model there is a latent or unobservable variable that takes all the values in ($-\infty$, $+\infty$). According to Alexander Spermann (2009) these two different alternatives and respective utilities can be quantified as: $Y_i^* = V_{1i} - V_{0i}$ and the econometric specification of the model is given in its latent as:

We start by deriving the odds ratio in a way that makes explicit the relationship between the estimated logit parameters β and the error term ε_i: - Suppose that a continuous latent variable y_i^* can be modeled as a linear function of K explanatory variables (covariates), x_{ki} , for k= 1,…,k for individuals i= 1…N. The equation for y_i^* can be written as

$$y_i^* = \beta_0 + \beta_1 x_{1i} + \beta_2 x_2 + \ldots\ldots + \beta_{ki} x_i + \varepsilon_i \qquad 1$$

If we allow the explanatory variables, including the constant term, to be represented by the vector x_i', then equation 1 can be represented in matrix notation as

$$y_i^* = x_i \beta + \varepsilon_i \qquad 2$$

However, the researcher observes only the explanatory variables and a binary (0, 1) variable y_i, which indicates whether y_i^* exceeds the threshold of zero

$$y_i = \begin{cases} 1\ if, y_i^* > 0 \\ 0\ \ otherwise \end{cases} \qquad 3$$

To make statements about the probability that $y_i = 1$ (or equivalently, y_i^* >0 we need to express the probability in terms of on error term with a known distribution. Substituting $x_i' \ \beta + \varepsilon_i$ for y_i^* allow us to write the probability that $y_i \ > 0$ in terms of the probability that the error term takes on a range of values

$$\Pr(y_i^* > \frac{0}{x_i}) = pr(x_i\beta + \varepsilon_i > \frac{0}{x_i}) = pr(x_i > -\frac{x_i'\beta}{x_i}) \qquad 4$$

If the error term has term has mean zero and is symmetric (which is true for the standard logstic and standard normal distributions) then

$$pr(y_i = \frac{1}{x_i}) = pr(y_i^* > \frac{0}{x_i}) = pr(\varepsilon_i < \frac{x_i'\beta}{x_i}) \qquad 5$$

Equation 5 holds for any arbitrary scaling of ε and β (eg; $\frac{\varepsilon}{3}$ and $\frac{\beta}{3}$). Thus, because the distribution of ε is unknown, the$pr(y_i = \frac{1}{x_i})$ cannot be evaluated without an additional step (Greene and Henser, 2010). To address that problem, the typical solution is to divide both ε and β by the standard deviation of ε: ε/σ and β/σ. Those transformations makes $Pr(y_i = \ \frac{1}{x_i})$ a cumulative distribution function (CDF) of a standard logistic (logit) variable, which is easy to calculate for logistic.

For the logit model, the standard deviation of $\frac{\varepsilon}{\sigma} = \frac{\pi}{\sqrt{3}}$ the cumulative distribution function for logit model is

$$pr(y_i = \frac{1}{logisic, x_i}) = pr(\frac{\varepsilon_i}{\sigma} < x_i \frac{\beta}{\sigma}) = \frac{1}{1 + \exp(-x_i' \frac{\beta}{\sigma})} \qquad 6$$

This derivation explicitly shows the important role of σ in making any statements about probabilities.

Many researchers prefer to estimate logit rather than probit models because of the odds ratio interpretation of the logit coefficients. The odds for individual i are expressed as the ratio of the probability $p_i$to 1− p_i where $p_i = Pr(\, y_i = 1|logistic, x_i)$.

$$odds = \frac{p_i}{1-p_i} = \exp\,(x_i' \ \frac{\beta}{\sigma}) \qquad 7$$

The odds ratio is the ratio of the odds in equation 7 for two different values of an explanatory variable. This is easiest to derive for a binary variable. Let $legumes\ technologies\ adoption1_i$ the indicator for adoption status and $\beta adopter$ be the corresponding coefficient the odds if individual $i$was $a\ adopter$ ($legumes\ technologies\ adoption1_i = 1$) and odds if individual i was $a\ non\ adopter$ ($legumes\ technologies\ adoption\ 1_i = 0$) are:

$$Odds\ for\ adopter = \exp\,(\frac{\beta_0+\beta_{adopter\ 1i}+\beta_2 x_2+\cdots\beta_k x_{ki}}{\sigma}) \qquad 8$$

$$odds\ for\ non\ adopter = \exp\,(\frac{\beta_0+\beta_2 x_{2i}+\cdots+\beta_k x_{ki}}{\sigma}) \qquad 9$$

Therefore, the odds ratio is the ratio of the odds, which simplifies to the exponentiated

Coefficient.

$$odds\ ratio\ = \frac{odds\ for\ adopter}{odds\ for\ non\ adopter} = \exp\,(\frac{\beta_{adopter}}{\sigma}) \qquad 10$$

X' is vectors of exogenous variables that explain adoption of legumes technologies adopter (e.g. age of household head, sex of the household head, education, membership to an agricultural association, access to credit, etc). Therefore, on the basis of dependent variables indicated: legumes technologies adoption, logit model was applied independently for each binary dependent variable;

Given below

$Y = a + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6 + \beta_7 x_7 + \beta_8 x_8 + \beta_9 x_9 + \beta_{10} x_{10} + \beta_{11} x_{11} + u_i$ ……………. (1)

Where Y, is the dependent variable that is measures the level of adoption legumes technologies.

X_1- Access to credit

X_2- Extension Agents' Contact

X_3- Technology access (access to improved seed/DAP fertilizer)

X_4-Market access of product

X_5-Tropical Livestock Unit

X_6- Education level

X_7- Membership to an Association

X_8 -Gender of household head

X_9 - Land Size for cultivation purpose of household headed

X_{10}- Plot size for legumes crop for cultivation purpose of household headed

X_{11} Off-Farm Participation

α-The constant term (intercept)

β_i- regression parameter for the it explanatory variables which indicates the slope of the predictor variable u_i= the error term of the model.

3.6.1. Propensity Score Matching Method (PSM) for impact analysis

Impacts are discreet (usually binary) variables. Treatments are heterogeneous in the population (Heckamn et al., 1997. Robin 1997), developed a framework that each household has two potential outcomes; an outcome when adopting technology (y_1) and not adopting technology (y_0). If we let the adoption status d, d=1 for adoption of technology and d=0, for not adoption, then it is possible to write the observed outcome y of the household performance as a function of the two potential outcomes as

$$Y = dy_1 + (1 - d)y_0 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..(1)$$

The causal effect of the adoption on its observed outcome y is the difference between the two outcomes (y_1-y_0). But because of the realization, the potential outcomes are mutually exclusive that is only one of the two outcomes has been observed at a time (Nguezet et.al, 2011). It is also impossible to measure the individual effects of adoption in any household. However, it can be possible to estimate the mean effect of adoption on a population household. Such mean parameter is called average treatment effect (ATE) (Imben and Wooldridge, 2009).

$$\text{ATE}= \frac{1}{n}\sum_{i=1}^{1}\frac{Di-(p(xi)yi}{p(xi)(1-p(xi)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

Where n is the sample size, n1=$\sum di$, is the number of treated variable i.e. the number of seed fertilizer technology adopting farmers and p(xi) is a constant estimate of propensity score evaluated at x. It is possible to employee logit specification to estimate the propensity score. Propensity score matching pursues a targeted evaluation of whether adopting a modern seed - fertilizer technology causes farmers to improve their performance. There will be problem of avert and hidden biases and deal with the problem of noncompliance or indigenous treatment variable. In order to remove such biases Robin (1974) introduces ignorablity (conditional) assumption which postulates, the existence of a set of covariate x, which controlled for renders the treatment outcomes (y_1 and y_0). The estimation using the conditional independent assumption) or they are based on a two stage estimation procedure, conditional probability of treatment called propensity score. From this we can develop two interrelated stages:

Estimating the propensity score- The first step in PSM method is to estimate the propensity scores by using logit models. Caliendo and Kopeinig (2008) noted that the logit model which has more density mass in the bounds could be used to estimate propensity scores, P(x) using a composite characteristics of the sample households and matching will then be performed using propensity scores, p-score, of each observation. Matching algorism will be selected based on the data to be collected after undertaking matching quality test. Overlapping condition or common support condition will be identified, estimating the average treatment effects of both outcomes (ATE1 and ATE0) after estimation of the propensity scores, seeking an appropriate matching estimator is the major task.

There are various matching estimators, which include the nearest neighbor matching, caliper and radius matching, stratification and interval matching, kernel and local linear matching (Caliendo and Kopeinig, 2008).The treatment effects will be estimated based on matching estimators selected on the common support region (owusu and Awudu, 2009).The average treatment effects can be estimated using the inverse propensity weighing estimates as stated in IPSW (Nguezet,, 2011) using matching techniques of Kernel Matching (KM), Nearest Neighbor Matching (NNM) and Radius Caliper Matching (RCM).

3.6.1.1. Nearest Neighbor Matching

Caliendo and Kopeinig (2008) said that NN matching is the most straightforward and frequently used matching estimator in PSM. The individual from the control group is chosen as a matching partner for a treated individual with the least distance in terms of propensity score (Becker and Ichino, 2002). Several variants of nearest neighbor matching are proposed, e.g. NN matching 'with replacement' and 'without replacement'. In the former case, an untreated individual can be used more than once as a match, whereas in the latter case it is considered only once. Matching with replacement involves a trade-off between bias and variance. If we allow replacement, the average quality of matching will increase and the bias will decrease while increasing the variance. This is of particular interest with data where the propensity score distribution is very different in the treatment and the control group. A problem which is related to nearest neighbor matching without replacement is that estimates depend on the order in which observations get matched. Hence, when using this approach, it should be ensured that ordering is randomly done. It is also suggested to use more than one nearest neighbor matching. Reduced variance will result from using more information to construct the counterfactual for each participant, with increased bias that results from on average poorer matches (Caliendo and Kopeinig, 2008).

3.6.1.2. Caliper Matching:

To avoid the problems of bad matches resulted from the Nearest Neighbor matching; economists impose a tolerance level on the maximum propensity score distance (caliper). Imposing a caliper works in the same direction as allowing for replacement. Bad matches are avoided and hence the matching quality rises. However, if fewer matches can be performed, the variance of the estimates increases. Applying caliper matching means that an individual from the comparison group is chosen as a matching partner for a treated individual that lies within the caliper ('propensity range') and is closest in terms of propensity score (Caliendo and Kopeinig, 2008).

Dehejia and Wahba (2002) suggest a variant of caliper matching which is called radius 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.

3.6.1.3.Kernel Matching

With Kernel matching, all treated groups are matched with a weighted average of all control groups with weights that are inversely proportional to the distance between the propensity scores of treated and control (Becker and Ichino, 2002). But the matching algorithms discussed so far have in common that only a few observations from the comparison group are used to construct the counterfactual outcome of a treated individual. Kernel matching is a non-parametric matching estimator use weighted averages of all individuals in the control group to construct the counterfactual outcome. Thus, one major advantage of this approach is the lower variance which is achieved because more information is used. Caliendo and Kopeinig (2008) concluded that like other matching algorithms, Kernel matching has also its own drawbacks that arise from the nature of the matching algorithm. The major drawback of this method is the possibility of inclusion of observations with a very low and high propensity scores and may give bad matches. Hence, the proper imposition of the common support condition is of major importance for Kernel matching. To apply Kernel matching one has to choose the bandwidth parameter. The choice of the bandwidth parameter is quite pertinent with the following trade-off arising: High bandwidth-values yield a smoother estimated density function, therefore leading to a better fit and a decreasing variance between the estimated and the true underlying density function. On the other hand, underlying features may be smoothed away by a large bandwidth leading to a biased estimate. The bandwidth choice is a compromise between a small variance and an unbiased estimate of the true density function and it may not be a predetermined issue (Habtamu, 2010).

The question remains on how and which method to select. Clearly there is no single answer to this question, Bryson et al. (2002) stated the choice of a given matching estimator depending on the nature of the available dataset that is it depends on the data in question, and in a particular on the degree of overlap between the treatment and comparison groups in terms of propensity score. 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. When there is a substantial overlap in distribution of propensity score between the comparison and treatment groups, most of the matching algorithms will yield similar results (Dehejia and Wahba, 2002).

Dehejia and Wahba (2002) also stated that a matching estimator which balances all explanatory variables (i.e., results in insignificant mean differences between the two groups), a model which bears a low pseudo R^2 value and results in large matched sample size is a preferable matching algorism. So, for this study among matching algorithms, kernel matching with bandwidth of 0.1 was found to be the best matching estimator for the data at hand and based on matching quality criteria.

Treatment effect on the treated: To estimate the effect of technology adoption to a given outcome (Annual income per household), is specified as:

$\tau ATT = Y_i (D_i=1) - Y_i (D_i=0)$………………………………..4

Where τ_i is treatment effect (effect due to adopting farm inputs), Y_i is the outcome on household i, D_i is whether household i has got the treatment or not (i.e., whether a household using farming technology or not). However, one should notice that Yi (di=1) and Yi (di=0) cannot be observed for the same household at the same time. Depending on the position of the household in the treatment either Yi (di=1) or Yi (di=0) is unobserved outcome (counterfactual outcome). Due to this fact, estimating individual treatment effect τ_i is not possible and one has to shift to estimate the average treatment effects of the population than the individual one. Two treatment effects are most frequently estimated in empirical studies (Dillon, 2008). The first one is the (population) Average Treatment Effect (ATE), which is simply the difference of the expected outcomes after using a technology or not:

$\Delta Y_{ATE} = E(\Delta Y) = E(Y_1) - E(Y_0)$ …………………………..5

This measure answers the question what would be the effect if households in the population were randomly assigned to treatment. But this estimate might not be of importance to policy makers because it includes the effect for which the intervention was never intended (Dillon, 2008). Therefore, the most important evaluation parameter is the so called Average Treatment Effect on the Treated (ATT), which concentrates solely on the effects on those for whom the interventions are actually introduced. In the sense that this parameter focuses directly on those households who participated, it determines the realized impact of improved farm input usage and helping to decide whether participation on technology is successful or not. It is given by:

$\tau_{ATT} = E(\tau/D=1)=E(Y_1/D=1)-E(Y_0/D=1)$ ……………………………6

This answers the equation, how much did households using farming technology benefit compared to what they would have experienced without using. Data on E (Y_1/d=1) are available from technology users. An evaluator's classic problem is to find E (Y_0/d=1). So the difference between E (Y_1/d=1) - E (Y_0/d=1) cannot be observed for the same household. Due to this problem, one has to choose a proper substitute for it in order to estimate ATT. The possible solution for this is to use the mean outcome of the comparison individuals, E (Y_0/d=0), as a substitute to the counterfactual mean for those being treated, E (Y_0/d=1) after correcting the difference between treated and untreated households arising from selection effect. Thus, by rearranging, and subtracting E (Y_0/d=0) from both sides of equation (6), one can get the following specification for ATT.

$E(Y_1/D=1)-E(Y_0/D=0) = \tau ATT+ E(Y0/D=0)$……………………………7

Both terms in the left hand side are observables and ATT can be identified, if and only if E (Y0/d=1)-E (Y0/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 (Caliendo and Kopeinig, 2008; Dillon, 2008). In non-experimental studies one has to introduce some identifying assumptions to solve the selection problem. The following are two assumptions to solve the selection problem.

Assumptions:

Assumption1: **Conditional Independence** (un confoundedness): There is a set X of covariates, observable to the researcher, such that after controlling for these covariates, the potential outcomes are independent of the treatment status

$(Y_1, Y_0) \perp D/X$

The potential outcomes are independent of the treatment status, given X. Or, in other words after controlling for X, the treatment assignment is "as good as random." This property is also known as unconfoundedness or selection on observables. The CIA is crucial for correctly identifying the impact of participation, since it ensures that, although treated and untreated groups differ, these differences may be accounted for in order to reduce the selection bias. This allows the untreated units to be used to construct a counterfactual for the treatment group (Heinrich et al., 2010).

Assumption 2: Common support (Overlap): This assumption rules out perfect predictability of d given X. That is

$0<P\ (D=1/X)<1$ ………………………………………..8

This equation implies that the probability of receiving treatment for each value of X lies between 0 and 1. By the rules of probability, this means that the probability of not receiving treatment lies between the same values. Then, a simple way of interpreting this formula is the following: the proportion of treated and untreated individuals must be greater than zero for every possible value of X (Caliendo and Kopeinig, 2008; Heinrich et al., 2010). The second requirement is also known as overlap condition, because it ensures that there is sufficient overlap in the characteristics of the treated and untreated units to find adequate matches (or a common support). When these two assumptions are satisfied, the treatment assignment is said to be strongly ignorable (Rosenbaum and Rubin, 1983). Given the above two assumptions, the PSM estimator of ATT can be written as:

$\tau_{ATT}=E\ (y_1-y_0/D=0,P(X))=E(y_1/D=1,P(X))-E(y_0/D=0,P(X))$

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

Estimation of standard error: Testing the statistical significance of treatment effects and computing their standard errors is not a straightforward thing to do. The problem is that the estimated variance of the treatment effect should also include the variance due to the estimation of the propensity score, the imputation of the common support, and possibly also the order in which treated individuals are matched. These estimation steps add variation beyond the normal sampling variation (Heckman et al., 1998). For example, in the case of NN matching with one nearest neighbor, treating the matched observations as given understate the standard errors.

Bootstrapping: this method is a popular way to estimate standard errors in case analytical estimates are biased or unavailable (Caliendo and Kopeinig, 2008). Each bootstrap draw includes the re-estimation of the results, including the first steps of the estimation (propensity score, common support). Bootstrap standard errors attempted to incorporate all sources of error that could influence the estimates. Because analytical standard errors are not computable for the Kernel density matching methods, Bernard et al., (2007) have used 100 bootstrap replications to compute robust estimates for standard errors of the outcome indicator. Thus, the bootstrapped standard error must be reported on the ATT.

3.7. Description of Variables and their expected Signs

3.7.1. Dependent variables

Table.3.2. Definition of dependent variables

R. No	Dependent variables	Symbol	Type	Measurement
1	Level of technology adoption (improved seed variety, chemical fertilizer, row planting & pesticide used)	LTA	Dummy	1 if adopting and 0 otherwise
	Outcome variables			
2	Annual Income Level	AIL	Continuous	Birr
3	Income from legumes Crop	IFLC	Continuous	Birr

The main variables that intended to be measured in this study were level of technology adoption and income change entertained from technology adoption. Level of technology adoption is the rate at which the intended package of technology implemented by farmers'. It tells us to what degree the adoption rate could vary by a unit change of various impacts. Participating in technology adoption is a dependent variable in impact analysis using PSM with outcome variables of income of households.

3.7.2. Explanatory Variables

The objectives of this study were to relate technology adoption with farmers' income and how the level of technology adoption is influenced by various impacts. The definition of variables and the respective hypothesized effect on adoption presented as follows:

Access to credit (CREDIT): most literature defined credit access as the supply side phenomenon of the credit market because mostly it is the lender who decides whether to access or not the credit (Okurut and Schoobe, 2007). This happens in area where there is limitation in accessing the credit service due to fewness of crediting agents. Economists usually view lack of credit as an indication of market failure. Improving credit access often regarded as the key element for increasing agricultural productivity and has been an effective strategy to increase smallholder productivity and alleviate poverty (Adugna and Heidhues, 2000). It enables to relax the liquidity constraints that smallholder farmers' face to improve their risk bearing capability, influencing adoption of new technology. Credit access can have positive influence on level of adoption. In this study credit refers to the availability of loan to afford technological packages under consideration. Many adoption studies considered credit availability with respect to the presence or not the credit service. However, farmers are sensitive to the cost of money, delivery the credit and returns of investment. Credit access was expected to influence level of adoption positively.

Access to technology (TECH_ACC): getting improved agricultural technologies close to the farm or near by the farmers' village, particularly improved seed, and chemical fertilizer is the key constraint that affect farmers' desire to adopt (Solomon et al., 2011). This is mainly due to imperfections in local input markets and lack of availability of the inputs in the desired quality, quantity, and time. There is a considerable shortage of improved seed in Ethiopia. Despite good reasons to invest in this market, private sector investments are not observed to the expected level (Hussmann, 2015). Accessibility in this context is the presence of the intended technology in the vicinity of the farmers and the farmers able to avail same at the required time without resourcing visible cost for mobilization and transportation. Accessibility supposed to have positive impact on level of technology adoption.

Development agent advice (EXTEN): Advice of development agent refers the involvement of agricultural experts in developing the general cognitive ability of farmers via training, experience sharing and practical help. Thus, any assistance that emanate from development agents for the proper implementation of the intended technology considered as development agent advice in this study. Farmers' Knowledge included the general cognitive ability that obtained from training, formal education and experience that expected to generate from development experts. If farmer get knowledge or help that enable him to put the technology into operation, we can say DA advice is there (Berihun, 2014).

Education level (EDUC): the accruement of knowledge via formal education is supposed to be important factor in a way that education would have the capacity to adopt the technology in a proper way and can assure the end target expected from the technology. As a result, education presumed as an important explanatory factor in household decision-making towards favoring the adoption process. Education level of household can be captured scale wise which ranges from illiterate to high school and above grade of accomplishment (Bihon, 2015).

Output market access (MKT_ACC): Getting secured market for improved product at acceptable price could be a riddled issue in the marketing front. There is significant limitation in terms of value addition of legume crops in Ethiopia where exporting may be difficult in raw form of the legume crops. On the consumer side, taking legume products cultivated via improved technology sometimes being perceived as losing of organic nature (own case study). Farmers sometime, are reluctant to invest time and money in crops which have no guaranteed market. So far the atomized structure of small producers did not organize common efforts to open new marketing channels. As a result, accessing appropriate market can be considered one of the factors for technology dissemination process. The inaccessibility of market for legume products is proposed to affect the adoption of seed and fertilizer technology adversely. The presence or absence of output market can be captured as dummy (Zenaye, 2016).

Membership in farmers' cooperative (ASSOCI): it is a dummy variable referring to whether a household member is an active member of farmers' cooperatives or not and is expected to influence the adoption of improved food legume technologies positively. The positive association is expected because the farmers' cooperatives are expected to provide members with necessary input and help farmers access more rewarding markets (Kassie et al., 2014).

Farm size in hectare (LANDSZ): it is a continuous variable that indicates the size of land owned by the farm household. Farmers with larger land size can afford the expenses on new agricultural technologies and can bear the risk in case of failure of crop production. This means that farmers who have relatively larger farm size will be more initiated to adopt legume technologies and the reverse is true for farmers with less land (Kibrom, 2014).

Household head participation in off farm activities (OFFFARM): this is dummy variable that shows whether the household head participates in off-farm activities or not. It is expected to affect the adoption positively as participating in off-farm activities can solve liquidity problem (Berihun et al., 2014). However, the positive role of off farm activities may not hold true in all cases of deciding to adopt agricultural technologies. Where the production crop is labor intensive, it adversely affects the adoption by taking away the labor from farming.

Livestock holding (TLU): this variable is measured in terms of Tropical Livestock Units (TLU) (Storck et al., 1999) and is hypothesized that as ownership of livestock increases, adoption of legume technologies increases (Debelo, 2015).

Gender of household head (GEN): It is a dummy variable 1 if gender of the household head is male and 0 otherwise. Male-headed households would have better opportunity to adopt legumes technologies since they are exposed to new information and tend to be risk takers (Adebiyi and Okunlola, 2013). In such instances, negative sign was hypothesized while adopting chemical fertilizer due to their reluctant behavior and higher probability of adopting manure as a proxy for chemical fertilizer; whereas positive coefficient was expected for legumes technologies adoption.

Plot size of legumes crop for cultivated purpose (PLTSZL): it is a continuous variable that indicates the plot size of allocated for legume crop cultivated purpose the farm household. Farmers with smaller plot size allocation for legumes crop can be not conducted on new agricultural technologies. This means that farmers who have relatively smaller plot size allocation for legumes will be not initiated to adopt legume technologies and the reverse is true for farmers with larger plot size allocation (Kibrom, 2014).

Table.3.3. Independent variables

R. No	Independent Variables	Symbol	Type	Expected sign	Measurement
1	Gender of household head	GEN	Dummy	+/-	1 if household gender for male and 0 otherwise
2	Education	EDUC	Continuous	+	Continuous
3	Farm Size	LANDSZ	Continuous	+	Hectare
4	Plot Size on legumes	PLTSZL	Continuous	+	Hectare
5	Distance main Market access for out put	MKT_ACC	Dummy	+	1 if a household head the market access to get travel near from the residential area, 0 otherwise
6	Off-Farm Participation	OFFFARM	Dummy	+	1if a household head participates in off-farm activities and 0 otherwise.
7	Access to Credit	CREDIT	Dummy	+	1 if household will be get credit access and 0 otherwise.
8	Extension Agents' Contact	EXTENS	Dummy	+	1 if households with extension services by development agents and 0 otherwise.
9	Membership to an Association	ASSOCI	Dummy	+	1 if a household will be a member of a certain farmers' cooperatives association and 0 otherwise.
10	Tropical Livestock Unit	TLU	Continuous	+	Countable number
11	Access to technologies	TECH_ACS	Dummy	+	1 if technology distributors organizations/ institutions and 0 otherwise

3.7 Reliability and Validity

Cronbach's alpha reliability coefficient normally ranges between 0 and 1. However, there is actually no lower limit to the coefficient. The closer Cronbach's alpha coefficient is to 1.0 the greater the internal consistency of the items in the scale.

Based upon the formula $= rk / [1 + (k - 1)r]$

Where k the number of items is considered and r is the mean of the inter-item correlations the size of alpha is determined by both the number of items in the scale and the mean inter-item correlations. George and Mallery (2003) provide the following rules of thumb: Cronbach's alpha is commonly used to establish internal consistency construct validity for similarity scales, with .60 considered acceptable for exploratory purposes, .70 considered adequate for confirmatory purposes, and .80 considered good for confirmatory purposes. Cronbach's alpha is both a validity coefficient and a reliability coefficient.

CHAPTER FOUR

.   **RESULT AND DISCUSSIONS**

The result of descriptive statistics and econometric model results and discussions are presented in this chapter in two sections. In the first section descriptive statistical results and main survey observation of household are presented and explained. In the second section, econometric model results for haricot bean chick pea faba bean and grains are presented and explained.

4.1. Descriptive Statistic Results

4.1.1. Demographic characteristic of farm households

The survey was conducted in three woredas of Gurage zones; Abeshge ,Gumer and Sodo woredas. Prior to conducting the formal survey, case study was made to have an insight about linkage of the community with the intended research objective. The demographic information of the sample household with respect to adopters and non-adopters is summarized in the table below.

Table.4.1. Demographic characteristics of sampled farmer

Character	Total Sample		Adopters of technology(improve seed fertilizer row planting inoculants &chemicals)		Non-adopter of Technology (improve seed fertilizer row planting inoculants &chemicals)		t-value
	Mean	st.dv	Mean	st.dv	Mean	st.dv	t-value
Age	37.25	6.681	35.392	5.994	39.108	6.842	4.1259
Family size	5.647	1.751	5.411	1.498	5.882	1.951	1.931
Farming Experience	16.015	6.538	14.049	5.566	17.980	6.865	4.492
Off farm	.098	.298	.156	.366	.039	.195	7.982

Source: Own computation from survey data (2019)

The average age of the sample household was 37.25 with a standard deviation of 6.681. The average ages of the adopter of legumes technology were 35.392 years and while the non-adopters have a mean age of 39.11 legumes technology in the respectively. If the farmers a year of age decrease or on adult age stage legumes technologies adoption increases. This result is consistent with Kibrom (2014).

In terms of the number of family member, a household has an average of 5.88 family members. There was no significant difference between adopters and non-adopters in terms of household family size.

4.1.2 Education status of sample farm households

Table 4.2. Education levels of sampled household

Education Level	Total Sample		Adopters of technology(improve seed fertilizer row planting inoculants &chemicals)		Non-adopter of Technology (improve seed fertilizer row planting inoculants &chemicals)	
	Number	%	Number	%	Number	%
Illiterate	20	9.8	5	20	15	75
Traditional/Religious	28	13.7	5	17.9	23	82.1
Elementary (1-6)	76	32.3	37	46.7	39	51.3
Junior level (7-8)	48	23.5	31	64.6	17	35.4
High school(grade9-10)	32	15.7	24	75	8	25

Source: Own computation from survey data (2019)

The educational background of the sample household shows that 20 (9.8%) household heads were not formally or informally getting the education except that of the experience derived from farming activity out of the enumerated households, 13.7 % were getting traditional education (mostly religious education) but not enrolled in formal education. Comparing the education level between the adopters and non adopters, 20% of the adopters were illiterate while the percentage grown to 75 % for non-adopters. Implication if the farmers more perform educational back ground increases the legume technologies adoption increases. This result is consistent with Zenaye (2016).

4.1.3 Farming system and characteristics

4.1.3.1 Land use pattern

The overall average farm size was 1.982 hectares per sample household, of which 0.591 ha is allocated for legumes crop cultivation purpose is (29.8%). Cereal crops take the largest portion of land in the cropping scheme in which 50.8% of the total landholding has been given for it. Leguminous crops are the second crop which takes the next largest proportion of land where chick pea was cultivated on 0.5ha (25 %) of land while 0.492ha (24.8%) was allocated for haricot bean production field pea & faba bean were .308 (15.5%) & .285 (14.4%) hectares production of land respectively of the household technology adoption status in the production season.

Table.4.3. Land use pattern of household

Farm size on average in legumes crops	Total Sample			Adopters of technology(improve seed fertilizer row planting inoculants &chemicals)			Non-adopter of Technology (improve seed fertilizer row planting inoculants &chemicals			t-value
	Mean	St.dv	N	Mean	St.dv	N	Mean	St.dv	N	
Landholding	1.928	.936	204	2.205	1.122	102	1.652	.590	102	4.403
Land for haricot bean	.492	.215	78	.59	.236	39	.391	.132	39	4.544
Land for faba bean	.285	.123	126	.338	.114	63	.233	.109	63	5.277
Land for chick pea	.500	.210	78	.59	.236	39	.410	.131	39	4.1658
Land for field pea	.306	.143	97	.392	.121	48	.222	.109	49	7.2400
Land for other crop	1.399	.863	204	1.578	1.067	102	1.219	.542	102	3.0263

Source: Own computation from survey data (2019)

4.1.3.2 Cropping system

Though there are various crops growing in the area, cereal (mainly wheat, maize, barely & teff) spice (red peper) dominate the farming activity. There are two main cropping seasons; one is the main Meher (June to September) season the other Belg (March-April) season. In these two cropping seasons, the farmers are engaged in cultivation activity such as land preparation, planting, weeding and field management, cultivation and finally harvesting.

Farmers use oxen for draft power for cultivation of crops in the area. However, sometimes rented tractors and combine harvesters from nearby seed enterprises are used based on the urgency of the need to perform farming activity. Most of the time tractors and combine harvesters are used in case of cereal crops while cultivation of legume crops is done using draft power.

More than 99% of chick pea, haricot bean and faba bean producer farmers used draft power (oxen) to plough the land. Considering the planting season, 100% of legumes crops produced farmers say chick pea haricot bean & faba bean in season. The whole chickpea production was made in meher season using residual moisture since chick pea needs comparatively less moisture. Row planting and broadcasting methods are used in chick pea, haricot bean & faba bean production. Row planting methods used of adopter for chick pea, haricot bean & faba bean were 24.2%, 24.2% & 40.8% respectively while the non adopter have a percentage of 1.3%, 6.4% & 3.1% for chick pea, haricot bean & faba bean row planting methods used in respectively. Both haricot bean and faba bean farms need weeding of at least two times in adopter a planting season while the whole chick pea some haricot bean & faba bean farms need weeding of at least once a times in non adopter a planting season . Generally, the legume agronomy summarized in the table below;

Table .4.4 agronomic activities of legume production

Agronomy activity		Total sample		Adopter						Non adopter					
				Chick pea		Haricot bean		Faba bean		Chick pea		Haricot bean		Faba bean	
		Number of respondents	%	Number of respondents	%	Number of respondents	%	Number of respondents	%	Number of respondents	%	Number of respondents	%	Number of respondents	%
Ploughing method	Oxen	280	99.6	38	13.6	37	13	64	22.8	39	13.9	39	13.9	63	22.5
	Tractor	1	0.4			1	100								
Ploughing frequency	Once	77	27.4	38	49	-	-	-	-	39	51	-	-	-	-
	Twice	89	31.6			26	29							63	71
	Thrice &more	115	41	-	-	38	33	64	55.7	-	-	13	11.3	-	-
Planting season	Belg	-													
	Meher	281	100	38	13.5	38	13.5	64	22.8	39	13.9	39	13.9	63	22.4
	Belg & Meher	-													
Planting method	Raw	157	55.9	38	24.2	38	24.2	64	40.8	2	1.3	10	6.4	5	3.1
	Broad cast	124	44.1	-	-	-	-	-	-	37	29.8	29	23.4	58	46.8
Weeding frequency	Once	179	63.7	38	21.2	-	-	-	-	39	21.8	39	21.8	63	35.2
	Two & More	102	36.3	-	-	38	37.3	64	62.7	-	-	-	-	-	-

Source: own computation from survey data result (2019)

While considering the cropping system of the farmers in the study area, the three Woredas have difference with respect to legume production. Abeshge is known in haricot bean, chick pea and lentil farming while Sodo & Gumer are mostly known in faba bean and field pea production. Out of the average cultivable land of 1.928 ha, about 45% (0.870ha) was allocated for wheat production. As mentioned above, more land is allocated for cereal production like wheat, maize barley, and teff.

Table.4.5. Plot size production of major crop

Major crop	**Plot size of major crops on average**	
	Mean	Std Dev
Wheat	0.870	0.791
Maize	0.788	0.552
Barely	0.641	0.232
Chick pea	0.500	0.209
Haricot bean	0.492	0.214
Teff	0.457	0.233
Red pepper	0.422	0.346
Field pea	0.307	0.142
Faba bean	0.283	0.121
Sorghum	0.245	0.326

Source: Own computation from survey data (2019)

4.1.4 Adoption of technologies in legume farming

4.1.4.1 Input supplying parties

There are various parties involved in distribution of farm inputs; improved seed, fertilizer, inoculants and chemicals of pesticides and herbicides. These technologies are distributed since long with various extents which vary along with the time and the advancement of the technology. The distribution channel; sometimes differ with respect to the technology. Development and multiplication of seed technology mostly performed domestically by research organization while other farm inputs like fertilizer and chemicals are imported from the international market. Improved Seed development in case of leguminous crops (pulses) is under taken by the Ethiopian Agricultural Research Institute, Ethiopian Seed Enterprise, and SNNP Seed Enterprise. These are the main sources in seed distribution for the SNNP Seed Enterprise in general. In case of fertilizer, regional government imported fertilizer and distribute to the farmers along with chain of the organization. Pesticides and herbicides chemicals are distributed both though governmental organization and private traders. Out of the household considered in this study 46 % of the households were preferred governmental organization like agriculture office at different level to distribute farming inputs. Input distribution through cooperatives and union takes the second ranked in farmer input distribution. There are public cooperative and union which are working to distribute farmer inputs. Adimas union, Walta & Edget input distribution and mechanization service is one of the unions working in the area.

Table.4.6. Households' preference of institution for input delivery

Input delivery institution	Number of sample house households	Percentage (%)
Government organization (Agricultural office, Development agent …)	198	46
Cooperatives & unions	178	41.3
Research institution	20	20
Traders	11	2.6
Community association(Idir & Equb)	2	0.4
Development partners (NGO)	22	3.1

Source: Own computation from survey data (2019)

4.1.4.2 Trait preference of farmers

Taking traits like level of yield, color, taste, drought resistance, maturity, disease resistance and storability as comparison parameters, farmers preferred improved variety than local varieties in all comparison parameter except taste of the crops. About 58.3 % of the farmers have been preferred improved legume variety as the yield level is quite higher compared to improved variety. Farming households preferred local varieties for its favorable taste. Out of the considered traits, color is not as such mattering where the households' shows almost equivalent preference for local and improved varieties of chick pea, haricot bean, field pea and faba bean varieties. Farmers' response regarding taste and drought resistance, 31.8% and 22.5% of the sample households preferred improved seed to local verities. Table 11 further shows the farmers varietal preference towards the various traits of chick pea, haricot bean, and field pea & faba bean variety.

Table.4.7. Variety's trait preference

Grain traits	Improve variety		Local variety	
	Number	%	Number	%
Yield	119	58.3	12	5.9
Color	80	39	36	17.6
Taste	101	49.5	65	31.8
Storability	92	45	20	9.8
Early maturity	97	47.5	19	9.3
Drought resistance	98	48	46	22.5
Diseases resistance	100	49	29	14.2

Source: Own computation from survey data (2019)

4.1.5 Adoption status of sample households for main farm inputs

Agricultural input adoption status like level of improve seed, fertilizer, chemical, inoculants & farming techniques implemented status comparison adopter & non adopter. About 50% of the farmers are quite higher compared to improved seed & farming techniques from technology adopter household headed.

Table.4.8. Agricultural input adoption status

	Current adoption status			
Agricultural input	Adopter		Non adopter	
	Number	%	Number	%
Improve seed	102	50	-	-
Fertilizer	101	49.5	9	4.4
Inoculants	92	45.1	14	6.9
Chemical	93	45.5	19	9.3
Farming techniques	102	50	14	6.9

Sources: **Own computation from survey data (2019)**

4.1.6 Farmers' typological arrangement

Dissemination of technology depends not only on the types of technology but also on the characteristics of the end users; in this research case farmer. Heterogeneity of attitudes of farmers affects the level of adoption and thus, leads to categorizing the farming community in various forms. A farm typology can be used to classify farming households based on farmers' current position of adoption of technology. Classifying farmer adoption status can exhibit different behavior of farmers with regard to the technology. The current adoption position has been measured using adoption index. Adoption index measures the extents of utilizing a particular technology per recommended unit (Umar et al.,2011). Based on the level of adoption and current status, it is possible to draw a typology of farmers with respect to status of adoption.

- ✓ **TECH_ORIENTED**: these are households who have future plan to adopt technology but currently they are not in a position to do so. Tech_ oriented farmers are farmers who have information about the technology but need further assurance and practical proving from earlier adopters. They are in need of time that enables them to focus on future particularly on how to achieve the future goal through adopting improved farm inputs in one hand. On the other hand, tech oriented farmers would like to assure the success/failure story of previous adopters. Solving the limitation of knowledge gap and demonstration in particular and smoothing the barriers in general will bring these farmers to the tech fledgling cluster.

✓ **TECH_FLEDGLING**: households who participate in technology adoption and these are new entrants to the adoption process. These adopters can be forced to utilize the technology but may not be sure about the outcome of the intended technology on their livelihood. In case of fledgling adopters, the adoption index is low. The tendency of continuity of the adoption status of these farmers mostly depends on the outcome of the technology. Impressive outcome will lead the farmers to adopter stage. Fledging adopters includes farmers adopting a technology for trial purpose.

✓ **TECH_ADOPTERS**: households who are adopting technology in the previous cultivation seasons and continuing the adoption process can be clustered to technology adopters. Theses farmers are normally disposed to take favorable events from technology consumption. As the farmers have familiar attachment with technology, they are not easily convinced by a spot bad adverse outcome of technology. Looking the adoption level, the index can increase to 100% in the adoption index scale.

✓ **TECH_DROPOUTS**: households who are adopting a technology in the past but terminated the adoption process at this juncture. There could be dropouts both from tech fledglings and tech adopters. Usually, technology impact can be slow while once farmers incurred costs, expecting outcomes are automatically in the coming harvesting season. But such expected outcome might not realize immediate to as planned by the farmers. Reasons associated with broader farming system, community believe change getting alternative technology; family and community pressure could contribute for the farmers to be lagged from the adoption process. The adoption categorization of the study area with respect to adoption of various technologies presented as follows:

Table 4.9. Adoption status of sample households for main farm inputs

Agricultural inputs	**Current Adoption Status**							
	Tech_ Fledgling		Tech_ Adopters		Tech-Dropouts		Tech_ Oriented	
	N	%	N	%	N	%	N	%
Improve seed	16	7.84	102	50	7	3.43	79	38.72
Fertilizer	19	9.3	102	50	-	-	83	37.74
Inoculants	10	4.9	102	50	-	-	92	39.7
Chemical	9	8.82	102	50	15	7.35	78	38.23
Farming techniques	9	4.4	102	50	17	8.33	93	45.58

Source: own computation from survey data 2019

The survey result reveals that 50% of the total sample households using improved seed since long and still continuing the adoption process. About 3.43% of the seed technology adopters have been dropouts of improved seed technology. Out of the total non-adopter of seed technology, 38.72% of sample households were oriented to adopt improved seed. About 50% of sample households were using fertilizer for legume production. There was no dropouts' status in case of adopting fertilizer technology. Inoculants are bio fertilizer where the adoption is started recently.

Generally the time period where inoculants started to be applied in the legume production in the study area is not more than four to five years. Currently, only 50% of the sample households brought the inoculants technology in to their farm in previous years. About 92 households (39.7%) have a plan to adopt inoculants in the coming production season. To summarize, the sample survey results revealed that, taking farm inputs (seed, fertilizer, inoculants row planting and chemicals of pesticides and herbicides) as a package, the overall adoption rate reached to 50% while the termination rate is 5.39%.

4.2. Econometric Analysis

Before taking the variables into the propensity score matching model, some assumptions were tested among the explanatory and dependent variables and there is no serious problem of propensity score matching assumption to be violated. The test results of some of the propensity score matching assumption has been described as follows.

Heteroskedasticity Test: Brusch pagen /cook Weisberg / The existence of problem of heteroskedasticity were tested by using Brusch pagen/cook Weisberg hettest. This test result shows there was not heteroskedasticity problem with chi^2 value 0.03 and the corresponding p – value of 0.85 which reject the null hypothesis that accept the alternative hypothesis.

H0: constant variance

Variables: fitted values of LTA

$Chi^2(1) = 0.03$

$Prob>chi^2 = 0.853$

4.2.1. Determinants adoption of legume technologies

Attempt was made to examine factors affecting adoption level of improved seed, chemicals, inoculants, fertilizer & agricultural techniques technologies adoption using econometrics analysis. Many variables may influence the adoption of technologies. The model estimation was projected in a way that the adoption of improved seed and fertilizers given that haricot bean, chickpea, field pea and faba bean as legume crops aggregated as legume packages. Variables with statistically significant odd ratios were then identified so that it can measure the level of importance to determine were proposed to affect the adoption. The result of the logistic model on determinant level of technology adoption is summarized in the table 4.9.

Table.4.10. Determinants adoption level of legumes technology

Explanatory variable	**Coeff.**	**Std. Error**	**t-value**	**p-value**	**Odd ratio**
GEN	-0.979**	.206	-1.78	0.075	0.375**
EDUC	0.539*	.329	2.81	0.005	1.714*
LANDSZ	0.993*	.904	2.97	0.003	2.701*
PLTSZL	-2.160**	.102	-2.42	0.016	0.115**
MKT_ACC	-0.131	.374	-0.31	0.759	0.876
OFFFARMP	1.386**	2.879	1.89	0.056	3.999**
CREDIT	1.550*	2.010	3.66	0.000	4.714*
EXTENS	1.420*	1.811	3.25	0.001	4.139*
ASSOCI	1.753*	2.360	4.29	0.000	5.772*
TLU	.384*	.146	3.85	0.000	1.468*
TECH_ACS	-.215	.317	-0.55	0.585	0.806
CONS	-6.293	.002	-5.10	0.000	

LR chi^{i2} (11) = 113.8

Prob > chi^2 = 0.000

PseudoR^2 =0.402

log likelihood = - 84.494

Source: Logistic result of own survey result (2019)

*, ** and *** refers significant at 1%, 5% and 10% respectively.

Gender ,educational level, land size of for cultivated purpose, off farm participants, credit accessibility, agricultural extension services agent, participants of farmers cooperative association , tropical livestock units are registered expected signs where as plot size for legumes crop of cultivated purpose , market accessibility & technologies accessibility are unlined with expected signs.

Education Level of household head (EDUC): Educational level was found significant at 1% level of significance. The odd ratio of education shows that, a one more year of education, increases the probability of odd ratio of legumes technologies by a factor of 1.714 on average.

It is observable that in the farming community, the higher the academic qualification of the household member will exposed to leading position in most of the hierarchy of the kebele administrative units. As a result, they will be the first community organs that receive the technology and initiated to be taken as the role model for the higher ruling organ. Besides, they will have better chance to get the technology. This finding in line with Asfaw et.al.(2011)

Extension Agents' Contact (EXTENS):- Agricultural extension agent service is significant at 1% level of significance positively influenced legume technologies adoption, scientifically derived, often complex input supplied to farmers by organizations with deep technical expertise and hence development agent advise was hypothesized to have significant effect towards the improving the adoption level of technology. The probability of legumes technologies adoption are about 4.139 times greater for the farmers get access of extension services than that farmers are not get access of extension services. This is the finding reported by Zinaye et,al.(2014) in relation to the factors affecting adoption of chick pea in Oromia region.

Off-Farm Participation (OFFFARM): Off-farm participation is significant at 1% level of significance positively influenced legume technologies adoption. The probabilities of odds being legume technologies adoption are about 3.999 times greater for the farmers Participate off-farm activities than that farmers are not participate off-farm activities. This could be because off farm activities takes away the labor from farming which will have a direct bearing on legume production which is entirely dependent on human labor in study area. Hassen (2014) and Asfaw et al. (2011) have reported similar findings.

Membership to an Association (ASSOCI): Farmers cooperative association are in principle established and operate based on the common interests of members; and are expected to provide production input at relatively lower price and better market for members to improve their bargaining power. Membership to an association is significant at 1% level of significance positively influenced legume technologies adoption. The odds of being legume technologies adoption are about 5.772 times greater for the farmers a membership of farmers' cooperative association than that farmers are not a membership of farmers' cooperative association. This is in line with the finding reported by Kassie et al. (2014) in relation to adoption of maize varieties in Tanzania.

Tropical Livestock Unit (TLU): Livestock are important source of income, food and traction power for crop cultivation generally in Ethiopia. Livestock possession is also an important indicator of household's wealth status in rural Ethiopia. This variable is significant at 1% level of significant, if the farmers have to get more tropical livestock unit holding the probability of the odd ratio of adoption of legume technologies by 1.468 on average. This relationship implies that household with more livestock possession might have the capacity to generate cash income to purchase input and could be able to take more risk associated with adoption of legumes technologies. Studies by Debelo (2015) on the adoption of Quncho teff in Wayu Tuka district, Oromia region and Berihun et al. (2014) on adoption of chemical fertilizer and high yielding variety in Southern Tigray reported similar positive influence of livestock holding on agricultural technology adoption**.**

Land Size (LANDSZ): Land size is significant at 1% level of significance positively influenced legume technologies adoption. The odds of being legume technologies adoption are about 2.701 times greater for the farmers have large landholding than those farmers have small landholding for cultivated purpose. This can be further interpreted as small land size can limit the adoptability of legumes technology. The more the farmers having cultivable land could able to adopt higher adoption rate of improved seed, fertilizer, chemicals & others than the one who has less land. This finding is in lined with Asfaw et al. (2011) reported for determinants of adoption of improved variety of chickpea in Ethiopia.

Access to credit: Access to credit is significant at 1 % level of significance. The probabilities of odds adoption of legume technologies are about 4.714 times greater for the farmers get access credit services than that farmers are not get access credit services. The result shows that, the impact of access to credit on adoption, and a good deal of it showing that credit has a positive effect on adoption. This finding is in line with Cornejo and McBrid (2002) highlighted that credit access is one of the key factor affecting technology adoption not only for legumes technology but also for most of agricultural innovation. The result of this study also proved that farmers' adoption level significantly improved given that the credit is available. However, case study result shows that there is a big limitation in delivering the credit service for the legumes crops farming. Household access to financial service influenced by the location, conditions to deliver the credit and the priority area that financing institutions steered. As the area is dominantly wheat and maize growing, the farming culture is cereal focused and the creditors pays more effort in financing cereal based farming activity.

Plot size of legumes crop (PLTSZL): Plot size of legumes crop is significant at 1% level of significance. The odds of being legume technologies adoption are about 0.115 times less for the farmers to allocated smaller plot size of legumes crop for cultivation purpose than that farmers to allocated larger plot size of legumes crop for cultivated purpose. The logit regression resulted that plot size of legumes has a negative impact on the adoption of legumes technology. This can be further explained that farmers are larger plot size allocated the other cereals crop relatively to plot size of legumes adoption level. The finding is in line with Menale et al. (2012).

Gender of household head (GEN): Gender is significant at 1% level of significance. The odds of being legume technologies adoption are about 0.375 times less for female household headed than that of male household headed. The result shows that, impact of gender on adoption has household headed participant a negative influence of adoption legumes technology sign. Female-headed households would have not better opportunity to adopt legumes technologies since they are limitation to new information and tend to be risk advers (Adebiyi & Okunlola, 2013). A negative sign was hypothesized while adopting chemical fertilizer due to their reluctant behavior and higher probability of adopting manure as a proxy for chemical fertilizer.

4.3. Impact of Adoption of Legume legumes technology

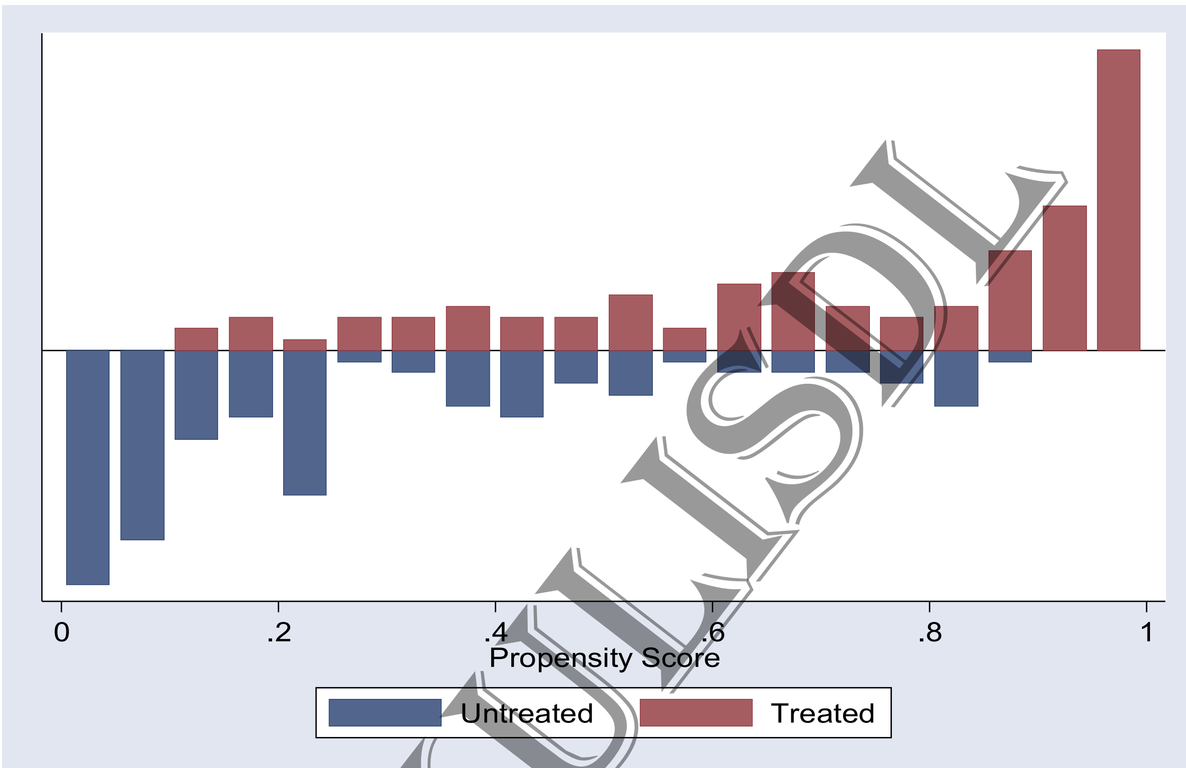
Identifying the factors behind adoption of agricultural technologies is not enough for the study that aims to the adoption of legumes technologies and their income impact of farmers. This section of the thesis discusses the impacts of adoption of legume technology, which was estimated by using Propensity score matching (PSM). The income indicators that the study focuses on are annual income, income from legumes crop, income from other crop & income from non agriculture.

4.3.1. Estimation of propensity score

The PSM is one of the non-parametric estimation techniques that do not depend on functional form and distributional assumptions. The method is intuitively attractive as it helps in comparing the observed outcomes of adoption of legume technology with the outcomes of counterfactual control that is non-adoption (Heckman et al., 1998). The PSM technique enables to extract from the sample of non-adopting households a set of matching households that look like those who adopted in all relevant characteristics. In other words, PSM matches each adopter household with control household/s that has/have (almost) the same characteristics.

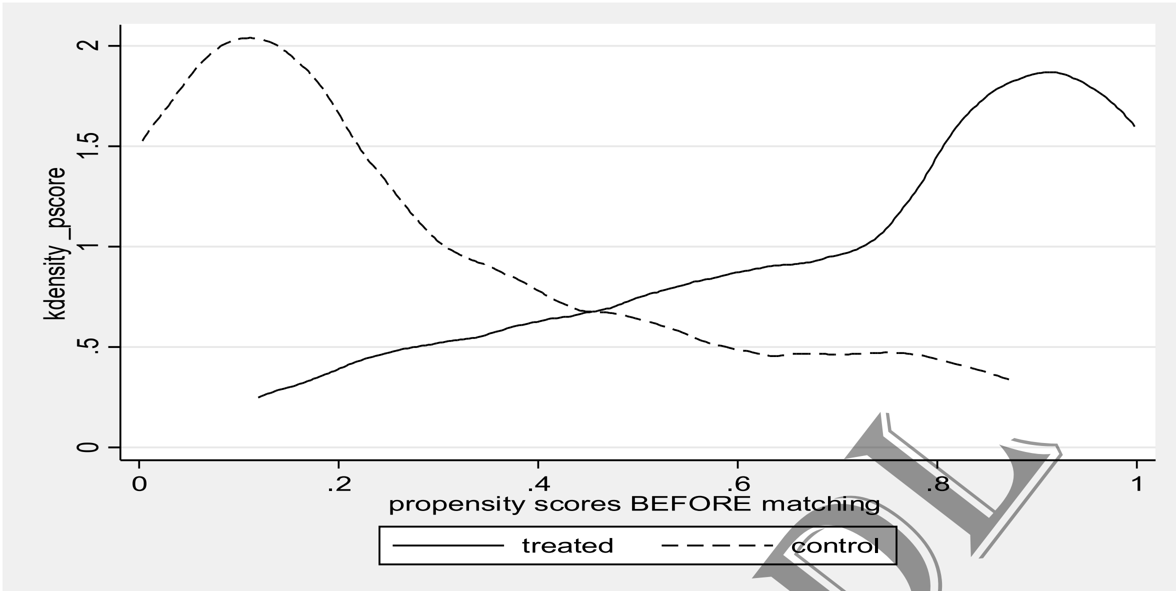
In the estimation of the propensity score, the focus is not on the effects of covariates on the likelihood of adoption (propensity score) as the intention is developing an index that can be used to match the two groups of sample households adopters and non-adopters. However, the choice of covariates to be included in the first step (propensity score estimation) is an important issue. Heckman et al. (1997) argue that omitting important variables can increase the bias in the resulting estimation. Here, pre-intervention characteristics that bring variation in outcomes of interest among adopters and non-adopters were used. In other words, variables which are not affected by being adopter or not or those covariates which are fixed throughout are used as explanatory variables. Accordingly, different demographic, socioeconomic, institutional and location factors were considered. The study is going to estimate Average Treatment Effect on the Treated (ATT), which concentrates only on the effects of adoption of legumes technology on the adopters.

To estimate propensity score for adopter and non-adopter households, logit regression model was used. The treatment or the dependent variable of the propensity score model is binary; i.e., adopter or non-adopter. The result of p-score estimation shows the estimated model appears to perform well for the intended matching exercise. A low Pseudo R2 value confirm that adopter households do not have much distinct characteristics overall and as such finding a good match between adopter and non-adopter farm households becomes easier as well, the Pseudo R2 is 0.40. The results indicate that the propensity to adopt legume technology was considerably influenced by plot size legumes crop, gender & household headed participation in off farm activity presents (Table .4.10.) (Figure.4.1.) the distribution of the sample households with respect to the estimated propensity scores. In this case, most of sample households are found in the left side of distribution, which indicates the lower propensity score of adoption of legume technologies. Most of adopter households are found in the upper right side of the distribution and partly middle of the distribution. On the other hand, almost all of the non-adopter households were found in the down left side of the distribution.



Source: own survey data result (2019)

Figure 4.1. psgraph propensity score matching distribution adoption of legumes technology



Source: Own survey data result (2019)

Figure .4.2 propensity score before matching legumes technologies adoption

4.3.2. Matching adopter and non-adopters

As Table .4.11. Below illustrates the estimated propensity score varies between 0.003 to 0.0.998 with mean of 0.5 and standard deviation of 0.342. The average p-score of adopters is 0.727 and ranges from 0.119 to 0.998 while that of non-adopters ranges from 0.003 to 0.878 with mean of 0.272.

Table. 4.11. Distribution of estimated propensity score

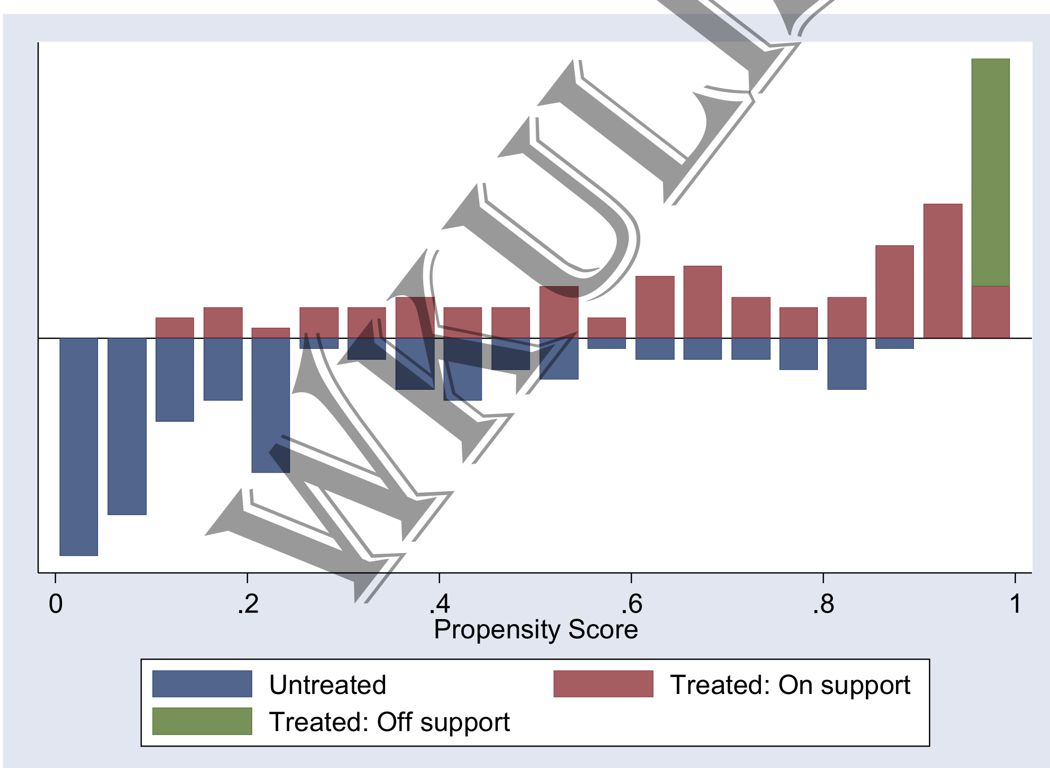
Group	Obs.	Mean	Std	Min	Max
Total hh	204	0.5	0.342	0.003	0.998
Adopter	102	0.727	0.256	0.119	0.998
Non adopter	102	0.272	0.255	0.003	0.878

Source: Own survey data result (2019)

4.3.3. Common support condition

After estimating values of propensity score for technology users and non-users the next step in propensity score matching technique is the common support condition. Only observations in the common support region matched with the other group considered and others should be out of further consideration. Once the region of common support is identified, sample households that fall outside this region have to be dropped and the treatment effect cannot be estimated for these sample households. The propensity score graph estimate in figure-2 revealed that the distribution of the total sample households in adopters, and non-adopters of sample household with respect to estimated propensity scores.

The common support region would then lie between 0.119 and 0.998 it excludes treated units whose propensity score is higher than the highest propensity score of the control units and control units whose propensity scores are lower than the lowest propensity score of the treated units. Therefore, households whose estimated propensity scores less than 0.119 and larger than 0.998 were not considered for the matching exercise. With this restriction, totally 13 households from adopter side were discarded from the analysis. The common support condition obliges to drop down observations with probability of participation greater than 0.998. Accordingly 89 observations from the participants and 102 participants from non adopters groups satisfy the common support condition.



Source: own survey data result (2019))

Figure-4.3. Propensity score graph propensity score matching distribution adoption of legumes technology after match.

In case some extent to which distribution of propensity scores in treatment & comparison group overlap. Deleted individuals outside of the range of common support 13 households from adopter or treaded individuals will be deleted after psmatch2 can run p score (pc_p score) to visualize of individuals it will be deleted. Individuals marked by green will be deleted or treated off support.

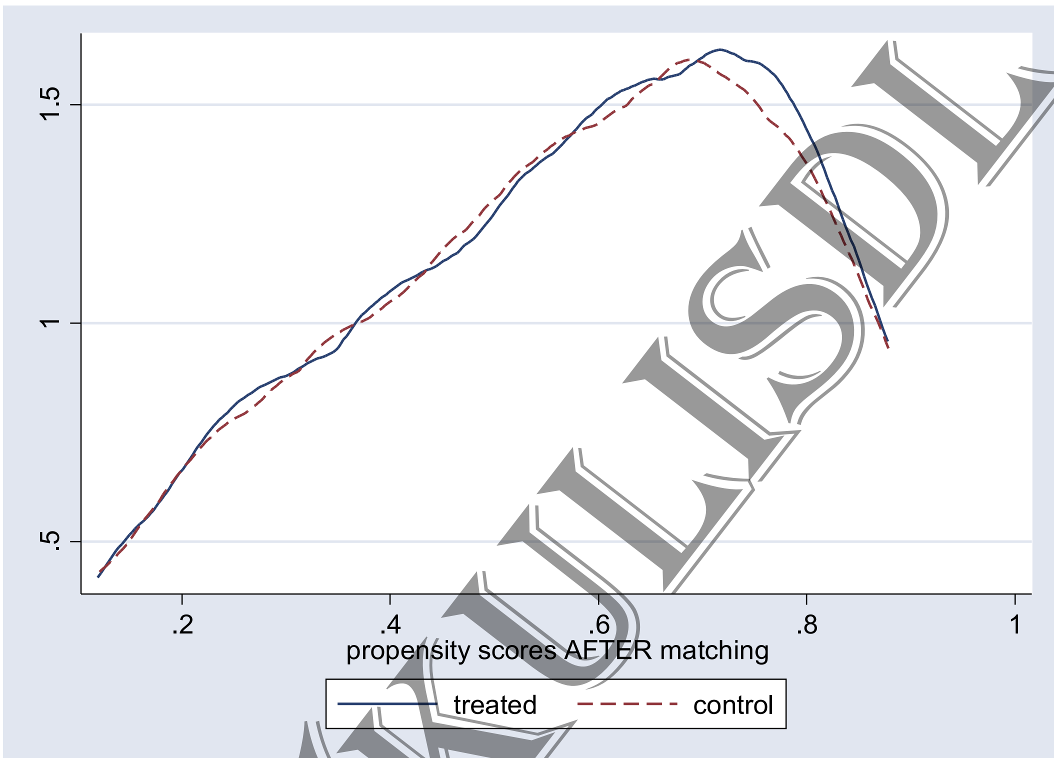


Figure .4.4. Propensity score after matching legume technologies adoption

The point of graphs like these is to visually inspect and show the closeness of the two groups and overlap between them before and after matching.

After matching, common support looks acceptable. The figure 4.2 and figure 4.4 show that the control group has higher max p score before matching but not after matching. Visual inspection suggests that the densities of the propensity scores are more similar after matching. The plot also reveals a clear overlapping of the distributions.

4.3.4. Choice of matching algorithm and matching

Alternative matching estimators can be employed in matching the treatment and comparison groups in the common support region. The final choice of a matching estimator can be done by taking selection criterion either of balancing test, pseudo-R2, and matched sample size. Accordingly, a matching estimator which balances all explanatory variables (i.e., results in insignificant mean differences between the two groups), a model which bears a low pseudo R2 value and results in large matched sample size is a preferable matching algorism (Dehejia and Wahba, 2002). The nearest neighbor matching that matches a treated unit to all control units weighted in proportion to the closeness between the treated unit and the control unit.

Table.4.12 Performance of different matching estimator

Matching estimate	Performance criteria				
	Balancing test*	Pseudo R^2	Matched sample size	Mean bias	med bias
NNM					
NN(1)	11	0.066	191.	15.7	11.1
NN(2)	11	0.031	191	10.5	11.1
NN(3)	11	0.013	191	6.6	6.6
NN(4)	11	0.013	191	6.3	6.4
NN(5)	11	0.007	191	4.2	3.4
KM					
Band width(0.1)	11	0.012	191	5.2	2.8
Band width(0.15)	11	0.012	191	5.8	4.6
Band width(0.25)	11	0.014	191	6.4	6.5
Band width(0.2)	11	0.012	191	6.1	5.1
CM					
cal (0.1)	11	0.056	191	11.2	9.3
cal (0.15)	11	0.044	191	8.6	5.6
cal (0.25)	11	0.040	191	10.1	8.6
cal (0.2)	11	0.040	191	10.1	8.6
Radius					
Rad (0.15)	11	0.015	191	6.7	4.8
Rad (0.25)	11	0.019	191	7.1	7.8
Rad (0.2)	11	0.014	191	6.5	5.8
Rad (0.1)	11	0.013	191	5.9	3.4

Source: Own survey data result (2019)

N.B. Number of 11 explanatory variables with no statistically significant mean differences between the matched groups of user and non-user households after matching.

4.3.5. Testing the balance of propensity score and covariates

This kind of test is carried so as to know whether there is a statistical significant difference in the mean values of covariates between adopter of technology and those of non-adopters. The higher the Balancing test in this context is a test conducted to know whether there is a statistical significant difference in the mean values of covariates adopters and non-adopters of technology. The higher the covariates with minimum mean difference after matching is the more balanced covariates. Keeping other selection criterion, the balancing test indicates the quality of the matching algorithm implemented.

While evaluating treatment effect, the major econometric problem is selection bias as stated in Maddala, (1983), percentage of bias before matching is in the range of 13 % and 85 % while after matching, percentage bias lies between 0.6 % and 10.2 %, which is below the critical level of 20%. 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. Similarly, t-values show that before matching nine of chosen variables exhibited statistically significant differences while after matching all of the covariates are balanced (no statistical difference).

Table .4.13.Pscore and covariates balance

Variable	Before matching				After matching			
	Treated	Control	% Bias	T	Treated	Control	% Bias	T
GEN	.813	.892	-22.2	-1.58	.850	.846	0.9	0.05
EDUC	3.667	2.802	80.4	5.74	3.383	3.346	3.4	0.18
LANDSZ	2.204	1.651	61.7	4.40	1.842	1.857	-1.7	-0.12
PLTSZL	.624	.558	25.0	1.78	.594	.617	-8.9	0.45
MKT_ACC	.745	.686	13.0	0.93	.766	.733	7.4	0.42
OFFFARMP	0.156	0.039	40.2	2.87	0.100	0.130	-10.2	0.51
CREDIT	0.735	0.433	64.5	4.61	0.616	0.596	4.2	0.22
EXTENS	0.745	0.579	47.9	3.42	0.683	0.676	1.4	0.08
ASSOCI	0.754	0.362	85.5	6.11	0.616	0.633	-3.6	0.19
TLU	6.018	4.695	66.9	4.78	5.534	5.522	0.6	0.03
TECH_ACS	0.372	0.480	-21.8	-1.56	0.433	0.416	3.8	0.18

Source; Own survey data result (2019)

The joint significance test and the pseudo R^2 are also good indicators of matching quality (Table 4.14). The low pseudo-R^2 and the insignificant likelihood ratio tests (indicated by the higher p-value after matching) support the hypothesis that both groups have the same distribution in covariates X after matching. .

Table .4.14. Chi-square test for the joint significance of variables

Sample	Pseudo R^2	LR chi^2	p>chi^2	mean bias	Med bias
Unmatched	0.408	115.36	0.000	48.1	47.9
Matched	0.007	1.21	1.000	4.2	3.4

Source: Own survey data result (2019)

The chi-square test result shows that the covariates in the unmatched and matched groups have been balanced. The result is important to compared observed outcomes for adopter of technology with those of non-adopter have shared a common support region.

4.3.6 ATT estimation of impact of technology on HH income

Farm income enables household to purchase its basic needs of life. Before proceeding to estimate the treatment effect of technology, we have to be sure that reliability of participants and controls to have uniform distribution on its observed and non-observed characteristics of sample households. The average treatment effect measures the average difference on the household income between the matched adopters and non-adopters of the intended technology. The ATE for the matched adopters and non-adopter has been found using nearest neighbor matching at of 5**.**

Table 4.15.Treatment effect on HH income

Matched estimator	Variable	Treated	Controls	Difference	S.E	T –stat
Nearest neighbor match	Annual income	76,486	40,807	35,679	4339	8.22
	Income from legumes	30,965	3,701	27,264	2104	12.96

Source: Own survey data result (2019)* Legume crop income refers the income earned from sales of haricot bean, chickpea, field pea and faba bean *statistically significant at 10 % probability levels.

The estimation result in table 16 provides supportive evidence about the effect of technology on household welfare performance. The study basically focused on impact of technology on the total income and legume crop income of household. Income of household indicates that the ability of household to purchase its basic needs of life and hence it ultimately shows the livelihood performance of the farmers as stated in Nguezet et.al. (2011). Results of the analysis farm income of the sample household who were adopting the improved seed and fertilizer technology earned Birr 76,486 while those non-adopters earned Birr 40,807 on average basis. In particular, the annual income that earned from sales of legume grains of chickpea, haricot bean, field pea and faba bean is Birr 30,965 for adopters while it is Birr 3701 for non adopters. The impact analysis of the PSM result showed, after controlling for pre-intervention differences of the adopter and non-adopters of improved seed , row planting ,fertilizer and integrated pest managements technologies use full packages, the gross income of adopters has been increased by 46.6% (to Birr 35,679 on average basis and the legume crop income increased by 88% (Birr 27,264) . The PSM result shows that adopting farming technology has significant contribution on both the annual income and income from legumes crops in particular. The t-test analysis revealed that the mean difference of income level between the two groups was statistically significant at 10 %probability level.

4.4. Average treatment effects (ATE) with test

To attain the main objectives of this study, on this section evaluated the programs impacts on the outcome variables for their significant impact on legumes technologies adopter, after the pre-intervention differences were controlled. The impact indicators which consider as outcome variables are annual income, income from legumes crops and income from other crops. Their estimated average treatment effect (ATE) is annual income (38, 232.62), income from legumes crops (30,784.97) & income from other crops (9815.20) (Table.4.16.).

Table .4.16. Average treatments effects

variable	Sample	Treated	Controls	Difference	S.E	T- state
AIL	Unmatched	93389.1863	36809.1765	56580.0098	7315.84321	7.73
	ATT	93389.1863	58203.7353	35185.451	10335.5057	3.40
	ATU	36809.1765	78088.9608	41279.7843	-	-
	ATE	-	-	38232.6176	-	-
IFLC	Unmatched	32230.7451		28496.3725	1550.86585	18.37
	ATT	32230.7451		28794.6765	1614.09628	17.84
	ATU	3734.37255		32775.2647	-	-
	ATE	-		30784.9706	-	-
IFOC	Unmatched	62278.951		29406.1569	6965.6124	4.22
	ATT	62278.951		8266.76471	10087.08	0.82
	ATU	32872.7941		11363.6373	-	-
	ATE	-		9815.20098	-	-

Source: Own survey data result (2019)

4.5 .Matching estimators of the ATT based on the propensity score outcome

4.5.1. Nearest neighbor matching (attnd.ado)

The most straightforward matching estimator is nearest neighbor (NN) matching. The individual from the comparison group is chosen as a matching partner for a treated individual that is closest in terms of propensity score.

Attnd AIL LTA EDUC LANDSZ PLTSZL MKT_ACC CREDT EXTENS ASSOCI TLU TECH_ACS,comsup boot reps(100) dots logit

The program is searching the nearest neighbor of each treated unit.

This operation may take a while.

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

Analytical standard errors.

Table.4.17. ATT estimation with nearest neighbor matching analytical standard errors

n. treat.	n. contr.	ATT	Std.Err	T
102	31	35185.451	10335.506	3.404

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

Source: Own survey data result (2019)

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

Bootstrapped standard errors.

Table**.4.18.** ATT estimation with nearest neighbor matching bootstrapped standard error

n. treat.	n. contr.	ATT	Std. Err	T
102	31	35185.449	9337.035	3.768

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

Source: Own survey data result (2019)

The nearest neighbor example only 31 different controls have matched to the 102 treated analytical standard error (10335.5) & bootstrapped standard error (9337.03) ATT is both of them are equal. These results are very close to the ones obtained by Dehejia & Wahba(1998).

4.5.2. Radius matching (attr.ado)

Dehejia and Wahba (2002) suggest a variant of caliper matching which is called radius matching. The basic idea of this variant is to use not only the nearest neighbor within each caliper but all of the comparison members within the caliper.

ATT estimation with Radius Matching method.

Analytical standard errors.

Table.4.19. ATT estimation with in radius matching analytical standard error

n. treat.	n. contr.	ATT	Std. Err	T
102	102	56580.010	7315.843	7.734

Note: the numbers of treated and controls refer to actual matches with in radius.

Source: Own survey data result (2019)

ATT estimation with Radius Matching method.

Boots trapped standard errors.

Table.4.20 ATT estimation with in radius matching bootstrapped standard error

n. treat.	n. contr.	ATT	Std. Err	t
102	102	56580.012	7218.796	7.838

Note: the numbers of treated and controls refer to actual matches with in radius.

Source: **own computed data result (2019)**

In radius matching all treated as well as controls (in the common support which has been imposed here) are used in this result analytical standard errors (7315.8) & bootstrapped standard errors (7218.7) ATT both of them are equals. The estimate of ATT is greater than to the one obtained with kernel matching.

4.5.3. Kernel matching (attk.ado)

The matching algorithms discussed so far have in common that only a few observations from the comparison group are used to construct the counterfactual outcome of a treated individual. As Smith and Todd (2005) note, kernel matching can be seen as a weighted regression of the counterfactual outcome on an intercept with weights given by the kernel weights. Weights depend on the distance between each individual from the control group and the participant observation for which the counterfactual is estimated.

ATT estimation with the kernel Matching method.

Boots trapped standard errors.

Table.4.21. ATT estimation with in kernel bootstrapped standard errors

n. treat.	n. contr.	ATT	Std. Err	t
102	62	45545.750	9037.020	5.040

Source: own computed data result (2019)

In kernel matching only 62 different controls have been matched to the 102 treated analytical standard errors cannot computed. The bootstrapped standard error (9037.02) then the estimate of ATT is less than to the one obtained with radius matching.

4.5.4. Stratification matching (atts.ado)

The idea of stratification matching is to partition the common support of the propensity score into a set of intervals (strata) and to calculate the impact within each interval by taking the mean deference in outcomes between treated and control observations. This method is also known as interval matching, blocking and sub classification (Rosenbaum and Rubin, 1983).

ATT estimation with Stratification Matching method.

Analytical standard errors.

Table.4.22. ATT estimation with the stratification analytical standard errors

n. treat.	n. contr.	ATT	Std. Err	t
62	102	34485.611	4572.530	7.542

Source: Own survey data result (2019)

ATT estimation with the Stratification Matching method.

Boots trapped standard errors.

Table.4.23. ATT estimation with the stratification bootstrapped standard errors

n. treat.	n. contr.	ATT	Std. Err	t
62	102	34485.609	4370.138	7.891

Source: Own survey data result (2019)

In stratification matching only 62 different treated have been matched with stratification out of 102 treated. The analytical standard errors (4572.5) & bootstrapped standard errors (4370.1) estimate of the ATT is quite close to the one obtained with nearest-neighbor matching. But overall the results obtained attnd, attr, attk & atts are a positive range (34,486.6 to 56,580).

4.6. Sensitivity Analysis

There may be hidden biases against the result of matching estimators and hence testing robustness the result is recommended. As it is not possible to estimate the magnitude of the selection bias with non-experimental data, the problem can be addressed through using sensitivity test.

The basic issue in testing sensitivity is to check whether the treatment effect is due to unobserved factor or not. Rosenbaum (2002) proposes using Rosenbaum bounding approach in order to check the sensitivity of the estimated ATT. The results shows that the impact of legumes technology adoption is not changing through adopters and non adopters' households if it is allowed to differ odds of being treated up to Gamma=3. That means for the outcome variable estimated, at various level of critical value of gamma, the p-critical values are significant which further indicate that consideration of important covariates that affected both adoption and outcome variables. We couldn't get the critical value gamma where the estimated ATT is questioned even if we have set gamma largely up to 3 in (Appendix I.11) show the result, which is larger value compared to the value set in different literatures which is usually 2 (100%). Thus, it can be concluded that the impact estimates (ATT) are insensitive to unobserved selection bias and are a pure effect of income due to technology adoption.

4.7. Consistency Testing

4.7.1. Cronbach's Alpha

In most empirical research Cronbach's alpha is estimated to obtain a measure of reliability of a set of question items (Henson, 2001). Cronbach's (1951) refers to the internal consistency as the proportion of the test variance that can be attributed to a group of items.

Cronbach's alpha is computed by correlating the score for each scale item with the total score for each observation (usually individual survey respondents or test takers), and then comparing that to the variance for all individual item scores: In (Appendix I .8) the alpha test before standardizing and the total result Show 0.2587(25.87%) (Consistency with questionable) and that is less consistence. So to increase the reliability or make more consistence must standardized and (Appendix I .9) shows the total result 0.7156(71.56%) (Good consistency) that explains the more internal consistencies as well as the reliability measurement.

CHAPTER FIVE

5. Conclusions and Recommendations

5.1. Conclusion

This research paper examined the underlying impact of technologies adoption on legumes producing farmer's income in Gurage zone, Ethiopia. The logit regression result showed that educational level of household headed, land size for cultivated purpose, off farm participants of household headed, TLU, access to credit, contact with extension workers and membership of household headed participants cooperative association were found to be positive in determining technologies adoption on legumes producing farmers adoption decision. Besides, gender and plot size of legumes crop for cultivated purpose were statistically significant while influencing technologies adoption on legumes producing farmers adoption decision negatively. Furthermore, the effect of technology on the livelihood of smallholder farmers basically reflected on its annual income and income from legumes crops. Impact of technology on income of households estimated using propensity score matching. The impact analysis result revealed adopting technologies has significant role on the improvement of level of total income and it has so impressive impact on crop income. It shown that total annual income of adopter improved by 46.6% and 88% improvement on the crop income relative to non adopting farmers. So based on this result the government focus especially agricultural sector, research institution and other stakeholder in the study area should give more emphasis dissemination legumes technologies adoption give special attention as a full package form.

The study brought out that adopting agricultural technology has a considerate impact on the improvement of livelihood of farming community. It is also observed that population density in highlands of the country is concentrated in which the cultivable land holding became small. One of the important strategies to meet the increasing food demand is boosting the production within a limited resource through the adoption of improved farming inputs.

According to the PSM estimation, the adoption of legumes technology has a dual impact on household wellbeing; yield increasing then increasing annual income. With this respect, allowing farmers to interact with farming technology not only have a direct impact on the income but also has a direct substitution effect on other livelihood aspects. This leads to a conclusion that adopting technology will be one of the basic instruments to enhance the leaving standard of farming community. Technology effect tends to optimized by addressing the possible influencing determinants.

5.2. Recommendations

- ✓ Access to credit can enhance technology adoption provided that the time, the condition of lending, and the cost of the money (interest) properly addressed. For farmers getting upfront cash at the time of harvesting is quite limited. As a result, credit availability became the outermost choice. With this fact, designing special line credit for purchase of farming inputs will be expected from policy makers.
- ✓ Farmer's agricultural adoption status as full packaging appropriate improve seed varieties, chemical fertilizers, inoculants, pesticide & fungicide as a package form is critical for decision making towards the adoption of technology there in designing a policy that enable to attain the target around a particular cluster. Status of adoption varied among farmers due to various factors. Generalized decision will not be effective while farmers belonged in different status of adoption. Thus, technology shall improve provided that decisions are given based on farmers' typical clusters of uniformity.
- ✓ If the female farmers were negative impact of legume technologies adoption this problem solved by governmental organization especially woman and children affair office, agricultural and natural resource development office, nongovernmental organization and other stakeholder more emphasis always continuous training and awareness creation give for farmers community.
- ✓ Plot size for legume crops is negative impact of adoption of legume technologies this impact solved by governmental organization especially agriculture and natural resource development office and nongovernmental organization more focus attention land use planning rule and regulation, land allocation for crops proportional, double cropping system and land management continuous training for farmers community.
- ✓ Tropical livestock unit is positive impact of adoption of legume technologies adoption this impacts shows mixed farming is important for agricultural technologies so minister of sciences and technologies and agricultural research institution focus appropriate improve varieties searching, adapting then release for farmers societies and minister of agriculture

more emphasis for farmers community give training and practical implementation as a demonstration on farmer training center.

- ✓ Education is a positive impact of legumes technologies adoption farmers' communities has getting formal and non formal education by minister of education and minister of agriculture more focus practical training.
- ✓ Agricultural extension services agent is a positive impact of adoption of legume technologies so government more emphasis especially minister of agriculture establishment of strengthening the institutionalizing extension linkage among different stakeholder at researchers, regional, zonal, woreda and kebel level and allocating adequate funding for linkage activities at all level.
- ✓ Membership of cooperative association is a positive impact of adoption of legumes technologies so the government more attention especially agricultural and natural resource department and cooperative office give always short term training and awareness creating for farmer's community and nongovernmental organization supports financial, logistic and training gives for each cooperatives associations.
- ✓ The impact of adoption of legume technologies annual income of household headed from legume crops the results inspiring so government focus especially agricultural sector, research institution and other stakeholder in the study area should give more emphasis dissemination legumes technologies adoption give special attention as a full package form.
- ✓ The household headed to participate in off-farm activities to the positive impact of income on the farmers and legumes technologies adoption. So based on this result the government especially ministry of agriculture and rural job opportunity agency to facilitate entrepreneurship training there farmers have diversity of skill to give continuous and sustainable training the farmers community.

Finally, technology is dynamic by its nature; it ever changing with a time and hence impacts continued to vary in similar pace. So, researcher should contemplate future possible impact of adoption in each particular period. In doing so, the stakeholders engaged in input development and distribution should identify the main concern of the farming community before releasing the technology. From cases study, Farmers are observed to have been better trust on the government organizations and hence tempting those organs will improve the intake of technologies.

5.3. Areas of Further Study

There is need to carry out a comprehensive future study on the following.

- ✓ The access technology problem needs further investigation on governmental institution especially research institution.
- ✓ The market access for output problem needs further investigation on other group.

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Appendix.I Table of results

Appendix Table.1. Standard conversion factors to compute Tropical Livestock Unit (TLU)

Animal category	TLU
Calf	0.25
Weaned calf	0.34
Heifer	0.75
Bull	0.70
Cow/Ox	1.00
Camel	1.25
Donkey (young)	0.35
Donkey (adult)	0.70
Mule	1.00
Horse	1.10
Sheep & Goat (young)	0.06
Sheep & Goat (adult)	0.13
Chicken	0.013

Source: Storck, et al. (1991 as cited in Arega and Rashid,2005)

Appendix Table .2 Logits result of PSM estimation

Explanatory variable	Coef	Std. Dv	p>value
GND	-0.979**	.550	0.075
EDUC	0.539*	.192	0.005
LANDSZ	0.993*	.336	0.003
PLTSZL	-2.160**	.893	0.016
MKT_ACC	-0.131	.427	0.759
OFFFARMP	1.386**	.719	0.056
CREDIT	1.550*	.426	0.000
EXTENS	1.420*	.437	0.001
ASSOCI	1.753*	.408	0.000
TLU	.384*	.099	0.000
TECH_ACS	-.215	.394	0.585
CONS	-6.293	1.233	0.000

LR chi^{2} (11) = 113.8

Prob > chi^2 = 0.000

PseudoR^2 =0.402

log likelihood = - 84.494

Source: own computation econometric data result (2019)

Appendix Table.3 Odd ratio after logit result

```
. logistic LTA GEN EDUC LANDSZ PLTSZL MKT_ACC OFFFARMP CREDIT EXTENS ASSOCI TLU TECH_ACS

Logistic regression                             Number of obs   =        204
                                                LR chi2(11)     =     113.81
                                                Prob > chi2     =     0.0000
Log likelihood = -84.494976                     Pseudo R2       =     0.4024
```

LTA	Odds Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
GEN	.3755135	.2067809	-1.78	0.075	.1276149	1.104968
EDUC	1.714294	.3293213	2.81	0.005	1.176432	2.498066
LANDSZ	2.701478	.9042432	2.97	0.003	1.401799	5.206154
PLTSZL	.1152423	.1029517	-2.42	0.016	.0200074	.6637937
MKT_ACC	.8768836	.3748694	-0.31	0.759	.3793601	2.0269
OFFFARMP	3.999998	2.879425	1.93	0.054	.9757006	16.39845
CREDIT	4.714088	2.010499	3.64	0.000	2.043483	10.87488
EXTENS	4.139699	1.811551	3.25	0.001	1.755817	9.760193
ASSOCI	5.77262	2.360077	4.29	0.000	2.590406	12.86406
TLU	1.468285	.1466443	3.85	0.000	1.20725	1.785763
TECH_ACS	.8063058	.3179253	-0.55	0.585	.3722821	1.746334
_cons	.0018486	.0022804	-5.10	0.000	.0001647	.0207433

Source: own computation econometric data result (2019)

Appendix .4 Marginal effects after logit

Explanatory variable	Coef	Std. Dv	t-value	p-value
GND	-0.231 **	.117	-1.97	0.049
EDUC	0.134 *	.048	2.81	0.005
LANDSZ	0.248 *	.083	2.98	0.003
PLTSZL	-.539**	.223	-2.42	0.015
MKT_ACC	-0.032	.106	-0.31	0.758
OFFFARMP	.307**	.127	2.42	0.015
CREDIT	.368*	.091	4.03	0.000
EXTENS	.339*	..094	3.58	0.000
ASSOCI	.411*	.086	4.87	0.000
TLU	.095*	.024	3.85	0.000
TECH_ACS	-.053	.098	-0.55	0.585

Source: own computation econometric data result (2019)

Appendix.5 Propensity score and covariate balance

Covariates	Mean			% bias reduction		T-test	
	sample	Treated	Control	% Bias	Bias	t	p>t
GEN	U	.813	.892	-22.2		-1.58	0.115
	M	.850	.846	0.9	95.7	0.05	.950
EDUC	U	3.667	2.802	80.4		5.74	.000
	M	3.383	3.346	3.4	95.8	0.18	.860
LANDSZ	U	2.204	1.651	61.7		4.40	.000
	M	1.842	1.857	-1.7	-97.2	-0.12	.908
PLTSZL	U	.624	.558	25.0		1.78	0.076
	M	.594	.617	-8.9	-64.2	0.45	.651
MKT_ACC	U	.745	.686	13.0		0.93	0.354
	M	.766	.733	7.4	43.3	0.42	0.676
OFFFARMP	U	0.156	0.039	40.2		2.87	0.000
	M	0.100	0.130	-10.2	-74.5	0.51	0.610
CREDIT	U	0.735	0.433	64.5		4.61	0.000
	M	0.616	0.596	4.2	93.4	0.22	0.610
EXTENS	U	0.745	0.579	47.9		3.42	0.001
	M	0.683	0.676	1.4	97	0.08	0.852
ASSOCI	U	0.754	0.362	85.5		6.11	0.000
	M	0.616	0.633	-3.6	95.8	0.19	0.852
TLU	U	6.018	4.695	66.9		4.78	0.000
	M	5.534	5.522	0.6	99.1	0.03	0.978
TECH_ACS	U	0.372	0.480	-21.8		-1.56	0.121
	M	0.433	0.416	3.8	84.5	0.18	0.855

Source: own computation econometric data result (2019)

Appendix.6 Joint significance test (likelihood ratio test)

Matching estimate	sample	Pseudo R^2	LR Chi^2	$p>Chi^2$	Man bias	Med bias
NNM						
NNM(1)	U	0.408	115.36	0.000	48.1	47.9
	M	0.066	11.01	0.442	15.7	11.1
NNM(2)	U	0.408	115.36	0.000	48.1	47.9
	M	0.031	5.10	0.926	10.5	11.1
NNM(3)	U	0.408	115.36	0.000	48.1	47.9
	M	0.013	2.17	0.998	6.6	6.6
NNM(4)	U	0.408	115.36	0.000	48.1	47.9
	M	0.013	2.17	0.998	6.3	6.4
NNM(5)	U	0.408	115.36	0.000	48.1	47.9
	M	0.007	1.21	1.000	4.2	19.9
KM						
Bandwidth (0.1)	U	0.408	115.36	0.000	48.1	47.9
	M	0.012	1.99	0.999	5.2	2.8
	U	0.408	115.36	0.000	48.1	47.9
Bandwidth (0.15)	M	0.012	2.03	0.998	5.8	4.6
Bandwidth (0.25)	U	0.408	115.36	0.000	48.1	47.9
	M	0.014	2.29	0.997	6.4	6.5
Bandwidth (0.2)	U	0.408	115.36	0.000	48.1	47.9
	M	0.012	2.07	0.998	6.1	5.1
Bandwidth (0.3)	U	0.408	115.36	0.000	48.1	47.9
	M	0.017	2.86	0.992	6.9	7.7
CM						
Cal (0.1)	U	0.408	115.36	0.000	48.1	47.9
	M	0.056	6.22	0.858	11.2	9.3
Cal (0.15)	U	0.408	115.36	0.000	48.1	47.9
	M	0.044	4.88	0.937	8.6	5.3
Cal (0.25)	U	0.408	115.36	0.000	48.1	47.9
	M	0.040	4.59	0.949	10.1	8.6
Cal (0.2)	U	0.408	115.36	0.000	48.1	47.9
	M	0.040	4.59	0.949	10.1	8.6
Radius						
Rad(0.1)	U	0.408	115.36	0.000	48.1	47.9
	M	0.013	2.21	0.0998	5.9	3.4
Rad (0.15)	U	0.408	115.36	0.000	48.1	47.9
	M	0.015	2.45	0.996	6.7	4.8
Rad (0.25)	U	0.408	115.36	0.000	48.1	47.9
	M	0.019	3.42	0.987	7.1	7.8
Rad (0.2)	U	0.408	115.36	0.000	48.1	47.9
	M	0.014	2.38	0.997	6.5	5.8

Source: own computation econometric data result (2019)

Appendix .7 variance inflation factors

Variables	VIF	1/VIF
PLTSZL	1.34	0.745
LANDSZ	1.30	0.769
EDUC	1.26	0.791
CREDIT	1.15	0.866
OFFFARMP	1.14	0.879
ASSOCI	1.12	0.894
TLU	1.12	0.895
TECH_ACS	1.06	0.945
EXTENS	1.04	0.962
GND	1.03	0.970
MKT_ACC	1.03	0.974
Mean VIF	1.14	

Source: own computation econometric data result (2019)

Appendix .8 multi co linearity

```
. corr LTA GEN EDUC LANDSZ PLTSZL MKT_ACC OFFFARMP CREDIT EXTENS ASSOCI TLU TECH_ACS
(obs=204)
```

	LTA	GEN	EDUC	LANDSZ	PLTSZL	MKT_ACC	OFFFARMP	CREDIT	EXTENS	ASSOCI	TLU	TECH_ACS
LTA	1.0000											
GEN	-0.1107	1.0000										
EDUC	0.3745	-0.0474	1.0000									
LANDSZ	0.2959	0.0489	0.1266	1.0000								
PLTSZL	0.1245	-0.0795	0.1711	0.3964	1.0000							
MKT_ACC	0.0652	-0.0469	0.0438	0.0611	0.0182	1.0000						
OFFFARMP	0.1978	-0.0027	0.3047	-0.0930	-0.0413	-0.0115	1.0000					
CREDIT	0.3082	-0.0421	0.1726	0.1199	0.3184	0.0404	0.0780	1.0000				
EXTENS	0.2338	0.0279	0.1116	0.1164	0.1228	0.0603	0.0463	0.0567	1.0000			
ASSOCI	0.3949	-0.0902	0.2586	0.1321	0.0931	0.0747	0.0937	0.1702	-0.0018	1.0000		
TLU	0.3185	0.0390	0.1797	0.2434	0.1580	0.0883	-0.0201	0.0762	0.0096	0.0799	1.0000	
TECH_ACS	-0.1090	0.0222	0.0132	-0.1734	-0.0880	-0.0937	0.0490	-0.0352	-0.0003	-0.0722	-0.1436	1.0000

Source: Own computation econometric data result (2019)

Appendix.9. Consistency test

Test scale = mean(unstandardized items)

Item	Obs	Sign	item-test correlation	item-rest correlation	average interitem covariance	alpha
AIL	204	+	0.9779	0.5674	604.1879	0.0003
IFLC	204	+	0.7270	0.5674	1667.878	0.0001
LTA	204	+	0.5994	0.5993	7795763	0.2602
GEN	204	-	0.0568	0.0568	7796018	0.2602
EDUC	204	+	0.2929	0.2929	7795728	0.2602
LANDSZ	204	+	0.7049	0.7049	7795435	0.2602
PLTSZL	204	+	0.3964	0.3964	7795941	0.2602
MKT_ACC	204	+	-0.0029	-0.0029	7796038	0.2602
OFFFARMP	204	+	0.0296	0.0296	7796029	0.2602
CREDIT	204	+	0.1871	0.1871	7795953	0.2602
EXTENS	204	+	0.0756	0.0756	7796004	0.2602
ASSOCI	204	+	0.2382	0.2382	7795929	0.2602
TLU	204	+	0.3538	0.3538	7795365	0.2602
TECH_ACS	204	-	0.1521	0.1521	7795968	0.2602
Test scale					6682317	0.2587

Source: Own computation econometric data result (2019)

Appendix .10 standardized consistency test

Test scale = mean(standardized items)

Item	Obs	Sign	item-test correlation	item-rest correlation	average interitem correlation	alpha
AIL	204	+	0.6493	0.5451	0.1368	0.6732
IFLC	204	+	0.7876	0.7165	0.1253	0.6506
LTA	204	+	0.7434	0.6607	0.1290	0.6581
GEN	204	-	0.2313	0.0784	0.1714	0.7289
EDUC	204	+	0.5192	0.3922	0.1475	0.6923
LANDSZ	204	+	0.5559	0.4345	0.1445	0.6871
PLTSZL	204	+	0.5183	0.3911	0.1476	0.6924
MKT_ACC	204	+	0.2495	0.0973	0.1699	0.7268
OFFFARMP	204	+	0.2477	0.0954	0.1700	0.7270
CREDIT	204	+	0.4424	0.3053	0.1539	0.7028
EXTENS	204	+	0.3050	0.1557	0.1653	0.7202
ASSOCI	204	+	0.4540	0.3184	0.1529	0.7012
TLU	204	+	0.4571	0.3218	0.1527	0.7008
TECH_ACS	204	-	0.2987	0.1491	0.1658	0.7210
Test scale					0.1523	0.7156

Source: Own computation econometric data result (2019)

Appendix.11. sensitivity analysis gamma test

rbounds income from legumes crops (IFLC) , gamma (1 (0.25) 3)

Rosenbaum bounds for IFLC (N = 204 matched pairs)

Gamma	sig+	sig-	t-hat+	t-hat-	CI+	CI-
1	0	0	15845.5	15845.5	13655.5	20047.5
1.25	0	0	14252.5	18412.5	11053	22620
1.5	0	0	13102.5	20900	8658	24277.5
1.75	0	0	10934	22720	7060	25327.5
2	0	0	9160	23973.8	5677.5	26275
2.25	1.1e-16	0	8024	24750	4884	27015
2.5	2.4e-15	0	6974	25395	4562.5	27687.5
2.75	4.1e-14	0	6100	26012.5	4315.5	28395
3	4.3e-13	0	5287.5	26575	4137.5	29350

* 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)

Source: Own computation econometric data result (2019

Appendix .12 before & after match summary of the distribution of the abs (bias)

Summary of the distribution of the abs(bias)

BEFORE MATCHING

	Percentiles	Smallest		
1%	13.00399	13.00399		
5%	13.00399	21.82868		
10%	21.82868	22.17298	Obs	11
25%	22.17298	24.9749	Sum of Wgt.	11
50%	47.86332		Mean	48.08404
		Largest	Std. Dev.	25.37687
75%	66.86457	64.48324		
90%	80.37443	66.86457	Variance	643.9853
95%	85.54441	80.37443	Skewness	.053038
99%	85.54441	85.54441	Kurtosis	1.595809

AFTER MATCHING

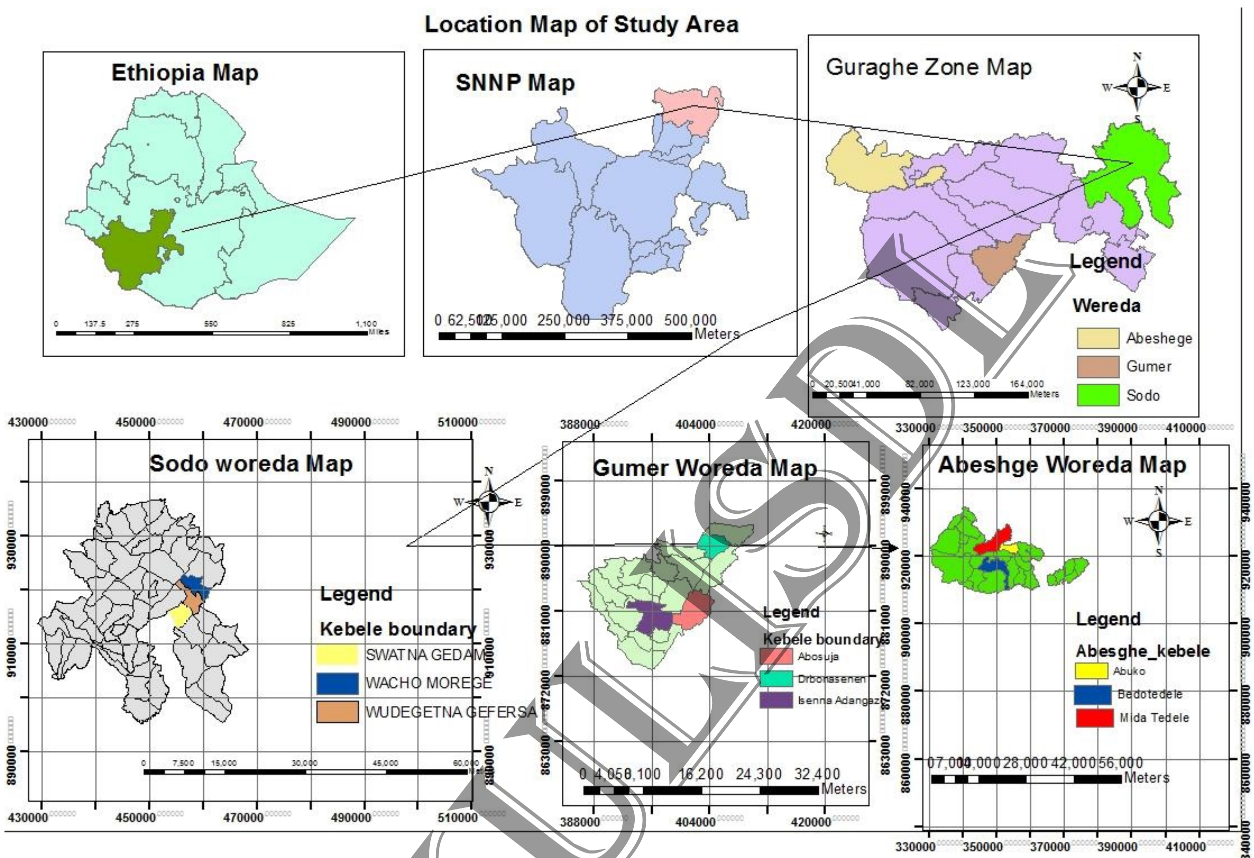
	Percentiles	Smallest		
1%	.6076273	.6076273		
5%	.6076273	.9423518		
10%	.9423518	1.415089	Obs	11
25%	1.415089	1.710092	Sum of Wgt.	11
50%	3.415913		Mean	4.171419
		Largest	Std. Dev.	3.2865
75%	7.368927	4.243413		
90%	8.931717	7.368927	Variance	10.80108
95%	10.24132	8.931717	Skewness	.7336911
99%	10.24132	10.24132	Kurtosis	2.207049

Sample	Pseudo R2	LR chi2	p>chi2
Unmatched	0.408	115.36	0.000
Matched	0.007	1.21	1.000

.

Source: Own computation econometric data result (2019

Appendix .13 location map of study area.



Appendix. II Questionnaire

Wolkite University

College of Business & Economics

Department of Economics

Questionnaire

Dear respondent! This survey questionnaire is designed with the objective of collecting information on the technology adoption of farmers. It therefore meant only for research purposes. For this purpose your genuine responses to each of the survey questions are highly useful.

There are no "right" or "wrong" answers. Your responses will be confidentially used for this research purpose only. We highly appreciate for your willingness to participate as a respondent in this survey.

For all closed type questions please put <X> mark where appropriate and please strictly follow the instruction given in each part of the questionnaire

Interviewer (Enumerator) Name: ____________

Tell: _____________________

Name of PA: _________ code; ________

I**. Demographic & geographic information**

1. Sex: Male ☐ Female ☐

2. Marriage status: married................ ☐ Divorced....... ☐ Unmarried........... ☐ widowed.......... ☐

3. Farming experience ____years

4. Religion: Orthodox Christian...... Muslim........... Protestant.................. Others (specify): ....

5. Household size (number of family members in a house hold)__________

6. Age of the household head:________________________

7. Education level of the respondent of household headed

a) No education (illiterate)_______

b) Traditional education (Mosque or church education)_____

c) Elementary education (1-6 grades)

d) Junior level education (6-8 grades)

e) Others: ---------------------

8. What is the house you owned and live in?

Grass roofed and muddy wall..............

Corrugated tin roof and muddy wall......

Corrugated tin roof and Bullock wall..........

Other (please specify)................................

II.Socio-economic characteristics

1. what is the source of income for your household (more than one answer is possible to give

- Farming (crop cultivation)..............
- Animal husbandry...........................
- Crafts man...
- Employed (salary)..............................
- Trading...
- Other (please specify) _________________

2. Landholding status (Timad):

2.1. Total landholding: _______

2.2. Total cultivable land: ______

2.3. Land allocated for legume production: _____

2.4. Land allocated for other activity (please specify): ________

3. Have you produce of legume crop? Yes ☐ No ☐

4. If yes, for Q#3 What are the main use of legume grain for you

Use of legume produced	% (from annual production)
For consumption	
For sale	
Source of livestock	
For soil fertility purpose (crop rotation)	
For other purpose (Please Specify)...................................	

5. What are the main crops you cultivate in your farm and how much area is allocated for each crops? Please fill the requested information here below:

Main crop	Area cultivated (Tmad)			
	2008 E.C Meher	2008 E.C Belge	2009 E.C Meher	2009 E.C Belge

6. Would you expect that use of farm inputs like improved seed, fertilizer, inoculants, pesticides and herbicides has improving role on yield of legume crops?

Yes ☐ No ☐

7. If your answer is yes for Q #6, would you give your response for the following information:

Farm inputs used for legume farming	Purchase price/unit	Quantity purchased/Year

8. What are the farming cultures that your implement in cultivation legume grains crops?

Practice	Faba bean	Haricot bean	Chickpea	Field pea	Others
Land plough (tractor/oxen)					
Frequency of ploughing before sowing (once, twice, three times)					
Planting time					
Planting method (raw or broadcasting)					
Weeding frequency					
Harvesting time					
Other activity (please specify...)					

III. Adoption status of agricultural technology

1. Have you ever used improved seed varieties of legume grain in your farm operation? Yes.....

No................

2. If yes, for Q# 1, where do you get these seed?

Research center..

Government supply..

Purchase from market..

Supply of development partners (e.g. NGO).........

Other source (please specify).................................

3. Have you applied fertilizer for legume production? Yes. .

4. If your answer is yes for Q #3, fill the type of fertilizer that you applied and the respective quantity as requested here below;

S.N	Type of Fertilizer	Quantity utilized per cropping season	Purchase Price per/Qt
1			
2			
3			
4			

5. Have you ever been utilized chemical inputs like herbicides, pesticides, and fungicides in production of grain legume? Yes No.

6. If yes for Q#1, 3, 5 why you using these improved farm inputs?

Improving yield performance ☐ Increasing income............. ☐
Reducing cost of production ☐ improving soil fertility..... ☐
Offsetting environmental effect ☐ food security....................... ☐
Other (please specify…) _________________

1. If you say no for Q#1,3,5, why you are not in a position to use these farm inputs?

   High purchase price.................................. ☐
   Accessibility problem.................................... ☐
   Incompatible weather condition....................... ☐
   Other (please specify)..

2. What is your current state in utilizing farm inputs (improved seeds, fertilizer, chemicals...) in your legume production? Put

   1-if you started adoption recently,
   2-if you continued adoption with increasing rate
   3- If you adopting with decreasing rate
   4- If you terminated adoption
   5- If you have a plan to adopt

Farm inputs	Adoption status
Improve seed	
Inoculants	
Fertilizer	
Chemical (pesticides, herbicides, ..)	
Farming techniques (spacing, raw planting, ...)	
Other (please specify)	

9. Do you face any challenge in adoption process of farm inputs (fertilizer, chemicals, seed, row planting) Yes ☐ No. ☐

10. If your answer is Yes for Q#9, what are the major challenges that affect the use of these farm inputs?

1. _________________ 3._________________

2. _________________ 5._________________

11. Which of the following ways is/are better to address farm inputs (seed, chemicals, fertilizers) to the farming community? Please rank the ways of inputs dissemination from best (first) to worst (the last)

Input dissemination institutions	Rank
Through gov't organization (Agri office, DA, kebele...)	
Through dev't partners (NGO…)	
Through community associations (Idir, equib, …)	
Through cooperatives, unions	
Through traders	
Through research institutions	
Others (please specify…)	

12. Do you think the improved legume inputs is better than local varieties in terms of the following traits (mark <X> for the better one in the table below)

Traits/characters	Faba bean		Haricot bean		Chick pea		Field pea	
	Local	Improved	Local	Improved	Local	Improved	Local	Improved
Yield								
Colure								
Taste								
Drought resistance								
Maturity period								
Disease resistance								
Storability								
Other (please specify......)								

13. Give a priority order for which you most focus from the above traits; first /most priority to last/least priority

1. _____________________ 5._________________

2. _____________________ 6. _________________

3. _____________________ 7. _________________

4. ______________________ 8. _________________

14. Have you used weed, disease & pest control? Yes

15. If your answer is yes question # 14 which method controlling system used?

Traditional ------------------ ☐ Biological------------------------ ☐

Mechanical ---------------- ☐ Chemical------------------------- ☐

IPM------------------ ☐ Other-----------------

16. Based on question #15 which controlling method prefer ---------------------? Why------------------
----

IV. Issues on factors of technology adoption

1. Do you have extension agent (DA) advice to use inputs in legume production? Yes ☐ No ☐

2. If your answer is yes, for the question #1, how often did the extension agent contact you? Weekly basis.................................. Twice per month..............................

Monthly basis.................................. Frequently at the time of cultivation....

Other (please specify..

3. If yes for Q#1, how can the development agent help you for the effective application of farm inputs?

Practical assistance at farm................

Demonstration..................................

Training at FTC.................................

Other (please specify) --

4. If yes for Q#1, How do you evaluate the assistance given by the development agent service for the successful adoption of farm inputs (improved seed, fertilizer, pesticides, herbicides. farming techniques etc)?

Excellent ☐ Very good ☐ ood ☐ or ☐

Other source (please specify)...

5. If your source of fund is credit for Agricultural input & the whole farm management practice cost, do you easily get credit? Yes ... ☐ No. ☐

6. If No for Q#5, What are the major problem you face to get farm input on credit? Absence of the credit agent............................

high interest rate .... (Interest rate..... %)

Problem of timely affording the credit.........

Bureaucratic nature of the credit process...........

7. If your farm is operating with credit for purchase of farm inputs, which of the fowling are source of your credit?

Commercial Bank of Ethiopia_____________ Agricultural office

Local money lender............ NGO (Development partners)

Cooperatives.............................. others (please specify) __________

8. Would the government encourage you to use farm inputs in your previous legume production activity? Yes No.

9 . If your answer is yes for the Q#8, in what way the government can support you?

Through giving subsidizing the inputs

Through giving incentives

Through easily availing the inputs on time

Other (please specify…) ________________________________

10. Have you participated in social organization in the community? Yes .

11. If your answer is yes for the above question, which of the community association do you involve? Fill your response as requested here below

Social participation	1- if participated, 2 - if not
Idir	
Equib	
Farming cooperatives/unions	
Trade unions	
Religious associations	
Females associations	
Other please specify	

12. Do you expect any risks to be driven due to devoting technologies in legumes production? Yes

No

13. If yes for Q# 12, what are the failures (risks) noticed in the adopting farm inputs in the legume production?

Reduction in yield.......... ☐ Increase in cost of production........ ☐

Loss output market......... ☐ other (please specify…)________________

Pollution of environment..... ☐

14. Would you have faced any agro - ecological problem in your legume farming activity? Yes ☐ No ☐

15. If your answer is yes the above question, what is the existing problem you faced in your previous legume cultivation?

Shortage of rain fall ☐ Snow ☐

Infertile nature of rain fall ☐ Disease occurrence ☐

Excess/erratic nature rain ☐ other please specify ---

V. Issues on Impact analysis

1. What is your total farm income in annual basis (please put your response in terms on Birr)

Crop sale..................................

Sales of fruit & vegetable..........

Livestock sale............................

Livestock products (e.g. butter or milk).......................

Off-farm activity (business other than agriculture).......... ....

Remittance...................................

Rental income..............................

Other (please specify)....................

2. What was your total farming and consumption expenditure in annual basis (please put the expenditure in terms of Birr)

Consumption expenditure..............................

(Expenditure for food, cloth, other...)

Labor (any labor cost related farming activity)..................

Purchase of farm tools................

Purchase of fertilizer..................

Purchase of seeds........................

Purchase of chemicals inputs........

Draft power..............................

Rent of farm machinery............

Other expenses...........................

3. If you are user of farm inputs, how much you produced from a hectare (4 -Timad) of land.

Legumes	With inputs	
	Yield (qt)	Income (Birr
Haricot bean		
Faba bean		
Chickpea		
Pea/ Field pea		
Other legumes		

4. If you are not user of farm inputs (improved seed, fertilizer, inoculants, chemicals...) how much you produced from a hectare (4- Timad of land)

Legumes	With inputs	
	Yield (qt)	Income (Birr
Haricot bean		
Faba bean		
Chickpea		
Pea/ Field pea		
Other legumes		

5. Have you faced marketing problem in selling of your product that produced using improved farm inputs?

   Yes ☐ No ☐

6. If your answer is yes for the above question, what is the challenge you faced in selling of your harvested legume crops?

   No surplus product for sale ☐ distance of market ☐

   No potential Buyer ☐ other (please specify) ---

   Poor price offered ☐

7. Give your response on the level of your argument on the marketing problem you faced in legume grain market as given below

Challenges for marketing of legume products	Very big problem	Big problem	Fairly big	Small problem	Not a problem at all
Distance to market is very far					
Very few buyers					
Transport cost is very high					
Prices offered is low					
Impassable roads					
There is oversupply of the commodity in the market					
Quality not acceptable to buyers					
Other (specify)					

7. Please fill the level of production that can be earned through using improved farm inputs and the level of income earned as requested here below:

Type of crop	Plot size in hectare (Timad)	Total production/annum	Consumption (Qt)/annum	Sold	
				Qt	Birr

8. If you are use Irrigation? Yes ☐ No ☐
9. If your answer is yes question #8 what source of water do you use for growing crops?

   Stream------------------------ ☐ community pond--------------------- ☐

   Lake--------------------------- ☐ dugout------------------------------ ☐

   Deep or shallow well-------- ☐ other---------------------------------

   Small pond---------------- ☐
10. If your answer is yes question #8 which crop growing?

    Vegetable ------------------ ☐ fruit-------------------- ☐

    Cereals---------------------- ☐ legumes--------------- ☐

    Oil seed-------------------- ☐ other-------------------
11. If your answer is yes question #8 how many times harvest annually?

    One------------------ ☐ two---------------------- ☐

    Three------------------ ☐ other---------------------
12. If your answer is yes question #8 in growing season area coverage irrigation on crop types & annual income.

Type of Crop	Area of cultivated land in hectare	Amount of production quintal per hectare	Selling price in quintal	Total price per annual

13. Livestock production and marketing

	Livestock ownership and estimated market value		
Ro.No	Livestock type	How many […] do you currently own?	What is the current market price of your […]? (*Birr*) (if more than one livestock, take average price)
1	Milking cows		
2	Non milking cows (mature)		
3	Trained oxen for plowing		

4	Bulls		
5	Heifers		
6	Calves		
7	Mature goats		
8	Young goats		
9	Mature sheep		
10	Young sheep		
11	Donkeys		
12	Horses		
13	Mules		
14	Mature chicken		
15	Traditional bee hives		
16	Modern bee hives		

14. Livestock and livestock products selling and buying activities over the last 12 months

		Selling			Buying		
		Have you sold any […] over the last 12 months? 1 = Yes 2 = No	Quantity sold	Average price (Birr/unit)	Have you bought any […] over the last 12 months? 1 = Yes 2 = No	Quantity bought	Average price (Birr/unit)
1	Milking cows						
2	Non milking cows (mature						
3	Trained oxen for plowing						
4	Bulls						
5	Heifers						
6	Calves						
7	Mature goats						
8	Young goats						
9	Mature sheep						
10	Young sheep						
11	Donkeys						
12	Horses						
13	Mules						
14	Mature chicken						
15	Traditional bee hives						
16	Modern bee hives						
	Animal products						
1	Milk and Yoghurt						
2	Butter						
3	Cheese						
4	Eggs						
5	Beef						

6	Mutton						
7	Honey						
8	Hide						
9	Skin						
10	Manure						

15. If you are influenced by the technology adoption, please indicate your level of agreement with respect to the following traits?

Item	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
Increase in my yield level from legume production	1	2	3	4	5
More income generated from legume production	1	2	3	4	5
I got more respect in my community after adopting legume technologies	1	2	3	4	5
I opened a small shop in a town	1	2	3	4	5
I built a nice house	1	2	3	4	5
I save more money than before	1	2	3	4	5
I started to diversifying my activities after adopting the new technologies	1	2	3	4	5
Other impact (please specify....)	1	2	3	4	5