ADOPTION AND WELFARE IMPACT OF IMPROVED FOOD LEGUME TECHNOLOGIES IN BALE HIGHLANDS OF ETHIOPIA: INTRA AND INTER-HOUSEHOLD EMPIRICAL ANALYSIS

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DEDICATION

I dedicate this MSc manuscript to my beloved father *Ato Degefu Agazhi* and my mother *w/ro Almaz Eshetu.*

STATEMENT OF AUTHOR

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BIOGRAPHICAL SKETCH

The author Zenaye Degefu was born on April 19, 1990 in Bishoftu Town of Eastern Shewa Zone of Oromia Region in Ethiopia. She attended her elementary school at Bethlehem Elementary School from 1994-1999 from Kg 1 to grade 4, then joined Bole elementary school in 2000 and complete grade 8 in 2003, high school education at Bishoftu Secondary School from 2004-2005, and her senior secondary school at Bishoftu Preparatory School in Bishoftu from 2006-2007. She joined Hawassa University in November 2008 and graduated with B.Sc. Degree in Agricultural Resources Economics and Management in July 2011.After graduating in 2011, Zenaye joined Madda Walabu University where she worked as assistant lecturer for 2 years. Then, she joined Haramaya University in 2013 to pursue her MSc studies in Agricultural Economics.

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ACRONYMS AND ABBREVIATIONS

AE	Adult Equivalent
BZADO	Bale Zone Agricultural Development Office
CSA	Central Statistics Agency
EATA	Ethiopian Agricultural Transformation Agency
EEPA	Ethiopian Export Promotion Agency
GDP	Gross Domestic Product
GPS	Generalized Propensity Score
hh	Household
ha	Hectare
ICARDA	International Center for Agricultural Research in the Dry Areas
ICRISAT	International Crops Research Institute for the Semi-Arid Tropics
MoARD	Ministry of Agriculture and Rural Development
NERICA	New Rice for Africa
OPHI	Oxford Poverty and Human Development Initiative
PSM	Propensity Score Matching
SARC	Sinana Agricultural Research Center
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

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ABSTRACT

This study was designed to investigate the adoption of improved food legume technologies and welfare impacts of improved food legume varieties specifically on income, consumption expenditure and calorie intake in Bale highlands of Ethiopia. The study focused particularly on the identification of factors determining adoption of improved food legume technologies, evaluation of welfare impacts of adoption status and intensity of improved food legume varieties, identifying intra-household impact dynamics due to adoption of improved legume varieties and spotting out the major challenges and opportunities faced by smallholders in their adoption of improved food legume technologies.. This study used cross sectional data that acquired from a total of 600 households, which were randomly and proportionately sampled from 12 major legume producer kebeles in 3 districts of Bale highlands by using three-stage sampling technique. Probit and Clog-log binary model were estimated to identify the underlying factors that determine adoption of improved food legume varieties; and fertilizer and pesticide, respectively and separately. PSM model was estimated to evaluate the welfare impacts of adoption of improved food legume varieties. In addition, continuous treatment effects model (GPS) was also employed to estimate the welfare impact of intensity of adoption by discarding non-adopters from the analysis. The results from probit and clog-log indicate that age, livestock holding, farm size, membership in farmers cooperatives, contact with agricultural research center, household head participation in off-farm activity, distance from agricultural extension office and main market; and location (district dummy) were factors that significantly determine farmers decision to adopt improved food legume technologies. The study also indicates that adoption of improved food legume technologies can motivate farmers to shift from the mono-cropping system to diversified one, improve income since they fetch higher prices than common cereals and they are the major source of protein for the household who cannot acquire it from animal products. However, adoption of improved food legume technologies is highly constrained by labor-intensive nature of the production, lack of improved food legume technologies especially water logging tolerant varieties and market irregularities. The outputs from PSM indicate that adoption of improved food legume varieties has positive and significant impact on the income and the adopter receive 25% higher income than non-adopter. The intra household analysis indicated that households with productive labor force receive better treatment effect while households with economically dependents female members receive considerably lower treatment effects from adoption of improved food legume varieties, suggesting the prevalent intra-household differences. The result of GPS also confirms the positive effect of intensity of adoption on income, consumption expenditure and calorie intake. The results generally suggests the need to design interventions enhancing adoption of food legume technologies focusing on improving adoption rates and minimizing intra household difference in income.

Key words: Adoption, Impact, Food Legume Technologies, Probit, Clog-log, PSM, GPS, Bale Highland, Ethiopia

1. INTRODUCTION

1.1. Background

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 46% of the gross-domestic product (GDP), 73% of labor employment and 80% of foreign export earnings (EATA, 2014).

Principal crops of Ethiopian agriculture include coffee, legumes, oilseeds, cereals, potatoes, sugarcane, and vegetables. The major staple foods in Ethiopia are grains (e.g. tef, 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 and legumes are estimated to be the third most important export crop in Ethiopia just next to sesame (MoARD, 2008).

Legumes are the second most important element in the national diet and a principal protein source. They are consumed as boiled, roasted, or as a stew-like dish known as '*wot'* that accompanies the locally made bread called *'injera'*. 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*., 2014and 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).

Increasing the production and productivity of food legumes provides Ethiopia with an opportunity to change the common trends of low productivity, poverty and food insecurity. This is essentially because legumes are essential for soil fertility, soil health, and the sustainability of production systems while they are intercropped or rotated with cereal crops. Legumes allow more intensive and productive use of land, particularly in areas where land is scarce. Legumes can be grown as a second crop using residual moisture and they can reduce malnutrition and improve human health especially for the poor who cannot afford livestock products. Finally, the growing demand in both the domestic and export markets for legumes could be an opportunity that provides the badly needed cash for smallholder producers (Asfaw *et al.*, 2010).

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 improved food legume technologies and evaluating the impacts of adoption and intensity of adoption on the welfare of household.

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. For several years, the performance of agriculture is poor to the extent that the country could not adequately feed its population from domestic production. Like many developing countries, the key challenge in Ethiopian agriculture is how to increase agricultural productivity to meet food security needs for the growing population and to reduce poverty and malnutrition in a sustainable way. To achieve sustainable growth in agricultural production, increasing area of cultivation is no more a viable option and use of improved agricultural technologies has become virtually the only option farming communities have at their disposal (De Janvry *et al.*, 2001; Evenson, 2003 and WDR, 2008).

High-yielding varieties, use of chemical fertilizers and pesticides, irrigation and improved planting and weeding practices provide higher productivity and improve the income and food security of farm households than conventional technologies (Adetola, 2009; Mulubrhan *et al.,* 2011; Sosina *et al*., 2014 and Tsegaye and Bekele, 2012). In recent years, Ethiopia has shown a sustained increase in the use of improved inputs notably seed varieties, fertilizer, chemical, and farm credit. Yet, improved input use in Ethiopia is still lower than that of many other countries and the adoption is highly and significantly affected by education level, market access, and contact with extension agent, farm size, active family member and access to credit (Alemitu, 2011 and Asfaw *et al.,*2011).

This study was conducted in the third poorest region (OPHI, 2015) of Ethiopia – i.e., Oromia regional state - specifically in Bale highlands. Even if so much has been done in developing improved technologies of food 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). This approach of estimating impact can only show the general tendency and fails to show differentials that happen due to the varying levels of adoption. Studies have shown that level of adoption of improved agricultural technologies varies across households and hence ignoring this heterogeneity in assessing impact could result in misleading information. In addition, most of the studies on the impact of adoption of agricultural technologies are limited to household level analysis (Mulubrhan *et al*., 2011; Berihun *et al*., 2014 and Asfaw *et al.,*2011)while intra-household dynamics is an important aspect of technology adoption and impact. Accordingly, this study analyzes welfare impact of status and intensity of adoption of improved food legume technologies in Bale Highlands of Ethiopia with due emphasis to inter and intra-household dynamics.

The study addresses the following major research questions:

1. Which factors determine adoption of improved food legume technologies?
2. What are the welfare impacts of status and intensity of adoption of improved food legumes varieties in Bale Highlands and are there any intra-household peculiarities in terms of the welfare impact of status of adoption of improved food legumes?
3. What are the challenges and opportunities of adopting food legume technologies for farm household?

1.3. Objectives of the Study

The overall objective of this study was to assess adoption and welfare impact of improved food legume technologies in Bale Highlands of Ethiopia.

The specific objectives of the study were to:

1. Identify the determinants of adoption of improved faba bean and field pea technologies;

2. Analyze the welfare impact of status and intensity of adoption of improved faba bean and field pea varieties, and

3. Identify the challenges and opportunities of adopting food legume technologies

1.4. Significance of the Study

The study analyzes the adoption and welfare impact of adoption of improved food legume technologies in Bale Highlands, which is one of the least researched corners of Ethiopia. The study has generated empirical information on challenges and opportunities of adoption of improved food legume technologies, determinants of adoption and its welfare impact by taking into account intra household differences and heterogeneity in intensity of adoption. The information generated is expected to be useful to academia, agricultural and rural development agents, federal and regional states in the farming systems, nongovernment organizations, private agricultural operators, researchers and the sample districts to make relevant decisions and intervene in the different aspects of development and dissemination of food legume technologies.

1.5. Scope and Limitations of the study

The study was limited to three districts in Bale 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 Bale highlands and 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.

2. LITERATURE REVIEW

2.1. Production and Importance of Food Legumes

Food legumes are very important elements of many cropping systems and make a significant contribution to diets and are often referred to as 'poor man's meat' and with few exceptions, direct legume consumption tends to drop or at best remain stable with increases in income. In fact, this does not necessarily apply to the use of soybean and other legumes in industrial food products (Robert, 2011). In Ethiopia, legumes are the second most important crop and in 2014/2015*'meher'* cropping season, legumes covered 12.41% of the total cultivated land that is 1.6 million hectare (ha) and provided 9.8% of the total crop production of the country, which is 2.67 million ton (CSA, 2015).

This study focused on the adoption and impact of improved faba bean (*Vicia faba*) and field pea (*Pisum sativum*) technologies that are available in Bale Highlands of Ethiopia. Faba bean is an annual legume that grows best under cool, moist conditions. Hot, dry weather is injurious to faba bean but it can tolerate frost. Evenly distributed rainfall of 650 to 1000 mm per annum and medium textured soils with pH ranging from neutral to alkaline (pH of 6.5 to 8.0 is ideal for faba bean (Abdel, 2008;Rajan *et al*., 2012). Since the crop requires a good moisture supply for optimum yields, moderate moisture supply is necessary. Faba beans do not tolerate standing water. It is grown in warm temperate and subtropical areas; hardier cultivars in the Mediterranean region tolerate winter temperatures of -10°C without serious injury whereas the hardiest European cultivars can tolerate upto -15°C. It can be grown anywhere and does not winterkill.

In Ethiopia, Faba bean is usually sown from mid-June to first week of July when sufficient moisture is available. Period of harvesting for Faba bean varies with altitude. It takes 135-160 days at high altitude (2300-3000 m.a.s.l) and 118-135days at mid altitude areas (1800 to 2300 m.a.s.l) to mature. Harvesting is performed manually by cutting the plant at ground level when the upper part of the buds turn black and the lower part turns yellow. It is then dried and threshed on traditional threshing plots (EEPA, 2012). According to CSA (2015) in 2014/2015 '*meher*' production season, faba bean covered 0.43 million hectares with total production of 0.83 million ton. More than 90% of the produced faba bean in Ethiopia is consumed locally in various ways.

Although the absolute figure is still small compared to the potential, Ethiopia's export of faba bean has shown an increase since the year 2008. In 2008, the country has exported 151 tons of faba bean valued at 0.055 million USD but this has increased to 2562 tons and USD 1.05 million in 2010. Major market destinations for Ethiopian faba bean are Sudan, South Africa, Djibouti, Yemen, Russia and United States of America (EEPA, 2012).

Similarly, Field pea is well adapted to cool; semi-arid climates and it can be grown on a wide range of soil types, from light sandy to heavy clay. The ideal soil for field pea production is with pH value ranging from 5.5 to 7.0 (Hartmann *et al*., 1988). Field pea has moisture requirements similar to those of cereal grains. However, field peas have lower tolerance to saline and waterlogged soil conditions than cereal grains. Field peas most often will die after 24 to 48 hours in a water-logged condition. Poorly drained and saline soils should be avoided when growing field peas (Blaine and Gregory, 2009).

Usually in Ethiopia, field pea is sown from mid-June to first week of July when there is sufficient moisture. It is ready for harvesting after 100-150 days at high altitude (2300-3000 m.a.s.l) and 100-126 day at mid-altitude (1800-2300 m.a.s.l) areas; this is when the color of the buds turns from green to yellow. Annual rainfall of 800-1100 mm and 700-900 mm is suitable for high and mid altitude field pea growing areas with maximum temperature of 20^0-25^0C. Harvesting carried out manually by cutting the vines from the ground and laying them to dry until the seed moisture approaches 9% for good storage (EEPA, 2012). According to CSA (2015), the national production was around 3.4 million quintal (= 3.4 ton) from an area of 0.23 million ha and most of the produce is consumed locally. Ethiopian export of field peas is very small compared to other pulses due to its high local demand. Field pea (dried) exported in 2010 was only 11.7 tones, which is 0.01% of the total pulse export (EEPA, 2012).

In Bale highlands of Ethiopia, there are two faba beans and eight-field pea varieties, which were distributed to farmers by SARC. In Bale Highlands, legume production helps the farmer to fulfill household food requirement and generate cash from sales of marketed surplus. The major role of legume production in Bale highlands is increasing the productivity of next season crop by improving soil fertility (SARC, 2014).

In tropical areas, food legumes present an opportunity in reversing the unfavorable trends in productivity, poverty and food insecurity. This is because legumes have the capacity to fix atmospheric nitrogen in soils and thus improve soil fertility and save fertilizer cost. Second, legumes enable more intensive and productive use of land, particularly in areas where land is scarce and the crop can be grown as a secondary crop using residual moisture. Third, legumes reduce malnutrition and improve human health especially for the poor who cannot afford livestock products. Fourth, the growing demand in both the domestic and export markets creates an opportunity for farm households to generate cash income from selling the crop produce. Even if food legumes bring important contribution to crop production and local diets, there are number of factors that hold back the development of productive technology and farmers' interest in pursuing such technology create a considerable challenge (Robert, 2011).

2.2. Theoretical Reviews

2.2.1. Adoption and Impact of Adoption

According to Feder *et al*. (1985), adoption is defined as the integration of an innovation into farmers' normal farming activities over an extended period. Similarly, adoption is defined as a decision to apply an innovation and to continue to use it over a reasonably long period of time (Ban and Hawkins, 1996). Adoption can be considered as a variable representing behavioral changes that farmers undergo in accepting new ideas and innovations in agriculture anticipating some positive impacts of those ideas and innovations. It further noted that adoption is not a permanent behavior. An individual may decide to discontinue the use of an innovation for a variety of personal, institutional, or social reasons, one of which might be the availability of an idea or practice that is better in satisfying his/her needs.

As noted by Feder *et al*. (1985), a complete analytical framework for investigating adoption process at the farm level should include farmer's decision-making model. This determines the extent and intensity of use of a new technology at each point throughout the adoption process and a set of equations of motion describing the time pattern of parameters that affect the decision made by farmer. Final adoption at farm level of the individual farmer is defined as the degree of use of a new technology in the long-run equilibrium when the farmer has full information on potentials of a new technology (Feder *et al*., 1985).

In most of the sub-Saharan Africa, agriculture remains large and the bulk of the poor are smallholders who benefit from it directly through increased agricultural profits or indirectly through increase in nominal income from other sources other than own agricultural production (WDR, 2008). Agricultural growth is widely considered as the most effective means of addressing poverty in the developing world. Growth in agricultural production can reduce food insecurity by increasing the amount of food available for consumption. This is particularly important for rural consumers whose food entitlement is mainly based on own production (Adekambi *et al.,* 2009).

Agricultural production can be increased through extensive resource use through expansion of farmlands or intensification by using more inputs and technologies per unit of land. However, extensive resource use is not a viable strategy to increase agricultural production in most of the food insecure countries where high population pressure is a critical bottleneck. Where land is scarce, intensification, which entails investments in modern inputs and technologies, is a better option to increase agricultural production and reduce food insecurity. New agricultural technologies and improved practices play a key role in increasing agricultural production (and hence improving national food security) in developing countries. Where successful, adoption of improved agricultural technologies could stimulate overall economic growth through inter-sectoral linkages while conserving natural resources (Sanchez *et al.,* 2009).

Agricultural research can contribute to poverty reduction in three major ways. First, agricultural research helps in developing yield-increasing technologies contributing to an increase in the supply of food on which the poor spend a considerable share of their income. The development of high-yielding varieties, which boost food production both by increasing yields per unit of land per cropping season and by facilitating multiple cropping. Second, agricultural research helps to conserve natural resources since the poor lack alternative means to intensify agriculture except forced to overuse or misuse the natural resource base to meet basic needs. Third, because the poor tend to reside in marginal agricultural areas, research should aim at developing technologies suitable for these. However, it is widely argued that research often neglected the marginal areas, thereby worsening poverty in them by reducing market prices of grains without improving technology (Lipton and Longhurst, 1989).

2.2.2. Household Welfare and Its Indicator

Every human being acts in order to maximize his or her own perceived level of happiness. Welfare can be defined as the potential to create happiness of a given commodity. It is not possible to make people happy, but certain tangible factors can contribute towards the development of an environment, which may increase one's natural inclination towards happiness. Generally, welfare of a household shows the general wellbeing of the household that indicating the household's state or condition with respect to health, safety, happiness or prosperity (Edward, 2009). Therefore, a proper understanding of welfare is critical for any economic analysis, which deals with the human condition (Joshua, 2011). The major indicators of welfare of a given household are income, food security, educational welfare, health welfare and asset holding of the household, which can classified as monetary and non-monetary welfare indicators.

Monetary welfare indicators

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

Income

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

Consumption Expenditure

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

Non-monetary welfare indicators

Welfare is associated not only to income or consumption expenditure of the household, but also to outcomes related to health, nutrition, literacy, social relations, to insecurity, and to low selfconfidence and powerlessness. In some cases, it is feasible to apply the tools developed for monetary welfare measurement to non-monetary indicators of wellbeing(Edward, 2009).

Education

Education is a well-known and widely used non-income welfare indicator. One could use the level of literacy as the defining characteristic, and some level judged as the threshold for literacy as the "poverty line". In countries where literacy is close to universal, one might opt for specific test scores in schools or for years of education as the relevant indicators.

Health

Health is another well-known and widely used non-income welfare indicator. One could focus on the nutritional status of household as a measure of outcome, as well as on the incidence of specific diseases (diarrhea, malaria, respiratory diseases) or life expectancy for different groups within the population.

Household amenities

The first welfare indicator under household amenities is source of drinking water and the distance of a household from its main source of drinking water in kilometers. The second type of amenity for which information is available is sanitation source. The third type of amenity for which information is available is lighting source mains which may be electricity, generator, kerosene/gas lamp, and candles/torches.

Household assets

The amount of assets that a household owns is likely to affect its welfare for two reasons. First, the more assets it owns, the higher will be its income-earning potential, which raises welfare. Second, the more assets it owns, the higher will be its ability to smooth its consumption level in response to income shocks. To the extent that households are risk-averse, this also increases household welfare (Edward, 2009).

This study uses daily calorie intake as a non-income welfare indicator following Sosina *et al.* (2014) who used household per capita maize available for consumption and Tsegaye and Bekele

(2012) who have used daily calorie intake per AE to evaluate impact of adopting improved crop varieties.

2.3. Empirical Review

2.3.1. Determinants of Adoption of Agricultural Technologies

The literature on adoption of high-yielding varieties and crop management technologies in developing countries points towards a number of factors operating in a quite complex and interactive ways that condition the adoption decision of farmers. Identifying the determinants of adoption of agricultural technologies is an important intervention to enhance the adoption of agricultural technologies, which finally results in agricultural development. There are many studies in Africa particularly in Ethiopia on the determinants of adoption of agricultural technologies.

Asfaw *et al.* (2011) analyzed the determinants of adoption of improved varieties of chickpea in Ethiopia by using double hurdle model. Their results suggest that the variable such as active family labor, per capita asset, farm size, non-oxen livestock and previous year knowledge of improved varieties were found to positively affecting the decision to adopt improved chickpea varieties. This study also identified the determinant factors of improved seed access by using double hurdle model. Accordingly, household head education level, number of oxen per capita, non-oxen livestock assets (TLU) per capita and frequency of contact with government extension agents were positively and significantly affecting the seed access of household. While, district dummy [being exists in Minjar-Shenkora and Gimbichu district] was found to affect seed access and adoption of improved chickpea varieties negatively by taking Lume-Ejere district as references, this is because the district is near to interregional road.

The study in Dale district of SNNPRS of Ethiopia by Alemitu (2011) using Tobit model identified the factors that determine intensity of adoption of improved haricot bean varieties and associated agronomic practices. The results indicate that sex of household head (being male), access to improved haricot bean varieties, participation in field days, membership of seed multiplication, participation in training and field demonstration had positive contribution for adoption while distance from both input and output market had adversely affecting to the adoption of improve haricot bean varieties.

Similarly study by Mulubrhan *et al*. (2011) identified the determinants of maize-pigeon pea intensification in Tanzania by using seemingly unrelated and recursive bivariate Probit models to identify the factors affecting adoption of given technologies while double hurdle model and Tobit model were employed to determine influential factor of level of adoption of pigeon pea and maize intensification. The model result indicate that inadequate local supply of seed, access to information, human capital, and access to private productive assets were found to be key constraints that determine the adoption.

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 tef. In this study, age of household head, owning oxen and distance from household residence to market center were 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 improved food legume technologies in Bale Highlands of Ethiopia where legumes are not the dominant crops. In addition, most of the studies above were undertaken in locations with entirely different socio-economic and biophysical features compared to Bale Highlands.

2.3.2. Impact of Adoption of Agricultural Technologies

Studying the impact of adoption of agricultural technology has a great advantage for a country like Ethiopia where the agriculture sector drives the entire economy. Technological improvement of farming systems and its adoption has positive impact on the economic development of a country. According to literature on the impact of adoption of agricultural technologies, improved varieties and other accompanying technologies have positive contribution towards food security, income improvement, household expenditure, poverty and generally on the welfare of farm households. The following symmetric reviews of literature also confirm the positive correlation of adoption of agricultural technologies and welfare of household.

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

Similar studies on welfare impact of maize pigeon pea intensification in Tanzania by Mulubrhan *et al*. (2011) revealed that positive and significant impact of adoption of improved agricultural technologies. The study estimated the causal impact of technology adoption on household welfare by using propensity score matching and switching regression techniques. Results from both estimations confirm that adoption of improved maize and pigeon pea intensification has a positive impact on consumption expenditure per capita even if the result from PSM is not significant for maize that is suggesting the importance of controlling for unobserved heterogeneities in establishing causality. The result generally confirms the potential role of technology adoption in improving rural household livelihood as higher incomes from improved agricultural technologies translate into lower poverty, higher food security and greater ability to with stand risk.

Similarly, Sosina *et al.* (2014) reported findings of a study that aimed at assessing the impact of improved maize on household welfare in Malawi using panel data of 3 years. The study used household per capita maize available for consumption from own production, household per capita income and household per capita assets holding as welfare indicator. Fixed-effects model was employed to estimate the relationship between adoption of improved maize technology and household welfare. Here instrumental variable was used to control the endogeneity problem. The model output confirms that improved maize planted has positive and significant relation with the welfare of farm households. An increase in improved maize plant was positively correlated with their own maize consumption for both male and female-headed households. Poor and better off households had benefited from improved maize planting with higher elasticity for poorest households.

Likewise studies in Nigeria on the impact of improved rice technology (NERICA varieties) on income and poverty among rice farming households by Dontsop *et al.* (2011) reflects the positive impact of adoption on the income and poverty reduction of farm households. The study employed instrumental variable method to estimate the Local Average Treatment Effect of adopting NERICA on income and poverty reduction. The empirical results of this study indicate that adoption of improved varieties was raising farmers' income and per capita expenditure, thereby increasing their likelihood of escaping poverty. This confirms the widely held view that productivity enhancing agricultural innovations can contribute to raising incomes of farm households, poverty alleviation and food security in developing countries.

The study by Degye *et al.* (2013) on the simultaneous interaction between adoption and food security of smallholders in rural Ethiopia also confirmed the positive and strong interdependence between adoption and food security. There were three agricultural technologies and two food security measures analyzed by simulated maximum likelihood multivariate Probit model to measure the link between the adoption of agricultural technology and food security indicators and to identify their underlying determinants. The results generally implies that an intensive effort is required to enhance household food security through the accelerated introduction and dissemination of appropriate agricultural technologies in rural Ethiopia.

Similarly, the study by Tsegaye and Bekele (2012) on the impact of adoption of wheat technology on household food consumption in southeastern part of Ethiopia (Lode Hetosa district of Oromia regional state) confirms the positive correlation of adoption of agricultural technologies with food security. Propensity score-matching method of impact evaluation was employed to assess the impact of adoption of improved wheat technology on food consumption of farm households. Adoption of improved wheat varieties planted in spacing positively linked with food consumption level of households. Though the adoption of improved wheat technologies was quite low, those households using the technologies could improve their food consumption levels. Scaling up the best practices of the adopters to other farmers was suggested as one option to enhance food security in the area while introducing new practices and technologies was another option.

Di Zeng *et al*. (2014) undertook similar study in Rural Ethiopia on adoption of improved maize varieties and its impact on child nutrition by using instrumental variables and quantile instrumental variable regressions. The result indicates that the positive impact of adoption of improved technology on the general welfare of rural households children nutrition improvement. The study concludes that child malnutrition can be reduced if the poorest nutrition outcomes were improved so adoption needs to be promoted among the poor.

Adoption and impact of agricultural technologies on farm income in southern Tigray of Ethiopia by Berihun *et al*. (2014) also presented a similar result. The ordinary least square regression results revealed that agricultural technology adoption has an encouraging effect on farm income by which adopters were better off than non-adopters. The study argues that to increase the likelihood of adopting modern agricultural technologies and to achieve the expected impact, it is important to improve credit market failures, irrigation problems by introducing drip and pipe irrigations, securing land ownership of farm households and empower female-headed households.

The study in rural Tanzania by Kassie *et al.* (2014) reported a positive impact of intensity of adoption of maize varieties on the food security of households by using the non-parametric continuous treatment effect estimation model called generalized propensity-score matching. Farm households' own subjective assessment of their food security, in addition to the standard per capita food-consumption was used as measure of food security situation of household. The results from this model indicated that maize technology adoption had a modest but significant positive impact on food security, which varies with the level of adoption. Finally, the study concluded that agricultural technology adoption has contributed positively on reducing rural food insecurity in Tanzania.

The aforementioned studies revealed the significant and promising effect of agricultural technologies on the general wellbeing of the farm households. However, most of the studies focus only on politically or financially important crops. Most of the studies also analyzed the impact of adoption of improved technologies regardless of the intensity of adoption. The recent literature on the impact evaluation warns that impact assessment by only considering adoption status (binary treatment) of farm households may not give precise information on the extent to which the technology has actually brought about the impact being assessed. In addition, the above literature does not consider the intra household differences while evaluating the impacts. Therefore, it is important to evaluate the impact of intensity of adoption in addition to adoption status of household and considering the difference with in households.

2.4. Conceptual Framework

The conceptual framework of adoption and impact of improved food 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 improved food 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.

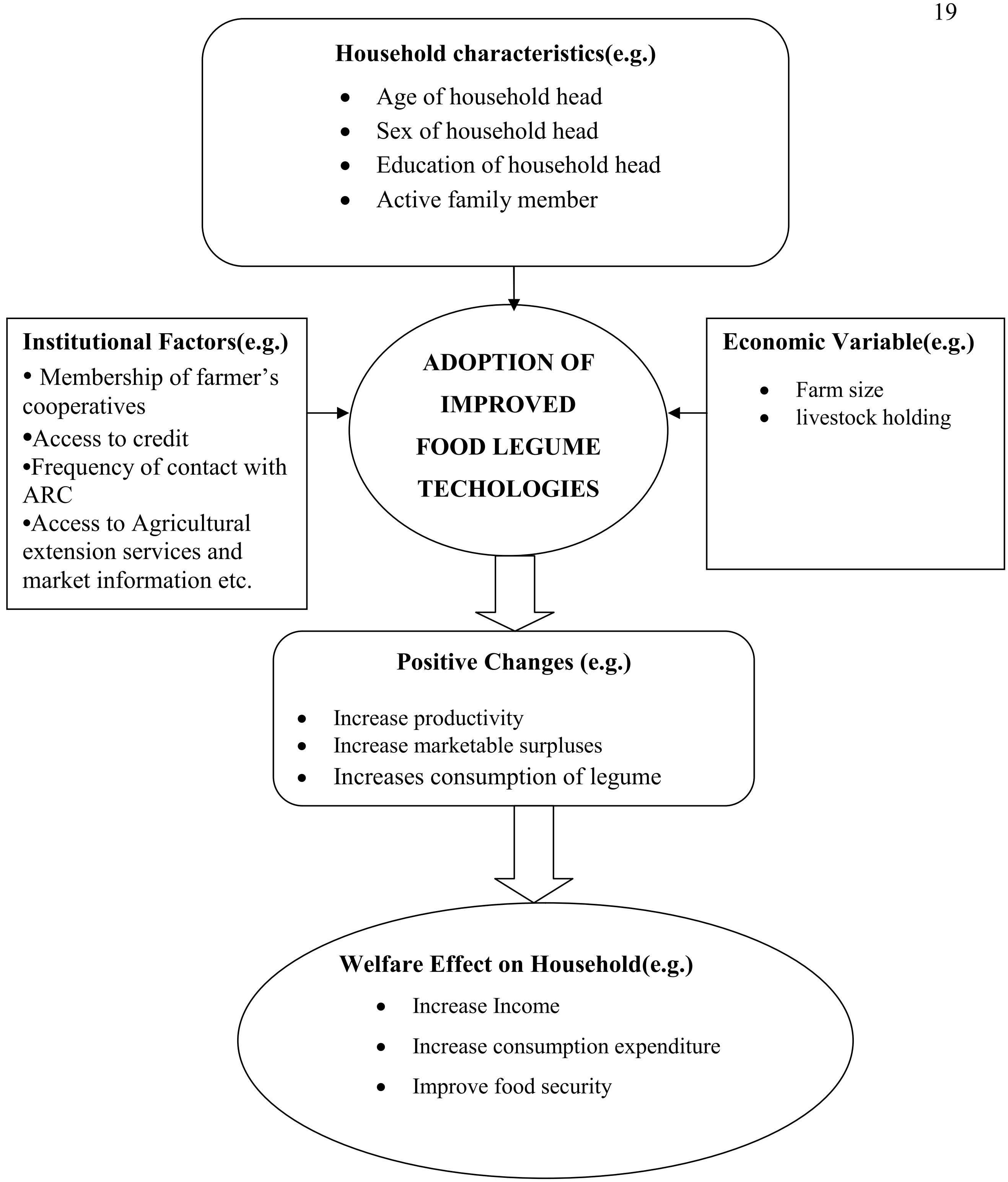

Figure 1: Conceptual Framework Adoption and welfare impact

Source: Own derivation from Literature

2.5. Analytical Framework of Impact of Adoption of Improve Technologies

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 improved food 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.

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 time 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.

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 welfare 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.

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 food 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 improved food 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 improved food legume varieties (adoption as continues treatment variable) on the adopter households by discarding non-adopter from the model.

3. METHODOLOGY

3.1. Description of Study Area

Bale zone is one of the 18 administrative zones in Oromia regional state in south-eastern Ethiopia situated at $5^o22'$–$8^o08'$N latitude and $38^o41'$ – $40^o44'$E longitude. It has 18 districts, of which nine are commonly called the Bale Highlands. The zone shares borders with Arsi, Guji, West and East Hararge zones as well as Somali and SNNP regions.

The altitude in Bale zone ranges from 300 to 4377 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 0.04%, 14.93%, 21.5%, and 63.53% of the zone, respectively. The topography of the area includes plain land, plateaus, hills and undulating landform. The area receives an average annual rainfall of 400-2500mm and minimum and maximum temperature of 3.5^oC and 35^oC, respectively.

Total area of Bale zone is about 63,555 square kilometres accounting for 16.22% of Oromia region. Only about 10.2% of the zone is arable land under crop production, whereas 24.3% is grazing land, 41.5% covered with forest, and the remaining 24% of the zone is under other land use forms (BZADO, 2015). The districts in the Bale highlands are known for their bimodal rainfall pattern and hence highly suitable for agriculture. They have two distinct seasons; i.e, *Belg* (from March to July) and *Meher* (from August to January). About 0.246 million ha of land in the zone is cultivated during *Belg* season while 0.162 million ha is cultivated during *Meher* season. Total crop production was 0.765 and 0.423 million tonnes during *Meher* and *Belg* 2014/15 production seasons, respectively (BZADO, 2015).

According to BZADO, the zone has an estimated total population of about 2.11 million out of which about 1.08 million are male and 1.03 million are female. Out of total population of the zone, more than 95% is dependent on agriculture and 88% lives in rural areas.Major crops grown in the zone are wheat, barley, faba bean (*Vicia faba*), field pea (*Pisum sativum*), maize, tef, sorghum and linseed. Enset (*Ensetumventricosum*), coffee and khat (*Cata edulis*) are also grown in the zone.

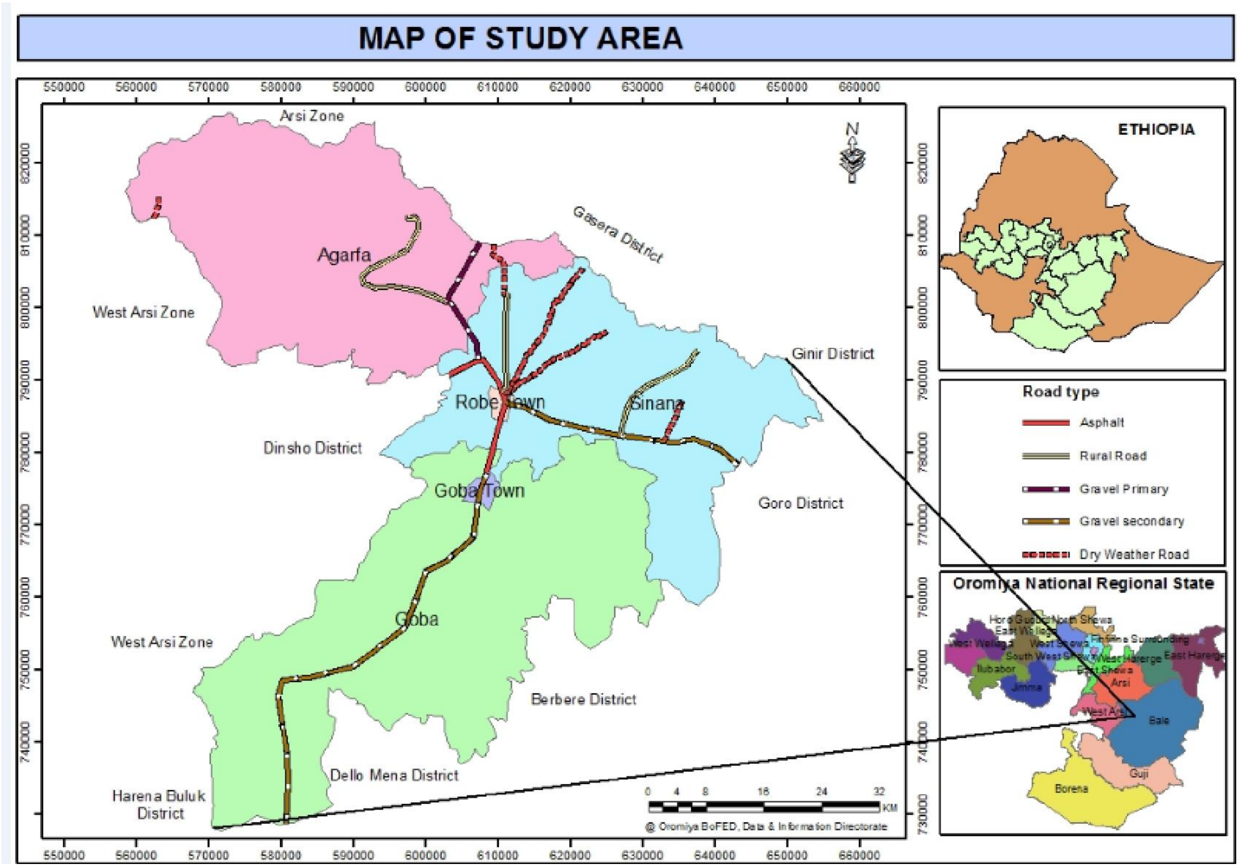

Figure 2: Map of study districts and Bale Zone in Oromia region

3.2. Description of the Legume Technologies

This study focuses on adoption and impact of improved food legume technologies on the welfare of farm households with due consideration of intra-household differences. The major legumes produced in Bale Highlands are field pea and faba bean. Discussions with researchers at Sinana Agricultural Research Center revealed that the districts with high potential for food legume production in Bale highlands are Sinana, Goba and Agarfa.

There are two faba bean varieties and eight field pea varieties released and/or disseminated in the Bale zone by SARC or its partners. The faba bean varieties are *Mosisa* and *Shallo.* The field pea varieties are *Harannaa, Urjii, Bamo, Wayyitu, Tullu-dimtu, Hursa, Tullu-shenen* and, *Dadimos* (SARC, 2014). It was reported by SARC that farmers in the Zone also use fertilizers like urea, DAP, manure and Bio-fertilizer and pesticides such as herbicide, insecticide and fungicide for legume production.

3.3. Method of Data Collection and Sampling Procedure

3.3.1. Type and method of data collection

Both qualitative and quantitative 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 food legumes research and 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 food 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 March to March 30 of 2015. The data were collected by enumerators (Staff of SARC) 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 food legumes, access and adoption of improved food legume technologies, household income and its source, food consumption and its expenditure, access to market, access to credit and membership in different rural institutions..

3.3.2. Sampling Procedure

In this study, three stage sampling technique was employed. First, major food legume producing districts in Bale highlands were identified with the help of key informants. At this stage, three major food legume producing districts were selected purposively. The districts were Agarfa, Goba and Sinana based on relative importance of food legumes in the crop production system. Then, four kebeles were randomly selected from each district. Accordingly, Selka, Gomera, Weltei-Berisa and Alage Kebles were selected from Sinana district. Weltei-Tosha, Wecho-Meshege, Aloshe-Tilo and Weltei-Kubisa Kebeles were selected from Goba district. Similarly, Ali, Asano, Elani and Sabaja kebeles were randomly selected from Agarfa district. Finally, out of total 12 kebles a sample of 600 farm households in total– 200, 197 and 203 sample households from Agarfa, Goba and Sinana, respectively- were selected proportionately across kebeles based on their total households. Table 1 shows the distribution of the sample households across the four Kebeles in each of the districts.

Table 1: Sample Distribution

District	**Kebeles**	**Number of household**	**Number of sample households**	**Total (%)**
Agarfa			200	**33.3**
	Ali	1038	76	12.67
	Assano	542	38	6 .33
	Elani	680	44	7.33
	Sabanja	644	42	7
Goba			197	**32.8**
	Alose Tilo	583	56	9.33
	Welti Kubsa	536	53	8.83
	Wecho Mesherge	570	56	9.33
	Welti Tosha	319	32	5.33
Sinana			203	**33.8**
	Alage	652	43	7.77
	Gomera	644	51	8.5
	Selaka	1007	70	11.67
	Welti Berisa	593	39	6.5
	Total		**600**	**100**

3.3. Method of Data Analysis

Descriptive statistics– e.g., student t and Chi-square (χ^2) tests -were used to summarize demographic characteristics of sample respondents and the intra household inequalities. Probit and clog-log econometric models were employed to identify determinants of adoption of improved food legume technologies. To evaluate the impact of adoption of improved food legume varieties on welfare of household, PSM was employed. In addition, GPS (continuous treatment effect) was estimated to quantify impact of intensity of adoption of improved food legume varieties.

3.3.1. Estimation of Adoption of Food Legume Technologies

In this study the adoption of improved food legume varieties were defined as a continuous planting of improved faba bean and field pea varieties. The dependent variable has a binary nature taking the value of "1" for adopters of improved food legume varieties and "0" for non-adopters. To identify the determinants of adoption of improved food legume varieties, a probit model was employed.

The probit model is often used in situation where an individual makes choices between two alternatives, in this case the decision to either adopt or not-adopt improved food legume varieties. Theoretically, an individual makes a decision to adopt if the utility associated with adopting the new technology (β_{1J}) is higher than the utility associated with decision not to adopt (β_{0J}).Following Koop (2003), the difference in utilities of the two alternative choices is stated as $\boldsymbol{Y_j^*} = \beta_{1J} - \beta_{0J}$ and the econometric specification of the model is given in its latent as:

$$Y_j^* = X_j\beta + \mathrm{e}_j \qquad (1)$$

Where Y_j^* is an unobserved (latent) random variable that defines farmer's binary (adoption) choices, X_j a matrix of explanatory variables associated with individual j. β is a vector of coefficients associated with the explanatory variables while e_j represents the random error terms assumed to be independently and identically distributed; i.e., $e_j \sim N(0,1)$. The relationship between the unobserved variable Y_j^* and the observed outcome Y_j can be specified as:

$$\begin{aligned} \mathrm{Y_j} &= 1 \quad \text{if } \mathrm{Y^*}_\mathrm{j} > 0 \\ \mathrm{Y_j} &= 0 \quad \text{if } \mathrm{Y^*}_\mathrm{j} \le 0 \end{aligned} \qquad (2)$$

The probability of the event occurring is the cumulative density function of e_j evaluated at given values of the independent variables.

$$\Pr(Y_j = 1 | X) = \Phi(X_j \beta) \quad (3)$$

where Φ is the standard normal cumulative distribution function for the probit model.

Furthermore, complementary log-log (clog-log) binary model was used to identify the determinants of adoption of fertilizer and pesticide for the production of legumes separately. Clog-log model represent third alternative to logistic regression and probit analysis for binary response variables, which is frequently used when the probability of an event is very small or very large(Cameron and Trivedi, 2009). Probit and logit model are symmetrical and hence weaker when *Pr* is close to 0 or close to 1 or *Pr* is around 10 percent or 90 percent (Vijverberg, 2012). In the case of this study, rates of adoption of fertilizer and pesticide were found to be 17% and 7.8%, respectively. Therefore, it is rational to apply clog-log for estimating determinants of adoption of fertilizer and pesticide for legume production. More importantly, the clog-log model assumes that the residuals can be represented by an extreme value distribution (Powers and Xie, 2000), which is crucial when the error term estimate is much closer to such an asymmetric distribution than to a normal or logistic symmetric distribution.

In this study, the adopters were coded 1 and non-adopters coded 0. The fitted clog-log model was expressed as:

$$\Pr(Y_i = 1 | X_i) = 1 - \exp\{-\exp(X_i \beta)\} \quad (4)$$

The predicted probability of each household "i"can thus be expressed as:

$$\log[-\log(1 - p_i)] = X_i \beta \quad (5)$$

where $Y_i$is adoption status of fertilizer or pesticide for production of legume, X_i denotes covariates that affect the adoption of fertilizer and pesticide and β the vector of parameters.

3.3.2 Welfare impacts of adoption of food legumes varieties

3.3.2.1. Impact of adoption status of improved food legume varieties

According to Heckman *et al*. (1998), the major problem in non-experimental treatment effect estimation methods is the presence of selection bias, which could arise mainly from nonrandom location of the project and the non-random selection of participant households. There are three potential sources of bias. The first one is that participant households may significantly differ from non-participants at community as well as household levels due to observable characteristics (such as geographic remoteness, or a household's physical and human capital stock) that may have a direct effect on outcome of interest. Secondly, the difference arises due to unobservable community level characteristic. For instance, particularly dynamic local leaders at community level may in part drive the existence of a project. At the household level, a household's expected benefits, its entrepreneurial spirit, or its relationship with other program/project may significantly influence behavior. Thirdly, externalities (spillover effect) exerted by project on non-participants are also important (Bernard *et al*., 2010).

Even if PSM controls households' observable characteristics by comparing the outcomes of program participants with those of matched non-participants, differences between adopters and non-adopters may either totally or partially reflect initial differences between the two groups rather than the effects of adoption of improved food legume varieties. Having control households from the same communities as program beneficiaries helps to reduce the risks of such bias. However, disregarding unobservable characteristics remains the main problem of this method.

As Ravallion (2005) argues, contamination of the control group can be hard to avoid due to the responses of markets and governments. For instance, Bernard *et al*. (2010) minimized the effect of spillover effect on comparison group by comparing cooperative members to similar households located in other kebeles where there are no cooperatives. Nevertheless, as argued by Heckman *et al*. (1998), treatment and comparison households should operate in the same markets and should have come from similar agro-ecology (from sufficiently close locations) and socioeconomic conditions in order to ensure the validity of PSM method.

To achieve objective of evaluating impact of adoption of improved food legume varieties on welfare of farm households in Bale highlands, PSM was estimated. It is chosen among other non-experimental methods because it does not require baseline data, the treatment assignment is not random and considered as second-best alternative to experimental design in minimizing selection biases (Baker, 2000).

The treatment in this study is the adoption of improved food legume varieties and the expected outcomes are income, consumption expenditure and calorie intake. On the other hand, controls are households that did not adopt improved food legume varieties. Ideally, comparison of the households with the adoption of improved varieties shall be compared with the situation these households would have been without adopting the varieties or vice versa. The households can however be only in one of the two states – either adopting or not adopting.

Specifications of PSM method

The PSM technique enables us to extract from the sample of non-adopting households a set of matching households that resemble the adopter households in all relevant characteristics. In other words, PSM matches each adopter household with non-adopter household or households that have (almost) the same characteristics. In this case, estimating the effect of household's status of adoption improved food legume varieties on a given outcome (*Y*) is specified as:

$$T_i = Y_i(D_i = 1) - Y_i(D_i = 0) \tag{6}$$

Where T_i is treatment effect (effect due to adoption of improved varieties), Y_i is the outcome on household *i*, D_i is whether household *i* has adopted improved food legume varieties or not.

Because of counterfactual nature of outcome means, households under study cannot be observed under both $Y_i(D_i = 1)$ and $Y_i(D_i = 0)$ at the same time. Therefore, only either $Y_i(D_i = 1)$ or $Y_i(D_i = 0)$ is unobserved and hence estimating individual treatment effect T_i is not possible and one has to shift to estimating the average treatment effect at the population level than individual level. Two treatment effects are most frequently estimated in empirical studies. The first one is the (population) Average Treatment Effect (ATE) that answers the question what would be the effect if households in the population were randomly assigned to treatment, which is simply the difference of the expected outcomes after adoption and non-adoption:

$$ATE = E(\Delta Y) = E(Y_1 \mid D=1) - E(Y_0 \mid D=0) \tag{7}$$

However, Heckman *et al*. (1997) note that this estimate might not be important to policy makers because it includes the effect for whom the intervention was never intended. 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 who are producing improved food legume varieties. ATT is given by:

$$ATT = E(T \mid D=1) = E(Y_1 \mid D=1) - E(Y_0 \mid D=1) \tag{8}$$

ATT answers the question, how much did households adopting improved food legume varieties benefit compared to what they would have experienced without adopting. Data on $E(Y_1/D = 1)$ are available from the program participants. 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 $E(Y_1/D = 0)$ 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 (9), one can get the following specification for ATT

$$E(Y_1/D=1) - E(y_0/D=0) = ATT + E(Y_0/D=1) - E(y_0/D=0) \tag{9}$$

Both terms in the left hand side are observables and ATT can be identified, if and only if $E(Y_0/D=1) - E(y_0/D=0) = 0$ when there is no self-selection bias. This condition can be ensured only in social experiments where treatments are assigned to units randomly (i.e., when there is no self-selection bias). In non-experimental studies, one has to introduce some identifying assumptions to solve the selection problem.

The validity of the outputs of the PSM method depends on the satisfaction of two basic assumptions namely: the Conditional Independence Assumption (CIA) and the Common Support Condition (CSC) (Becker and Ichino, 2002). CIA (also known as unconfoundedness assumption) states that the potential outcomes are independent of the treatment status, given X. In other words, after controlling for X, the treatment assignment is "as good as random". The CIA is crucial for correctly identifying the impact of the program, since it ensures that, although adopter and non-adopter groups differ, these differences may be accounted for in order to reduce the selection bias. This allows the non-adopter units to construct a counterfactual for the treatment group. The common support condition entails the existence of sufficient overlap in the characteristics of the adopter and non-adopter units to find adequate matches (or a common support). When these two assumptions are satisfied, the treatment assignment is said to be strongly ignorable.

Estimating propensity scores

First, the samples of adopter and non-adopter should be pooled, and then adoption D should be estimated on all the observed covariates X in the data that are likely to determine adoption. When one is interested only in comparing outcomes for that adoption $(Y = 1)$ with those not adopting $(Y = 0)$, this estimate can be constructed from a probit model of adoption of improved food legume technologies.

Estimated participation equation is

$$Y = dY_1 + (1-d)Y_0 \tag{10}$$

The adoption status of a farm household is denoted by *$(d = 1)$* if the household adopted improved food legume varieties and *(d=0)*if the farm household did not adopt improved food legume varieties.

After the participation equation is estimated, the predicted values of Y can be derived. The predicted outcome represents the estimated probability of participation or propensity score. Every sampled adopter and non-adopter will have an estimated propensity score,

$$P(X \mid D = 1) = P(X) \tag{11}$$

As for the relevant covariates, PSM will be biased if covariates that determine participation are excluded from the participation equation for non-specification reasons. These reasons could include, for example, poor-quality data or poor understanding of the local context in which the program is being introduced.

Heckman, Ichimura, and Todd (1997, 1998) show that the bias in PSM program estimates can be low, given three broad provisions. First, if possible, the same survey instrument or source of data should be used for participants and nonparticipants. Using the same data source helps ensure that the observed characteristics entering the logit or probit model of participation are measured similarly across the two groups and thereby reflect the same concepts. This study used the same questionnaire both for adopters and non-adopters. Second, a representative sample survey of eligible non-adopters as well as adopters can greatly improve the precision of the propensity score. In addition, the larger the sample of eligible non-adopters is, the better the matching will be. This study has limited number of households adopting the improved food legume varieties accompanied by majority of the households using none of the improved varieties.

Nevertheless, including too many explanatory variables in the participation equation should also be avoided as over specification of the model can result in higher standard errors for the estimated propensity score $P(X)$and may result in perfectly predicting adoption for many households$[P(X)=1]$. In the latter case, such observations would drop out of the common support.

Rosenbaum and Rubin (1983) recommend that standardized bias (SB) and t-test for differences were used to check matching quality. If the covariates X are randomly distributed across adopter and non-adopter groups, the value of the associated pseudo-R^2 should be low and likelihood ratio should be insignificant. A bootstrapping method was used to compute the standard error for the estimate of the adoption impact.

Choice of matching algorithm

After estimation of the propensity scores, seeking an appropriate matching estimator is the major task. The choice of matching method involves a trade-off between matching quality and its variance. Various matching estimators have been suggested in the literature. These include the nearest neighbor matching, caliper and radius matching, stratification and interval matching, kernel and local linear matching (Caliendo and Kopeinig, 2008). The final choice of a matching estimator was guided by different criteria such as equal means test referred to as the balancing test (Dehejia and Wahba, 2002), pseudo-R^2 and matched sample size. Specifically, a matching estimator that balances all explanatory variables (i.e., results in insignificant mean differences between the two groups), bears a low pseudo-R^2 value, lower mean bias and results in large matched sample size is preferable.

3.3.2.2. Intra-household impact of adoption of improved food legume

Although household-level analysis appears to have an intuitive and universal basis, it ignores the realities of interpersonal relations in many cultures and intra-household differences within households. The assumption that there are easily-identifiable entities which can be called 'households' which have the same level of importance in determining peoples' poverty by income and/or other measures across cultures and contexts, or even for individuals in the same locality is misplaced (Mayoux, 2004).

Intra-household differences affect the very success and sustainability of interventions because of differing degrees of support and resistance to interventions, which may positively or adversely affect the interests of particular individual (Haddad *et al.,* 1997, cited in Mayoux, 2004). Therefore, impact assessment needed to come across not only at aggregate on household or enterprise level, but also on individuals and relations within the household. Understanding intra-household inequalities is important not only for measuring impacts but also to look into poverty: vulnerability, voice and empowerment. These are critical dimensions of longer-term sustainability of any impacts assessment. Moreover, impacts on intra-household relations are often of themselves the subject of impact assessment, not only in terms of gender but also other dimensions of intra-household difference such as age and their role in household (Mayoux, 2004).

ATT from PSM model tells only how much adopter of improved varieties were benefited compared with non-adopter households without considering intra-household dynamics. To capture the intra-household impact of adoption of improved varieties, predicted ATT estimates were summarized using t-test between dummies that were generated to denote different age and sex groups of household members contributing labor to farming.

Household members were disaggregated principally based on age and gender. The female and male household members were divided in to four classes such that group 1 encompassed those aged less than 5 years, group 2 those aged between 5 and 16, group 3 those aged between 16 and 70 and group 4 those aged above 70 years. The intra-household differences were also taken into account when the participation in household farm activities dimension, which was added onto gender and age. After generating these variables, household with greater or equal to 1 value of each generated intra household dummy variables receive one (1), where the household with 0 values the variable will be zero. Accordingly, each household has dummies of intra-household differentials, which were used to summarize predicted ATT.

3.3.2.3. Impact of intensity of adoption of improved food legume varieties

Currently, propensity Score Matching methods are extended to analyze effects of continuous treatments, where the focus is on assessing the heterogeneity of treatment effects arising from different treatment levels, that is, different amount of adoption (Hirano and Imbens, 2004). Assessing impact of agricultural technology adoption as a binary treatment is more applicable where all adopter of a given technology receive same amount of technology on same plot of land. This is not at all the case in Bale highlands and hence, thereof this study employed continuous treatment effects model (Generalized propensity Score Method) to quantify the impact of intensity of adoption on household welfare in addition to PSM.

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 intensity of adoption is random, conditional on observable characteristics (unconfoundedness) which have been identified to be important determinants of intensity of adoption. However, it is important to note that unobservable variables may still create mismatching and biased estimators because the GPS does not directly account for the unobservable variables that may affect both the outcome variables and the choice of technology.

To build the model consider a random sample of individuals which is indexed by i where $i = 1,......N$. Let $w_i(r)$ be the potential welfare outcome for individual 'i' under treatment level $\boldsymbol{r}, \boldsymbol{r} \in \tau$ where τ is an interval of the treatment (r_0, r_1), and z denotes the dosage - meaning the farm area under improved food legume varieties. For each i^{th} individual, there is a set of potential outcomes $\{w(r)_i\}$, $r \in \tau$ referred to as the individual level dose–response function.

In treatment effects modeling using observational data, missing data is a common problem and hence the interest is in the identification of the curve of average potential effect of intensity of adoption, $\mu(r) = E[w_i(r)]$ which represents the function of the average potential welfare outcomes (income, consumption expenditure and calorie intake) over all possible treatment levels. In this study, $w_i(r)$ is the welfare indicator for adopters of improved food legume varieties. The observed variables for each unit i are covariates X_i, the intensity of the treatment received, $R_i \in (r_0, r_1)$, and the potential outcome corresponding to the intensity of the treatment received, $w_i = w_i(R_i)$. Here non-adopter households were excluded from this analysis because including untreated units might lead to misleading results (Guardabascio and Ventura, 2013). Accordingly, in the GPS and dose–response estimation, it is only considered positive observations.GPS methods are designed for analyzing the effect of a treatment intensity; therefore they specifically refer to the subpopulation of treated units in this case adopters of food legume varieties.

The key identifying assumption in estimating the dose–response function is the weak unconfoundedness assumption (also known as the assumption of selection on observables), where the treatment assignment mechanism is independent of each potential outcome conditional on the covariates: $w_i(r) \perp R_i \mid X_i$ for all $r \in \tau$. Under unconfoundedness, the average dose–response function can be obtained by estimating average outcomes in sub populations defined by covariates and different levels of treatment.

Let $q(r,x)=f_{R/X}(t|x)$ denote the conditional density of the treatment given the covariates. The GPS is defined as $Q_i=q(R_i,X_i)$. Hirano and Imbens (2004) indicated that GPS is a balancing score in the sense that, within strata with the same value of $X: X\perp 1\{R=1\}|q(r,X)$, the probability that $R=r$ for a given individual does not depend on the value of $X: X\perp 1\{R=1\}|q(r,X)$ and demonstrated that if the treatment assignment mechanism is weakly unconfounded given the covariates, then it is also weakly unconfounded given the GPS: $W_i(r)\perp R_i|q(r,X_i)$ for all $r\in\tau$. Therefore, GPS can be used to remove biases associated with differences in the observed covariates.

Hirano and Imbens (2004) also illustrates that if assignment to the treatment is weakly unconfounded given pre-treatment variables X, then

$$\beta(r,q)=E[W_i(r)|q(r,X_i)]=E[W_i|R_i=r,Q_i=q];\text{ and }\lambda(r)=E[\delta(r,q)(r,X_i)]. \tag{12}$$

This result suggests that the dose–response function at a particular treatment level "*r*" can be estimated by using the following three steps:

As the first step, the study employed a binomial distribution to model the intensity of adoption (R_i) given the covariates, and β_0, β_1 *and* σ^2 were estimated by maximum likelihood.

$$\ln(\mathrm{R_i})\,|\,\mathrm{X_i}\approx \mathrm{N}(\beta_0+\beta_1'\mathrm{X_i},\sigma^2) \tag{13}$$

Estimating the GPS helps to ensure that the covariates are balanced across treatment categories; so that as long as sufficient covariate balance is achieved, the exact procedure for estimating the GPS is of secondary importance (Kluve *et al.,* 2012). The GPS is estimated based on the parameters estimated in equation (14) as:

$$\hat{\mathrm{Q}}=\frac{1}{\sqrt{2\pi\hat{\sigma}^2}}\exp\left(-\frac{1}{2\hat{\sigma}^2}(\ln(\mathrm{R_i})-\hat{\beta}_0-\hat{\beta}_1{}'\mathrm{X_i})^2)\right) \tag{14}$$

The second step involves estimating the conditional expectation of the outcome as a function of observed treatment (R_i) and estimated GPS (Q_i). As Hirano and Imbens (2004) pointed out, the conditional expectation of the outcome can be estimated as a flexible function of treatment level and estimated GPS, which might also involve some interactions between the two. Quadratic approximation were used here specified as:

$$\beta(\mathrm{r,q}) = \mathrm{g}(\mathrm{E}[\mathrm{W_i} \mid \mathrm{R_i}\widehat{\mathrm{Q}}_\mathrm{i}] = \alpha_0 + \alpha_1 \mathrm{R_i} + \alpha_2 \widehat{\mathrm{Q}}_\mathrm{i} + \alpha_3 \mathrm{R_i}^2 + \alpha_4 \widehat{\mathrm{Q}}_\mathrm{i}^2 + \alpha_5 \mathrm{R_i} \widehat{\mathrm{Q}}_\mathrm{i} \tag{15}$$

Here “g” is a link function, and it is suggested by the functional form of the relationship between the treatment and the explanatory variables. In our set up, $R \in [0, 1]$ showing that the proportion of intensity of adoption lies between 0 and 1. It means that if R is bounded, the effect of any particular covariate in X_i cannot be constant over its range. Augmenting the model with non-linear functions of X_i does not overcome the problem as the values from an OLS regression can never be guaranteed to lie in the unit interval (Guardabascio and Ventura, 2013). The common practice of regressing the log-odds ratio, i.e. $log\ [R/(1-R)]$ in the linear regression instead of R, generates problems whenever any observation R_i takes on the values 0 or 1 with positive probability. As a practice, in this situation when R_i are proportions from fixed number of groups with known group size, the extreme values are adjusted before taking the transformation. However, not always the fraction R_i is a proportion from a discrete group size. In addition, if a large percentage is at the extremes the adjustment mechanism is at least debatable. Therefore it is suggested by Guardabascio and Ventura (2013) to use logit as a link function and as a result, this study used logit model as link function.

The coefficients estimated with the GPS equation do not have a causal interpretation, except that testing whether the joint significance of all coefficients associated with GPS were equal to zero can be used to assess whether the covariates introduce bias (Hirano and Imbens, 2004).

Lastly, the average dose–response function at a particular value of the treatment “*r*” was estimated by averaging the (estimated) conditional expectation $\beta(\mathrm{r, q})$ over the GPS at that level of the treatment as:

$$\mu(r) = E(\widehat{W}_i(r)) = \frac{1}{N}\sum_{i=1}^{N} q^{-1}(\widehat{\alpha}_0 + \widehat{\alpha}_1 r + \widehat{\alpha}_2 r^2 + \widehat{\alpha}_3 \widehat{q}(r, X_i) + \widehat{\alpha}_4 \widehat{q}(r, X_i)^2 + \widehat{\alpha}_5 r\widehat{q}(r, X_i))$$
(16)

where $\widehat{\alpha}$ is the vector of parameters estimated in the second stage and $q(r, X_i)$ is the predicted value of $q(r,X_i)$ at level "*r*" of the treatment. The entire dose–response function can then be obtained by estimating this average potential outcome for each intensity of the treatment. The average dose–response function indicates how the magnitude and the nature of the causal relationship between the treatment variable and the outcome variable change according to the values of the treatment variable, after controlling for covariate biases. On the other hand, the marginal treatment effect function indicates the marginal effects of changing the treatment variable by a given unit on the outcome variable.

3.3. Definition of Variables and Working Hypotheses

DEPENDENT VARIABLE:

Adoption of improved food legumes technologies: as Feder *et al.* (1985) and Doss (2006) state, adopters of agricultural technologies are the ones who adopt a component or more of technology and continue using it, where non-adopters are those who never tried it. Here the adopting households are the ones who have tried the improved varieties of legume (Faba bean and/or Field pea) and kept on using them in the last five years – and they were coded as 1. The rest of the households were considered as non-adopters and they were coded as 0. The second technology is fertilizer application for the production of faba bean and/or field pea and the users are the ones who applied fertilizer in 2014/2015 production season for the cultivation of faba bean or field pea. The final technology is the pesticide application for the production of faba bean and/or field pea. The adopting households are the ones who used chemical in 2014/2015 production season for cultivation of faba bean and/or field pea.

TREATMENT VARIABLES

For PSM model: Adoption status of improved food legume varieties – representing households that have been using improved varieties of faba bean and/or field pea continuously for the last five years

For GPS model: intensity of adoption of food legume varieties which is continuous variable captured by the current total land in hectare under improved faba bean and/or field pea varieties.

OUTCOME VARIABLES: the following welfare indicators were used as outcome variables

Total income per adult equivalent: it is the total amount of daily income received by the household in Ethiopian birr per adult equivalent.

Consumption expenditure per adult equivalent: it is the total amount of money the household spent on consumables items in Ethiopian birr per day per adult equivalent.

Calorie intake per adult equivalent: it is the daily food available for consumption for all household members in kilocalories.

EXPLANATORY VARIABLES:

The following explanatory variables have been hypothesized to influence the adoption of improved food legume technologies in the study area.

Age of household head: this is a continuous variable hypothesized to have a positive effect on adoption of improved food legume technologies as the accumulated experience of older farmers is expected to help them make adoption decision rather ahead of younger farmers. However, as the age of household head increases to the limit where the farmer would be quite old and unable to contribute in farming activities, decisions on adopting improved technologies could be very slow. Therefore, a quadratic relationship was expected between adoption decision and age of the household head.

Years of schooling: this variable includes both formal and informal education level of the household head, which indicates the total number of years of education of the individual either from formal or informal school. Here, education is measured as a continuous variable and it is expected to affect adoption positively by improving consciousness of the farmer to obtain, process, and use information relevant to the adoption of technological package (Debelo, 2015).

Number of household members involved in farm activities: it is a continuous variable that shows the total number of household members involved in farm activities and it is expected to influence adoption positively (Asfaw *et al.,* 2011). Human labor is an important input for agricultural production especially for the labor-intensive production of legumes. Therefore, a farm household with higher number of workers is expected to adopt improved food legume technologies.

Farm size in hectare: 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 improved food legume technologies and the reverse is true for farmers with less land.

Livestock holding: 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 improved food legume technologies increases (Debelo, 2015).

Membership in farmers' cooperative: 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).

Access to credit: Access to credit improves farmers' purchasing power of new production technologies like improved varieties, fertilizer and other agricultural inputs. Access to credit was hypothesized to affect the adoption of improved food legume technologies positively by improving the liquidity status of the farm household (Alemitu, 2011).

Frequency of contact with research center: This continuous variable, which measures frequency of contacts the household had with agricultural research centers in the past 12 months.

It was expected to affect the adoption of improved food legume technologies positively due to the access to information regarding improved agricultural technologies and better instructions for uses of agronomic practices.

Distance from near town: as Maertens and Barrett (2013) suggested it is essential to control all potential source of information in estimation of learning links (adoption of agricultural technologies). Therefore, it is important to include households proximity to town where there is better infrastructure, access to information and good market integration. The higher the value of this variable therefore the less likely it is that households would be able to adopt improved legume varieties. This variable indicates the walking distance in hour from household residence to near town.

Distance from agricultural extension office: This variable is continuous and measures the distance in walking hours from the household residence to agricultural extension office and it is expected to affect the adoption decisions negatively (Alemitu, 2011).

Distance from main market: this denotes the distance from the output market in walking hours to farmers' residence. It is expected to affect the adoption decisions negatively. The closer farm households to the market are the more that they will receive higher prices for their products at least due to less marketing transaction costs (Alemitu, 2011).

Household head participation in off farm activities: 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.

District dummies: there are numerous sources of variation that could possibly happen across locations. Given the size of the districts and the independence of the district offices in planning and implementing agricultural development activities, it was hypothesized that there might be differences across districts in terms of the likelihood of adoption of improved food legume technologies. The district dummies are also expected to at least partially capture the variations in agro-ecological factors.

Table2: Expected sign of hypothesized explanatory variables

Explanatory variables (Expected impact)	Nature of variable	Expected effect
Age of household head	Continues	+
Age square of household head	Continues	-
Years of schooling	Continues	+
Number of household members involved in farm activity	Continues	+
Total livestock in TLU	Continues	+
Member in farmers cooperatives(Yes =1)	Dummy	+
Frequency of contact with agricultural research center	Continues	+
Distance from agricultural extension office (hours)	Continues	-
Distance from near town (hours)	Continues	+
Distance to main market (hours)	Continues	-
Participation in off farm activities (Yes =1)	Dummy	+/-
Access to credit (Yes =1)	Dummy	+
District	Dummy	+/-

4. RESULT AND DISCUSSION

This part of the thesis presents the results of the statistical analyses and the discussions thereof based on the primary data generated through formal and informal survey. This chapter has five main sections. In the first section, the adoption of improved food legume technologies, summary of variables, which characterize the sample households that used in the descriptive and inferential statistical are discussed. The second section describes the results of estimated models of adoption of improved food legume technologies while the third and the fourth sections illustrate the results of treatment effect models of adoption rate and intensity of adoption of improved food legume varieties on welfare of household. The fifth section describes the challenges and opportunities of adoption of improved food legume technologies.

4.1. Adoption and socioeconomic characteristics of sample households

This study was based on data generated from 600 randomly selected farm households in three districts of the Bale highlands. The sample comprised 90.7% of male headed and 9.3% of female-headed farm households with an average age of 43 years.

Figure 3 below presents the adoption rate of improved food legume technologies across the three sample districts of Bale Highlands. Adopter of improved food legume varieties was 127 households (21% of total sample households); adoption rate was highest in Sinana district (50.39%) and lowest in Goba district (21.26%). It was also observed that households who were using fertilizer and pesticide for the production of legumes are 103 (17%) and 47 (7.8%) of the total sample households, respectively. The adoption of both fertilizer and pesticide for the production of legume was high in Agarfa (45% for fertilizer and 72% for pesticide) and lower in Sinana (17% for fertilizer) and Goba (2% for pesticide).

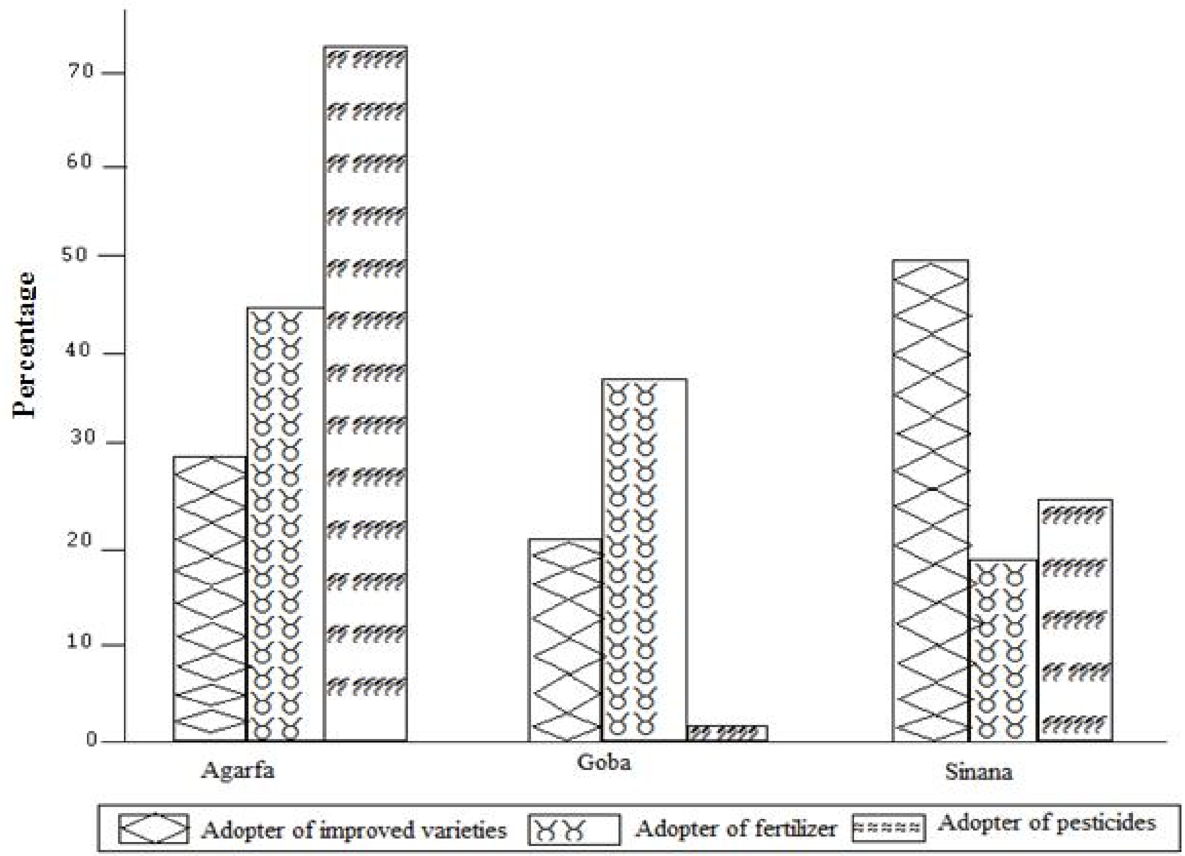

Figure 3: Adopter of improved food legume technologies among sample district

Table 3 presents the t-test and chi-square comparison of means of selected variables by adoption of improved food legume technologies for the surveyed 600 households. Some of these characteristics are explanatory variables of the estimated models presented in sections further below. Amongst the 127 adopters of improved varieties, 95% were male headed. Most of the adopters of fertilizer for legume production were female headed households whereas pesticide adopters were male headed even if there is no significant difference between observed frequencies. Household head participation in off-farming activities was significantly lower for adopters of improved varieties - was only 7.2%.

Education is an important variable that positively contributes towards the decision to adopt agricultural technologies by improving consciousness of farmers to obtain, process, and use relevant information leading to the adoption of improved technological package (Debelo, 2015).

Accordingly, the adopter of improved food legume varieties and fertilizer were found to have significantly higher education level than non-adopters.

The average family size of the sample households was 6.5,which is higher than the national average of 4.7 and the dependency ratio within the sample households was computed to be 126.55%, which is again higher than the national average of 83.5% (CSA, 2014).The production of legumes in the study area is highly labor intensive from land preparation to trashing. Therefore, household labor availability is a critical requirement for the farm households to, among others, facilitate the adoption of improved food legume technologies. Thus, family size in AE and number of household member involved in farm activities of the family were higher for adopters compared to non-adopters.

In addition, livestock holding and farm size are the most common indicators of household assets that contribute in favor of adoption of agricultural technologies (Debelo, 2015 and Asfaw *et al*., 2011). The average land holding of sample respondents was 4.66 ha, which was again higher than the national average of 1.37 ha (World Bank, 2013). Farm size was found to be significantly higher for adopters of improved food legume varieties and pesticide. Similarly, livestock wealth measured in TLU was observed to be higher for adopters compared to non-adopters of improved food legume technologies with an average of 7.14.

Membership in farmers' cooperatives enhances the likelihood of adopting improved technologies as it provide farmers with necessary inputs at relatively lower prices and assist farmers to access more rewarding markets (Kassie *et al*., 2014). Hence, about 42.5% of the adopters of improved food legume varieties were members of farmers' cooperatives, which was significantly higher than the case for non-adopters.

The chief source of improved varieties and agronomic practices for farmers in study area is Sinana agricultural research center (SARC). Frequency of contact with research center is expected to affect the adoption of improved food legume technologies positively and here the adopters have had significantly higher frequency of contact. On average, adopters of improved legume technologies were closer to agricultural extension office, towns and main market, which are places where the rural farmers get information and undertake marketing.

Generally, adopters of improved food legume technologies were relatively more endowed in terms of livestock holding and farm size. They also have higher frequency of contact with agricultural research center and are closer to agricultural extension and main input and output markets. The users of improved food legume technologies were also found to have higher proportion of active labor force within the household and it is important to note that production of legumes in Bale Highlands is labor demanding.

Table 3: Summary of explanatory variables– compared between adopters and non-adopters

Variables	Improved varieties			Fertilizer			Pesticide			
	Non-adopter	Adopter	t-value/ chi^2	Non-adopter	Adopter	t-value/ chi^2	Non-adopter	Adopter	t-value/ chi^2	**All**
Sex(% Male)	89.43	95.28	4.04**	90.95	89.32	0.27	90.31	95.4	1.2	90.7
Off-farm participation(% Yes)	13.74	7.20	4.10**	11.69	15.69	1.24	12.79	6.98	1.24	12.3
Access to credit(% Yes)	36.15	29.13	2.17	35.81	29.13	1.68	35.01	30.2	0.4	34.7
Farm cooperative (% Yes)	29.60	42.52	7.6***	32.80	30.10	0.28	32.32	32.6	0.001	32.3
Age	42.93	43.81	-0.64	42.95	43.93	-0.6	43.04	44.1	-0.49	43.1
Literacy	4.94	5.47	-1.43*	4.92	5.66	-1.9**	5.05	5.13	-0.15	5.06
Family size	6.29	7.29	-3.8***	6.48	6.63	-0.5	6.49	6.67	-0.43	6.51
Total adult equivalent	4.79	5.61	-3.9***	4.93	5.14	-0.94	4.96	5.02	-0.16	4.97
No. hh member involve in farm	3.12	3.51	-2.2**	3.16	3.42	-1.4*	3.17	3.62	-1.6**	3.21
Livestock holding in TLU	6.58	9.20	-6.0***	6.81	8.7	-3.9***	7.02	8.60	-2.2**	7.14
Farm size in ha	3.14	4.20	-2.2**	3.4	3.23	0.3	3.12	6.61	-4.8***	3.37
Freq. of contact with res. center/ year.	.42	.81	3.9***	.47	.62	-1.27	.46	1	-3.3***	.50
Distance from ag. ext. office (hour)	.69	.62	0.19	.75	.39	3.4***	.70	.52	1.15	.68
Distance near town(hour)	1.71	1.81	-0.67	1.80	1.40	2.5***	1.78	1.08	2.92***	1.73
Distance main market(hour)	1.49	1.39	0.84	1.54	1.15	2.8 **	1.53	.73	4.0***	1.48
Land under improved varieties	0	.36	-17.4***	.05	.18	-4.7***	.07	.17	-2.5***	.07
Income (ln)	2.65	2.9	-2.4***	2.71	2.66	0.45	2.706	2.72	0/014	2.7
Consumption expenditure (ln)	2.20	2.14	0.77	2.18	2.24	-0.79	2.19	2.16	0.25	2.19
Daily Calorie intake (ln)	8.43	8.31	1.6*	8.42	8.31	1.34*	8.40	8.39	0.141	8.40
District			20.8****			15.6***			34.9***	
Agarfa	34.67	28.35		30.99	44.66		30.34	72.1		33.3
Goba	35.94	21.26		31.79	37.86		35.19	2.33		32.8
Sinana	29.39	50.39		37.22	17.48		34.47	25.6		33.8

***, ** and * is significant at 1%, 5% and 10% level of statistical error.

4.2. Adoption of Improved Food Legume Technologies

An important purpose of adoption models is identifying the factors that determine the likelihood of adoption of a given technology or set of technologies in a given context. Identification of these factors alone is not enough unless the relative influence of each factor is known for priority-based intervention. The econometric models employed here to identify determinates of the adoption were used to see the relative influence of different socio-economic, institutional and market access variables on the adoption of improved food legume technologies. This study addresses three food legume technologies, namely improved food legume varieties, application of fertilizer and pesticide for food legume production.

Adoption of improved food legume varieties was estimated by using binary Probit model. The specification of the model is significant for the estimation of determinants of adoption of improved food legume varieties implying that the null hypothesis that all slope coefficients are zero does not hold true at 1% statistical error. The estimation result indicates that adoption of improved legume varieties is significantly affected by eight variables out of 15 hypothesized variables. Age square in year, livestock holding in TLU, membership in farmers cooperatives, frequency of contact with agricultural research center, household head's participation in off farm activities, distance from main market and district dummies were found to be significantly affecting the likelihood of adoption of improved food legume varieties in the study area (Table 4).

Age square of household head: To capture the quadratic relation of age with adoption of improved food legume varieties, both age and age square of household head were included in the model estimation. Even if age of household head does not have significant effect on the adoption of improved varieties, age square was found to be negatively affecting the likelihood of adoption at 10% statistical error. The negative coefficient of age square indicates the adverse effect of getting older of household head on the likelihood of adoption of varieties. The likelihood of adoption of improved food legume varieties decreases by 0.02% as age square increases in one unit. This indicates that as the household head gets older and older, his/her ability to engage and manage farm activities goes down and hence the tendency to learn about and adopt new technologies will decline. It is also important to note that legume production in the area is entirely human labor dependent contrary to the mechanized cereal production, which is the predominant cropping system.

Livestock ownership: Livestock are important source of income, food and traction power for crop cultivation generally in Ethiopia and particularly in the Bale highlands. Livestock possession is also an important indicator of household's wealth status in rural Ethiopia. The model result shows the positive and significant influence of livestock holding on adoption of improved legume varieties at 1% statistical error. The model output indicates that the likelihood of adoption increases by 1.7% for a unit increase in livestock holding in TLU. 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 improved varieties. 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.

Membership in farmer cooperatives: Farmers' cooperatives 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. The model output illustrates that households' membership in farmers' cooperative has positive and significant effect on the adoption of improved food legume varieties at 10% statistical error. Being member in farmers' cooperative increases the likelihood of adoption of improved food legume varieties by 5.7%. This is in line with the finding reported by Kassie *et al*. (2014) in relation to adoption of maize varieties in Tanzania.

Frequency of contact with agricultural research center: this variable was found to be significantly and positively affecting the adoption of improved food legume varieties at 5% statistical error. When the frequency of contact with agricultural research center increases by one day per year, the likelihood of adoption increases by 3.3%. This is obviously related to the fact that agricultural research centers are the major source of agricultural technologies and reliable source of information for farmers. Mulubrhan *et al*. (2011) and Salifu *et al*. (2015) support this finding by reporting the positive role of information for the adoption of agricultural technologies based on their study on adoption of pigeon pea and maize intensification and on the adoption of improved maize varieties in Ghana, respectively.

Distance from main market: The model result confirms that distance of farmers' residence from the main market is associated with adoption of improved food legume varieties negatively at 5% statistical error. As walking distance from main market to farmers residence increase by one hour, the likelihood of adoption deceases by 3.4%. This implies that farmers closer to the main markets may have better access to input and output markets and hence access more information about improved technology that could concomitantly enable them to try and use new technologies than those who are in distant areas. The findings by Hassen (2014) and Debelo (2015) report similar results based on studies on adoption of improved forages in North East highlands of Ethiopia and on Quncho teff in Wayu Tuka district, respectively.

Household head's participation in off farm activities: The coefficient of this variable shows the negative effect of household head participation in off farm activities on the adoption of improved food legume varieties at 10% statistical error. Participation of head of the household in off-farm activities decreases the household's likelihood of adopting improved food legume by 10.2%. 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.

District: District dummy as explanatory variable helps to capture many important geographical features like soil type, rainfall distribution, weather condition and infrastructural facilities that are important determinants of adoption of agricultural technologies. District dummies were therefore included in the model with Sinana district as reference. The result from model indicates farm households in Agarfa and Goba are less likely to adopt improved food legume varieties compared to those in Sinana district at 1% statistical error. This could be because Sinana district has the advantage of hosting Sinana Agricultural Research Center where the technologies are developed with the participation of farmers. Compared to being in Sinana, being in Goba and Agarfa districts decreases the likelihood of adoption of improved food legume technologies by 13.4% and 16%, respectively.

Table 4: Probit model estimation of likelihood of adoption of improved food legume varieties

Covariate	Robust std. Err.	Marginal effect
Age	0.03	0.013
Age square	0.0003	-0.0002*
Education (Years)	0.02	0.002
Farm size (hr)	0.01	0.000
Livestock holding (TLU)	0.02	0.017***
Member in farmers cooperatives	0.13	0.057*
No. hh member involve in farm	0.04	0.012
Contact with research center	0.06	0.033**
Distance from (walking hour)		
Agri. extension office	0.07	-0.024
Town	0.05	0.016
Main market	0.06	-0.034**
Access to credit	0.14	-0.016
Off farm activity	0.22	-0.102*
District		
Agarfa	0.16	-0.134***
Goba	0.16	-0.160***
Constant	0.73	
Observation	600	
Wald $chi^2(15)$	64.59***	
Log pseudo likelihood	-268.89	
pseudo R- square	0.13	

***, ** and * is significant at 1%, 5% and 10% level of statistical error.

Source: own computation

Even if the adoption rates of fertilizer and pesticide for the production of legumes are very low in the study area, it is important to identify the underlying factors behind the lower rate of adoption to suggest research and development interventions. To identify the determinants of adoption fertilizer and pesticide for the production of food legume, clog-log model was estimated separately for the two technologies. The specification test shows that the model is significant implying that the null hypothesis that all slope coefficients are zero does not hold true at 1% of statistical error. Four variables were found to be statistically significant in explaining farmer decision to adopt fertilizer for food legume production. The likelihood of adoption of fertilizer for the production of legume was affected by livestock holding in TLU, distance from agricultural extension office, distance from main market and district dummies. In the same way, six variables were found to be statistically significant in explaining farmer likelihood to adopt pesticide for food legume production. These included farm size, livestock holding in TLU, frequency of contact with agricultural research center, distance from main market and district dummies (Table 5).

Livestock holding: Livestock was the economic variable that was highly significant in explaining the likelihood of adoption of both fertilizer and pesticide for the production of legume. As livestock holding increases by one unit of TLU, the likelihood of adoption of fertilizer and pesticide increased by 1.1% (1% statistical error) and 0.5%(5% statistical error), respectively.

Farm size: Farm size has a positive effect on the likelihood of adoption of pesticide for legume production. If farm size increase in one hectare, the household's likelihood of adoption of pesticide for the production of legumes increases by 0.7% at 1% statistical error. This finding is in line with what Asfaw *et al*. (2011) reported for determinants of adoption of improved variety of chickpea in Ethiopia. As farm size increases, the disease control and weeding practices become difficult to handle manually which may force the households to use chemicals to address the challenges in their legume production.

Frequency of contact with agricultural research center: Results also confirmed that the likelihood of adoption of pesticide was strongly correlated with households' contact with agricultural research center. This may actually prove that the key source of agricultural technologies and reliable source of information is the research center at Sinana. When the frequency of contact with agricultural research center increases by one day per year, the likelihood of adoption increases by 1.8% at 1% statistical error.

Distance from agricultural extension office: Farmers closer to the agricultural extension office have more access to input material and information about the technology than those who are in distant areas. Distance from agricultural extension office to household residence was found to be negatively affecting the adoption of fertilizer for the production of food legumes. The likelihood of adopting fertilizer decreases by 9.8% for an hour increase in walking distance from agricultural extension office to household residence at 1% statistical error. This result is consistent with the finding of the study on the adoption of improved haricot bean varieties and associated agronomic practices in Dale district of SNNPRS of Ethiopia (Alemitu, 2011).

Distance from main market: the results also confirmed that the likelihoods of adoption of fertilizer and pesticide for production of food legume were negatively affected by distance of farmers' residence from the nearest main market at 10% and 1% statistical error, respectively. As walking distance from main market to farmer's residence increases by one hour, the likelihoods of adopting fertilizer and pesticide decrease by 2.4% and 4.3%, respectively. This shows that farmers closer to the main markets have more access to input and outputs as well as more information about improved technology that positively influence the decision to adopt improved technologies earlier than others.

District: Taking Agarfa as reference or base, the comparison of districts in terms of likelihood of adoption of fertilizer and pesticide for legume production indicated that farm households in Goba and Sinana districts were less likely to adopt these inputs. Being in Goba district decreases the likelihood of adopting pesticide by 11.9% at 1% statistical error compared to being in Agarfa. Similarly, being in Sinana district decreases the likelihood of adoption of both fertilizer and pesticide by 10.7% (1% statistical error) and 6.4% (10% statistical error) compared to being in Agarfa district.

Table 5: Clog-log model results of adoption of agricultural inputs

	Fertilizer		**Pesticide**	
Covariate	Robust std. Err.	Marginal effect	Robust std. Err.	Marginal effect
Farm size (hr)	0.019	-0.002	0.05	0.007***
Livestock holding (TLU)	0.019	0.011***	0.04	0.005**
Member in farmers Association	0.227	-0.038	0.37	-0.032
No. hh member involve in farm	0.059	0.008	0.08	0.003
Contact with research center	0.079	0.017	0.09	0.018***
Distance from (walking hour)				
Agri. extension office	0.222	-0.098***	0.21	-0.018
Main market	0.100	-0.024*	0.24	-0.043***
Access to credit	0.235	-0.027	0.37	-0.009
Off farm activity	0.277	0.035	0.65	-0.040
District				
Goba	0.264	-0.027	1.10	-0.119***
Sinana	0.292	-0.107***	0.43	-0.064*
Constant	0.341		0.47	
Observation	600		600	
Zero outcomes	497		557	
Non Zero outcomes	103		43	
Wald chi2(11)	52.01***		54.75***	
Log pseudo likelihood	-248.00		-116.40	

***, ** and * is significant at 1%, 5% and 10% level of statistical error.
Source: own computation

4.3. Impact of Adoption of Food Legume Varieties

Identifying the factors behind adoption of agricultural technologies is not enough for the study that aims to improve the adoption of improved technologies and their welfare impact at scale. This section of the thesis discusses the welfare impacts of adoption of improved food legume varieties, which was estimated by using Propensity score matching (PSM). The welfare indicators that the study focuses on are income per day per AE, consumption expenditure and calorie intake per day per AE.

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 improved food legume varieties 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 improved varieties 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 R^2 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 R^2 is 0.10. The results indicate that the propensity to adopt improved food legume varieties was considerably influenced by livestock holding, membership in farmers corporative, distance from town, using fertilizer and pesticide and household head participation in off farm activity (Appendix Table 5).

Figure (4) presents 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 improved food legume varieties. Most of adopter households are found in the left 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 left side of the distribution.

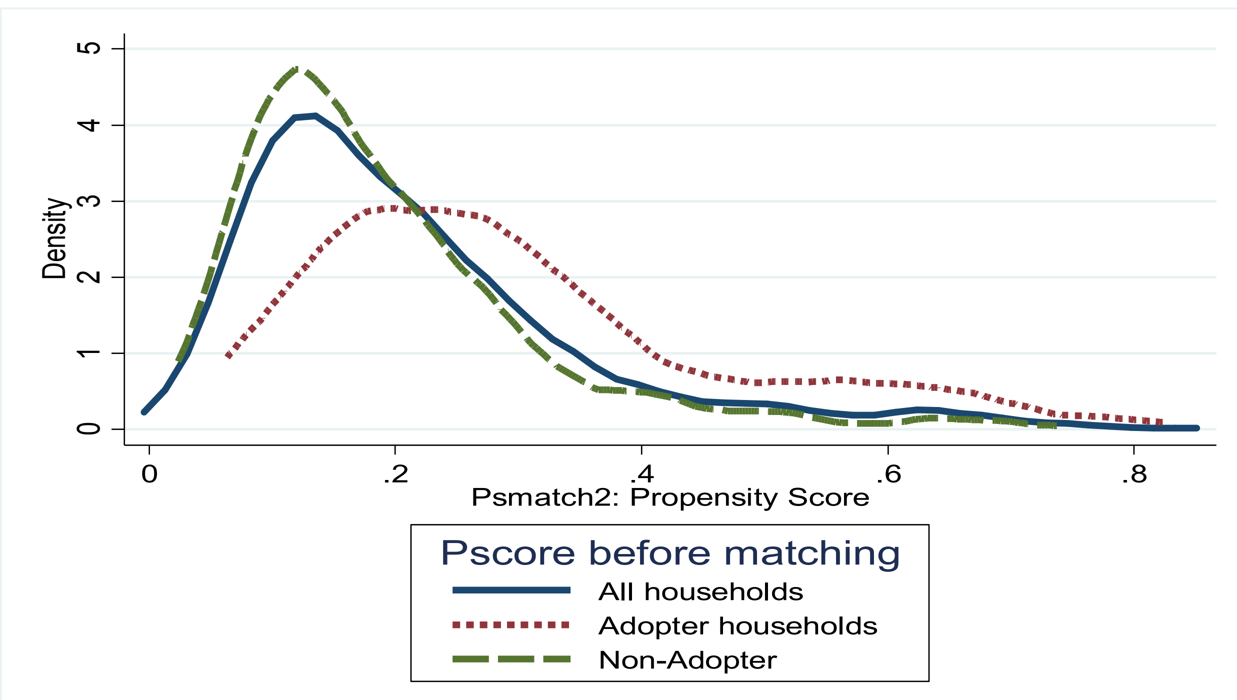

Figure 4: Kernel density of propensity score distribution of adoption of food legume varieties

4.3.2. Matching adopter and non-adopters

As Table 6 below illustrates the estimated propensity score varies between 0.024 to 0.823 with mean of 0.212 and standard deviation of 0.13. The average p-score of adopters is 0.29 and ranges from 0.063 to 0.823while that of non-adopters ranges from 0.024 to 0.74 with mean of 0.19.

Table 6: Distribution of estimated propensity score

Group	Obs.	Mean	Std	Min	Max
Total Households	600	0.212	0.138	0.024	0.823
Adopters	127	0.298	0.165	0.063	0.823
Non-adopter	473	0.189	0.120	0.024	0.737

Source: Own computation

Accordingly, the common support region would lie between 0.06 to 0.74 by discarding 34 household from non-adopter and 2 households from adopters and totally 564 households happened to be in the support regions for the estimation of the treatment effect. In other words, households whose estimated propensity scores are less than 0.06 and larger than 0.74 are not considered for the matching exercise. The Figure 5 below confirms the discarding of 36 households from the impact analysis.

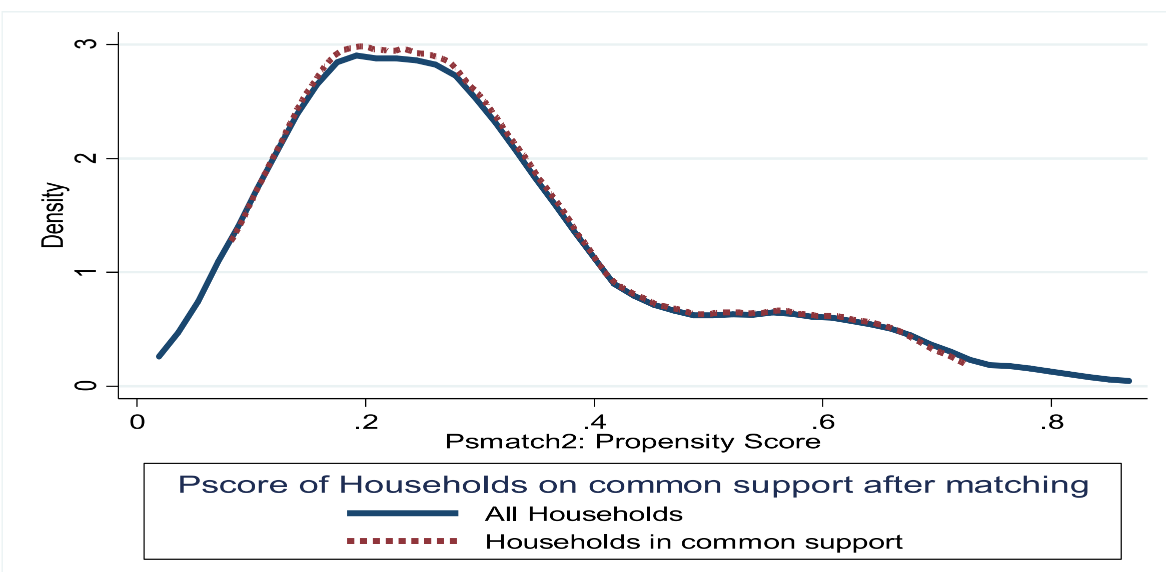

Figure 5: Kernel density of P-score with common (off) support regions of sample households

4.3.3. Choice of matching algorithm

Table 7 below indicates estimated results of tests of matching quality based on the above-mentioned performance criteria. Accordingly, by following Dehejia and Wahba, 2002, kernel matching with a bandwidth of 0.1 is the best estimator for the data at hand. The matching was found to be lowest pseudo-R^2, all sample households on support region are matched and the mean differences for all explanatory variables between adopters and non-adopters were found to be insignificant.

Table 7: Performance of different matching estimator

Matching estimate	Performance criteria				
	Balancing test*	pseoudo-R^2	Matched sample size	Mean bias	Medbias
NNM					
NN(1)	9	0.028	564	9.8	11.1
NN(2)	11	0.012	564	6.3	4.9
NN(3)	11	0.012	564	6.3	5.7
NN(4)	11	0.009	564	5.8	5.4
NN(5)	11	0.008	564	5.4	6.1
KM					
Band width 0.1	11	0.002	564	2.8	2.0
Band width 0.25	10	0.019	564	7.4	4.9
Band width 0.5	9	0.068	564	13.5	10.8
CM					
0.01	10	0.021	550	8.2	8.2
0.25	9	0.028	564	9.8	11.1
0.5	9	0.028	564	9.8	11.1

Source: own calculation result

* Number of explanatory variables out of 11 with no statistically significant mean differences between adopters and non-adopters.

Kernel matching is nonparametric matching estimator that compares the outcome of each adopter to a weighted average of the outcomes of all non-adopters; with the highest weight being placed on those with scores closest to the adopters (Heinrich *et al*., 2010). Kernel matching has an advantage of lower variance because more information is used (Heckman *et al.,* 1998).

After selecting matching algorithm that is most appropriate for the data generation process, the bandwidth was set to be 0.1. Then, the balancing property of the propensity score is checked. The main purpose of the propensity score estimation is not to obtain a precise prediction of selection into treatment, but rather to balance the distributions of relevant variables in both groups. The balancing powers of the estimations are ascertained by considering different tests such as the reduction in the mean standardized bias between the matched and unmatched households, equality of means using t-test and chi-square test for joint significance for the variables used.

The mean standardized bias before and after matching are presented in the fifth column of Appendix table (8) while column six indicates the total bias reduction obtained by kernel matching with bandwidth 0.1.

In the present matching models, the standardized difference in X before matching is in the range of 1.8 % and 58% in absolute value. After matching, the remaining standardized difference of X for almost all covariates lie between 0.4% and 7.5%, which is below the critical level of 20% suggested by Rosenbaum and Rubin (1983). 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 adopters and non-adopters that are ready to use in the estimation procedure. Similarly, t-values in Appendix table (8) indicates that before matching some of chosen variables exhibited statistically significant differences while after matching all of the covariates are balanced.

Low pseudo-R^2, insignificant likelihood ratio tests and lower mean bias support the hypothesis that both groups have the same distribution in covariates after matching. The mean bias after matching reduced to 2.8% from 20.5% (Table 8). These results show that the matching procedure is able to balance the characteristics in the adopter and the matched comparison groups.

Table 8: Chi-square test for the joint significance of variables

Sample	Pseudo R2	LR chi^2	$p>chi^2$	Mean Bias	Medbias
Unmatched	0.104	64.49	0.000	20.5	15.0
Matched	0.002	0.78	1.000	2.8	2.0

Source: Own estimation result

4.3.5. Estimating treatment effect on the treated (impact of adoption on the adopters)

The results of PSM indicate that adoption of improved food legume varieties has positive and significant impact on household income. However, it does not have any significant impact on household consumption expenditure and calorie intake probably because consumption behavior of the household in the short run may not adjust immediately with income (Asfaw *et al*., 2010).

As indicated in Table 9, the daily income of household per AE is relatively higher for adopters (2.89) than non-adopters (2.65). Adopter households receive 25% higher income than non-adopters do which is significant at 1% statistical error. This might be because as the household adopts improved varieties of food legumes, the yield per unit of land increases that possibly boosting the marketable surplus.

Table 9 : Estimated effect on the welfare indicator

ATT	Treated	Control	Difference	SE*	t-value
Income	2.90	2.65	0.25	0.10	2.5***
Consumption expenditure	2.14	2.18	-0.046	0.077	-0.6
Calorie intake	8.31	8.30	0.011	0.079	0.14

*The bootstrapped SE was obtained after 100 replications.
*** is significant at 1% statistical error.

4.3.6. Sensitivity Analysis

In order to control for unobservable biases, it is important to undertake sensitivity analysis after PSM. Table 10 below presents the output of Rosenbaum bounding approach to analyze sensitivity. The e^{γ} (Gamma) is critical value at which the causal inference of sensitively analysis evaluates. Result from sensitivity analysis indicates that the inference for the impact of the adoption of improved food legume varieties will not be changing even if the adopter and non-adopter households were allowed to differ in their odds of being adopter up to 200% (e^{γ} =3) in terms of unobserved covariates. This means for all outcome variables estimated, at various level of critical value e^{γ}, the p-critical values are significant which further indicates important covariates that affected both adoption and outcome have been considered. Accordingly, impact estimates here are insensitive to unobserved selection bias and are a pure effect of adoption of improved food legume varieties.

As noted by Hujer *et al*. (2004), sensitivity analysis for insignificant impact is not meaningful and therefore sensitivity analysis for the effect of adoption of improved food legume varieties on consumption expenditure and daily calorie intake of household were not done.

Table 10: Result of sensitivity analysis using Rosenbaum bounding approach

outcome	e^{γ} =1	e^{γ} =1.25	e^{γ} =1.5	e^{γ} = 1.75	e^{γ} =2	e^{γ} =2.25	e^{γ} =2.5	e^{γ} =2.75	e^{γ} =3
income	p<0.000	p<0.000	p<0.000	p<0.000	p<0.000	p<0.000	p<0.000	p<0.000	p<0.000

Source: Own estimation

e^{γ} (Gamma)=log odds of differential due to unobserved factors where Wilcoxon significance level for each significant outcome variable is calculated.

4.3.7. Intra-household impact of adoption of improved varieties

Intra-household impact analysis has practical policy importance given the relevance of the intra-household patterns that might influence the welfare outcomes of adoption of improved food legume varieties. Intra-household difference cannot be captured by simple treatment effect model in this case - PSM. The ATT from PSM tells only the estimated impact of adoption on adopters compared to non-adopters without considering the intra-household dynamics.

The intra-household impact analysis was captured by using simple mean comparison test (t-test) of predicted ATT merely for the significant welfare impacts of adoption that is daily income per adult equivalent. Predicted ATT was summarized by the dummies generated to capture the age, sex and involvement in farming differences within the household to look into intra-household differentials of impact of adoption of improved food legume varieties.

Even if adoption of improved food legume varieties provides the farm households with better income, the treatment effects vary from one household to other as per their intra household differences. The income effect of adoption of improved food legume varieties is significantly lower for the household with female headed by 2.8% while taking all other intra household differences constant (Table 11).

As Table 11 indicates, households with females aged less than 5 years and females older than 70 years are considerably disadvantaged in terms of income at 10% and 5% statistical error, respectively, *ceteris paribus*. However, households with females aged between 5 and16 and 16 to70 years receive significantly better income effect at 5% and 10% statistical error, respectively. Likewise, households with males aged between 5 and 16 years receive better treatment effect on income at 1% statistical error.

Table 11: Summary of predicted ATT of income by intra household differences variables

Intra Household Differences	**ATT of Adoption of Improved Varieties on Income of hh**			
(Dose the household have [--])	NO	YES	Difference	Std. Err
Male hh head	2.68	2.70	-0.028**	0.014
Gender and age disaggregation				
Female ageless 5	2.71	2.69	0.012*	0.009
Female in 5 to 16	2.69	2.71	-.018**	.0084
Female in 16 to 70	2.67	2.70	-.028*	.018
Female age >70	2.70	2.66	.041**	.023
Male ageless 5	2.70	2.71	-.01	0.008
Male ageless 5 to 16	2.68	2.71	-.030***	0.008
Male age in 16 to 70	2.68	2.70	-.027	.023
Male age >70	2.70	2.69	.016	.017
Participation in household farming				
Female young (age< 16)	2.69	2.71	-.015**	.008
Female Adult (age in 16 to 70)	2.69	2.70	-.021**	.013
Female old (age >70)	2.70	2.65	.052*	.03
Male young (age< 16)	2.70	2.71	-.01*	.009
Male adult (age in 16 to 70)	2.67	2.70	-.036**	.019
Male old (age >70)	2.70	2.69	.013	0.02

***, ** and * is significant at 1%, 5% and 10% level of statistical error.

Source: own computation

In addition, households with young and adult (both male and female) members who participate in farming activities obtain significantly better income due to adoption of improved food legume varieties (Table 11). This may be due to the active participation of these members that enhance the adoption of improved varieties, which increases income of adopters. This finding is in line with Hassen *et al.* (2014) that reported positive role of active labor force in the adoption of improved varieties. However, households with old female members who participate in farming activities receive significantly lower income by 1% at 10% statistical error.

Generally, the result of the intra-household analysis indicates that households with economically dependent female household member received significantly lower income from adoption of improved food legume varieties. This finding implies that the impact from adoption of improved food legume varieties vary among households as per their intra-household dynamics.

4.4. Impact of intensity of adoption of improved food legume varieties

Current literatures indicate that assessing impact of agricultural technologies by taking adoption as a binary treatment is not enough in a context where there is heterogeneous intensity of adoption at household level due to different factors. Thereby, this study estimates the impact of intensity of adoption on welfare indicators besides the impact of status of adoption reported above.

This part of the study explains the output of the Generalized Propensity Score (GPS) or continuous treatment effects model that was fit to estimate impacts of intensity of adoption of improved food legume varieties on the welfare of households. The GPS model (dose-response function) estimated for adopters of improved food legume varieties as continuous dependent variable – which is intensity of adoption – takes only positive values. Therefore, the non-adopters were discard from the analysis.

4.4.1. Estimation of generalized propensity scores

GPS is a non-parametric method used to correct for selection bias in a continuous treatment setting by comparing units that are similar in terms of their observable determinants of "adoption intensity" within the adoption group. Hence, it does not require control groups (Magrini *et al.,* 2014). The intensity of adoption of improved food legume varieties that is "adoption intensity" that indicates proportion of adoption, which ranges from 0 to 1, that was captured by dividing land under improved varieties of food legume of each household to maximum amount of land under improved legume varieties. Here missing important variables may create mismatching and biased estimators because the GPS does not directly account for the unobservable variables that may affect both the welfare of household and intensity of adoption of improved food legume varieties. Therefore, different demographic, socioeconomic, institutional and location factors were included in the analysis. Alike to PSM analysis in previous section, GPS focuses on estimation of welfare impacts by using income, consumption expenditure and daily calorie intake per AE per day as indicator variables.

Before estimating the generalized propensity score, it is required to drop non-adopters from the analysis and group the intensity of adoption in to three clusters at 30% and 70% following the procedure suggested by Kluve *et al* (2007). Three groups of comparable size were formed on the basis of proportion of intensity of adoption, i.e. group one (less than 0.0532); group two (greater than 0.0532 and less than 0.18) and group three (greater than 0.18 to 1). Group one presents the households with relatively lower proportion of adoption that consists of 39 households; the second group indicates the household with medium proportion of adoption which contain 50 households and the third group indicate relatively higher proportion of adopter that consists of 38 sample households.

As Table 12 indicates, the estimated GP score varies in the range of 0.0243to 0.659 with mean of 0.148. For group one, the GPS scores was in the range of 0.036 to 0.24with mean of 0.108. For group two, GP score ranged from 0.024 to 0.424 with mean of 0.141 while the last groups GP score vary between 0.030 and 0.659 with mean of 0.198.

Table 12: Distribution of estimated generalized propensity score

Variable	Observations	Mean	Std. Dev.	Min	Max
Total household	127	.148	.097	.0243	.659
Group 1	39	.108	.051	.036	.240
Group 2	50	.141	.079	.024	.424
Group 3	38	.198	.130	.030	.659

Source: Own computation

Consequently, the common support region would then lie between 0.036 and 0.240 by discarding two households from group one, eight households from group two and 11household from group three and totally 108 households were found on common support region for GPS estimation.

Figure 6 below portrays the distribution of the treated households with respect to the estimated GPS scores and the household on the common support. The kernel distribution shows that most of households are found in the left side of the distribution, which suggests that the lower proportion of adoption of improved food legume varieties.

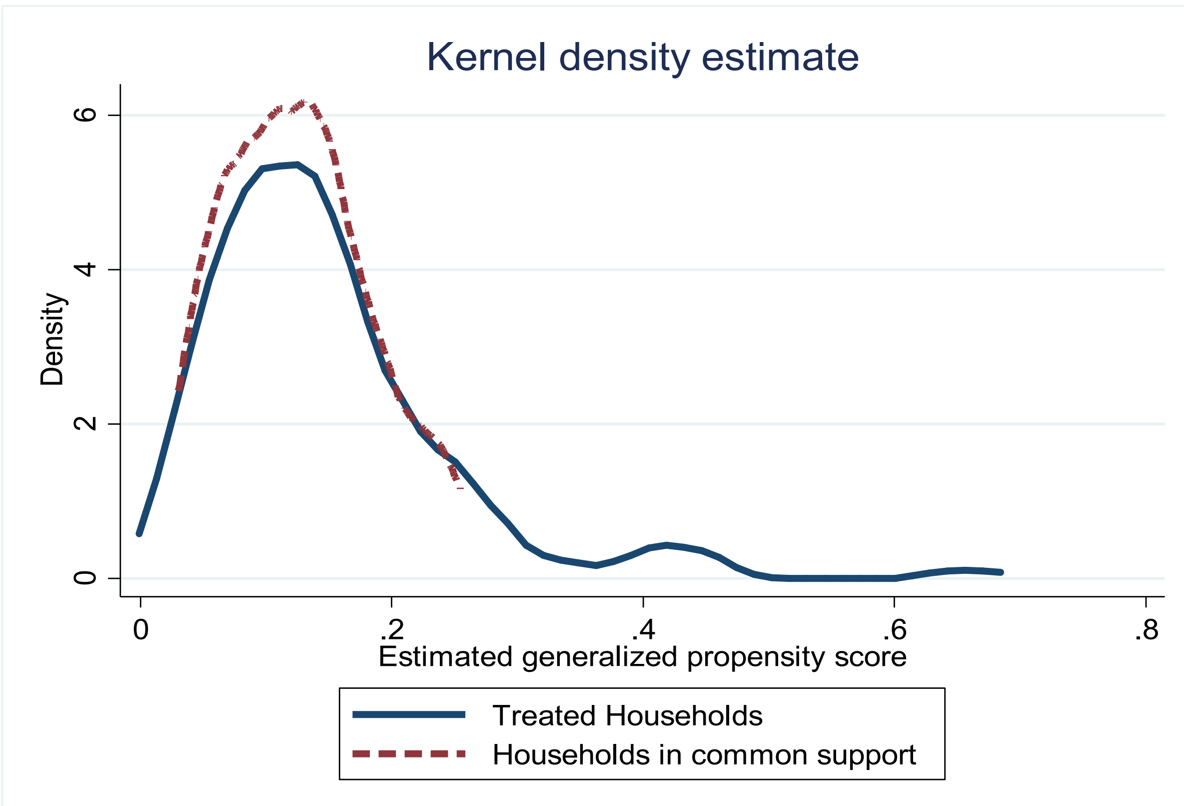

Figure 6: Kernel density of GPS-score with common (off) support regions

4.4.2. Test for covariate balance

The main purpose of estimating the GP score is to check the balancing of the covariates and not to obtain a precise prediction of determinant of intensity of adoption. Accordingly, testing of balancing property by comparing the covariates across groups with and without GPS correction was done. Finally, strong evidence was found that showed the satisfaction of the balancing property at level lower than 1% statistical error after GPS adjustment.

Table 13 presents the result of standard two-sided t-test of covariate balance for each group before and after GPS adjustment. The results point out that the covariate balance has improved by making the adjustment for the GPS. The equality of mean across groups without GPS adjustment indicates as there were 4 covariates with significant mean difference, whereas after GPS correction it was reduced to one significant mean difference variable.

Table 13: Covariate balancing: t-statistics for equality of covariate means

Covariates	Before match t-statistics of mean difference						After match t-statistics of mean difference					
	0 to 0.0531		.060 to 0.179		.192 to 1		0 to 0.0531		.060 to 0.179		.192 to 1	
	Mean diff	t-value	Mean diff	t-value	Mean diff	t-value	Mean diff	t-value	Mean diff	t-value	Mean diff	t-value
Age	0.298	0.135	-2.47	-1.19	2.51	1.14	-3.12	-1.5	2.39	1.35	-0.46	-0.22
Education	-0.126	-0.182	.078	0.11	.039	0.056	0.6	0.97	-0.38	-0.63	-0.16	-0.23
Livestock in TLU	-1.74	***-1.91***	.117	0.135	1.63	***1.78***	0.31	0.45	-0.61	-0.92	-0.69	-0.82
No. hh in farm activity	0.445	1.21	-.514	-1.48	.133	0.35	-0.24	-0.69	0.4	1.2	-0.12	-0.3
Freq cont with research center	-.134	-0.50	.245	0.981	-.143	-0.53	0.28	1.11	-0.23	-0.92	0.16	0.55
Distance from agri ext office	.394	***1.81***	-.161	-0.77	-.21	-0.98	-0.12	-0.59	0.16	0.79	0.09	0.4
Distance to main market	-.189	-0.69	-.29	-1.16	.528	***1.96***	0.17	0.7	0.34	1.33	-0.58	***-2.13***

Source: own computation

4.4.3. Results of the dose-response function

The final step of GPS is estimating the GPS-adjusted dose-response function, which was undertaken to evaluate the impact of intensity of adoption of improved food legume varieties on income, consumption expenditure and daily calorie intake per AE. The model itself was found to be significant which leading to non-acceptance of the null hypothesis that all slope coefficients are zero.

4.4.3.1. Effect of intensity of adoption on income of households

Table14 below displays the impact of intensity of adoption of improved food legume varieties on the income of households at specified treatment level. The result from GPS estimation indicates at 0.33 proportion of intensity of adoption, the daily income per AE of households increases by 3.8% due to increase in intensity of adoption of improved food legume varieties, which is significant at 1% statistical error. As the proportion of land allocated for improved food legume increased to 0.7, the daily income of household per AE raised by 4.3% at 10% statistical error. However, at 1 (100%) proportion of intensity of adoption there is no significant income effect while taking all other factors constant. This positive correlation of intensity of adoption with the income of households is in line with findings of Kassie *et al* (2014) in rural Tanzania on welfare impact of intensity of adoption of improved agricultural technologies by using continuous treatment effects model (GPS).

Table 14: Impact of level of adoption on income of households

Treatment level	Dose response	Standard error*	treatment effect	Standard error*
0.33	2.912***	0.996	0.038***	0.013
0.7	3.058***	0.687	0.043*	0.022
1	3.189***	1.250	0.046	0.375

***, and * is significant at 1%, and 10%level of statistical error.
*The bootstrapped SE is obtained after 10replications.
Source: own computation

Figure7below indicates the graphic representation of average effect of treatment (Dose Response) and Marginal effect (Treatment Effect) on the selected proportion of adoption intensity. Both dose response and treatment effect function of intensity of adoption substantiate the positive and direct correlation of income of households with proportion of intensity of adoption of improved food legume varieties.

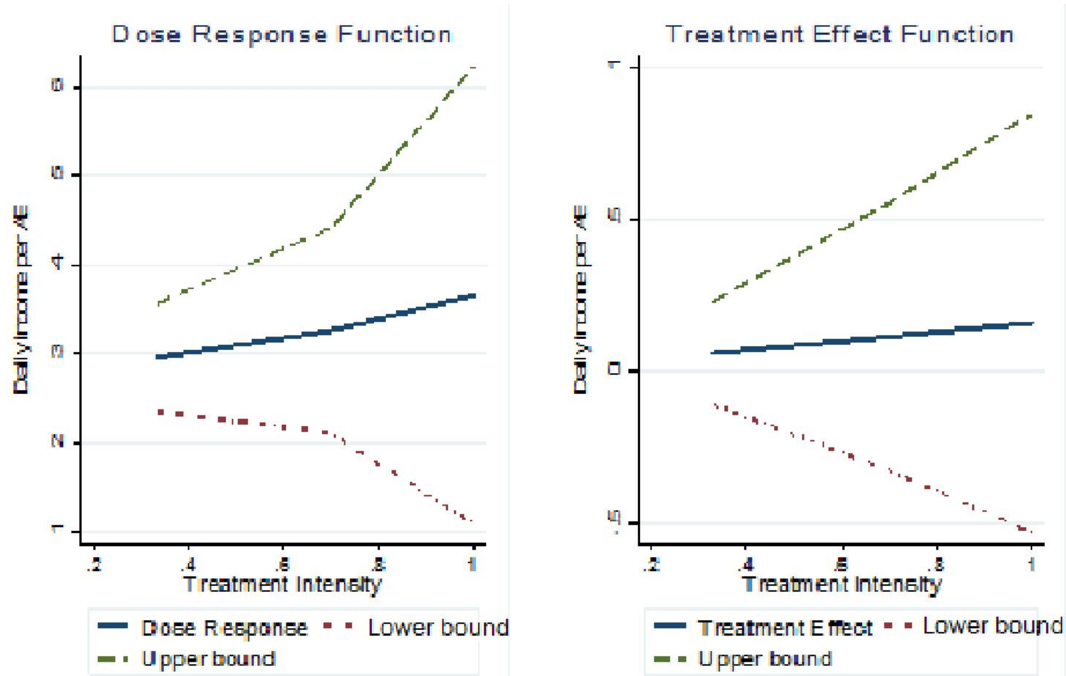

Figure 7: Dose response and treatment effect of intensity of adoption on household income

4.4.3.2. Effect of intensity of adoption on consumption expenditure of households

The amount of money spend on the purchase of consumable items by the household (food and drinks) was expected to be enhanced as the production and productivity of farming activities increases. As Table 15 illustrates, at 0.33 proportion of intensity of adoption, the marginal increase in consumption expenditure was estimated to be 6.2%at 10% statistical error. As intensity of adoption increased to 0.7 and 1, the marginal effect of intensity of adoption of improved food legume varieties on consumption expenditure was observed to be statistically insignificant and ended to be negative if the intensity is increased beyond 1. This may due to the nature of the consumption, which set at some specific pick beyond that the household could not consume.

Table 15: Impact of level of adoption on consumption expenditure

Treatment level	Dose response	Standard error*	Treatment effect	Standard error*
0.33	2.349***	0.277	0.062*	0.032
0.7	2.497***	0.389	0.002	0.184
1	2.453***	0.679	-0.047	0.280

***, and * is significant at 1% and 10%level of statistical error.
*The bootstrapped SE is obtained after 10replications.
Source: own computation

Similarly, Figure 8 confirms the positive relation of intensity of adoption with average effect (dose response) on daily consumption expenditure of the households. However, the marginal effect decreases to zero as the intensity gets close to 1.

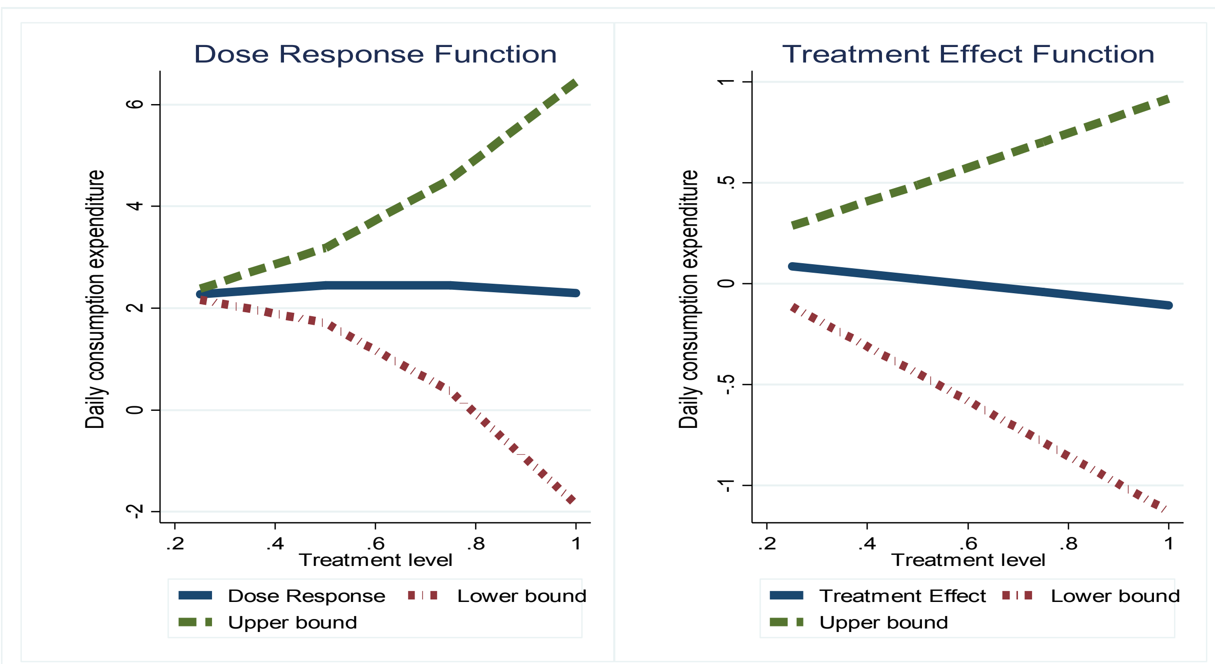

Figure 8: Dose response and treatment effect of intensity of adoption on consumption expenditure

4.4.3.3. Effect of intensity of adoption on daily calorie intake

Result from GPS estimation indicates the intensity of adoption of improved food legume varieties has positive relationship with daily calorie intake per AE. Table 16 below demonstrates that at 0.33 proportions intensity of adoption, the daily calorie intake improved by 9%, which is significant at 5% statistical error. As intensity of adoption increases to 0.7 and 1, the treatment effect on the daily calorie intake of households increased by 23% and 35%, which is statistical significance at 5% and 10% statistical error, respectively. This result is in line with the findings of Kassie *et al*. (2014) that reported the positive impact of the intensity of adoption of improved maize varieties on status of food security in rural Tanzania.

Table 16: Impact of intensity of adoption on Daily calorie intake per AE

Treatment level	Dose response	Standard error*	Treatment effect	Standard error*
0.33	8.35***	0.24	0.09**	0.04
0.7	8.89***	0.46	0.23**	0.11
1.	9.70***	1.84	0.35*	0.18

***, ** and * is significant at 1%, 5% and 10% level of statistical error.
*The bootstrapped SE is obtained after 10 replications.
Source: own computation.

Figure9 below confirms the positive relation of intensity of adoption of improved food legume varieties with daily calorie intake. Both average treatment effect (dose response) and marginal effect (treatment effect) increased as the intensity of adoption of improved food legume varieties increased.

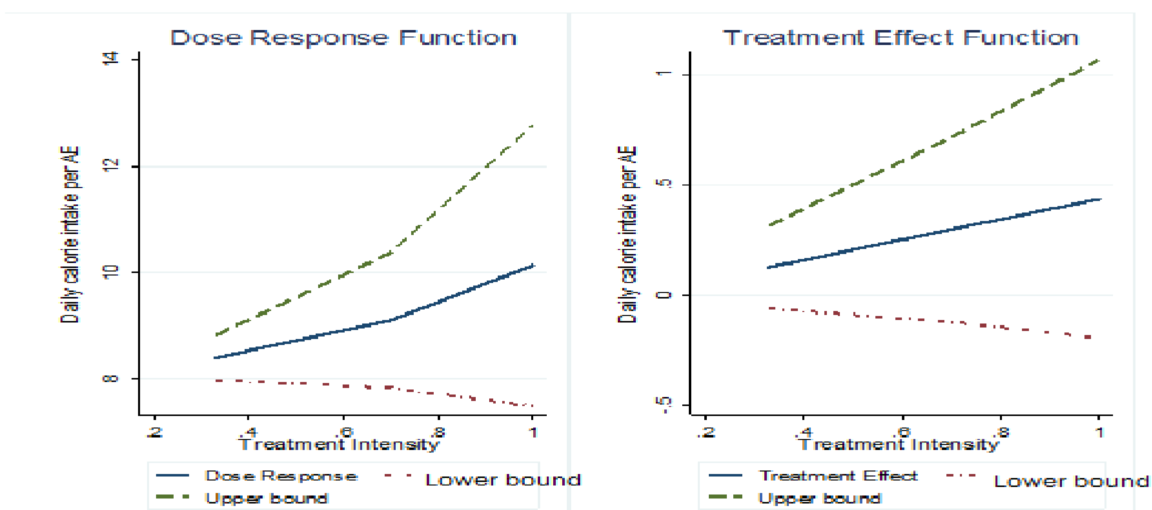

Figure 9: Dose response and treatment effect of intensity of adoption on daily calorie intake

4.5. Challenges and opportunities of adoption of food legume technologies

The informal survey done as part of this study that used to summarize the challenges and opportunities of adoption of improved food legume technologies that farm households are facing in the study districts.

Bale Highlands are characterized by mixed farming that includes more of crop production and less of livestock rearing activities. Even if the area has the potential for food legume production, the crop production is dominated by mono-cropping system, where wheat is the most dominant crop. Wheat is mainly produced in the *meher* (main rainy) season mainly using mechanization while farmers produce food legumes in both *meher* and *belg* (short rain) seasons using human labor. Faba bean is largely produced in the *meher* season while field pea is produced in the *belg* season. This is essentially associated with the susceptibility of faba bean to water logging in the *belg* season and that of field pea to aphids in the *meher* season.

As farmers and development agents indicated, the district office of agriculture provides various agricultural extension support to farmers including dissemination of improved technologies, capacity strengthening for farmers, facilitating farmers' seed multiplication effort, and monitoring and evaluation of agricultural production activities in collaboration with different governmental and non-governmental institutions like SARC, Madda Walabu University, ICARDA and Africa RISING.

Adoption of improved food legume technologies provides farmers in Bale Highlands with many opportunities and potential challenges. According to experts at the district offices of agriculture, food legumes are produced for household consumption and to generate cash income due to their higher market values. Moreover, the production of food legumes in rotation with cereals significantly reduces disease and pest infestation in the area. Experts in the districts have also observed that the incidence of diseases is more severe in mono-cropped fields than in rotation of legumes and cereals.

Key informants of the informal survey emphasized that shortage of improved food legume technologies, as one of the major challenges farmers are faced with, undermining their effort to improve production and productivity of food legumes. Especially lack of disease resistant and water logging tolerant varieties was indicated as a critical challenge. In some locations, farmers also desist from planting their field due to possible damage caused by frost.

It was also learnt that there was limited effort to support farmers to access market information. Experts in the districts indicated that weak market integration is one of the major challenges that affect legume crop production and productivity in the area. Farmers in the districts have limited access to market information. In addition, there is no any functional cooperative or union, which provides market information or facilitates market linkages in the study districts. As a result, food legume farmers are usually affected by market irregularities.

5. CONCLUSION AND RECOMMENDATIONS

In this section, the major findings of the study are summarized, and conclusion and policy implications are drawn based on the key results of the study.

5.1. Summary

Adoption of agricultural technologies is crucially important in order to feed the rapidly growing population of Ethiopia, which has already become almost unachievable by extensive farming due to limited opportunities for farm area expansion. Agriculture in Ethiopia is semi-subsistence oriented in nature. In order to raise the agricultural output and productivity to bring about, albeit in the long run, improvement in household income, reduction of poverty and enhancement of food security on a sustainable basis in developing countries large-scale adoption and diffusion of new technologies is very essential.

This study was conducted in Bale highlands of Ethiopia, which are among the sections of the country where there is immense potential and need for production of food legumes. Even if a number of food legume research and extension activities have already been done in many districts of Ethiopia, very little (if any) is known in Bale Highlands about the status and impact of adoption of improved food legume technologies. Therefore, this study was undertaken to fill the glaring gap of data and information about the determinants of adoption of improved food legume technologies, the impact of rate and intensity of adoption of improved food legume varieties on income, consumption expenditure and daily calorie intake. In addition, this study identified the major challenges and opportunities of adoption of improved food legume technologies in Bale highlands of Ethiopia.

This study was undertaken in three districts of Bale Highlands, namely Agarfa, Goba and Sinana. Both formal and informal survey was carried out to generate the primary data needed for the study. The formal survey acquired from 600-randomly selected sample farm households. It compromises 90.7% of male headed and 9.3% of female-headed farm households with an average age of 43 years.

The result of simple descriptive statistics revealed that 21% of sample households adopted improved food legume varieties, 17% adopted fertilizer while only 7.8% of the sample households adopted pesticides for the production of food legumes. Larger farm size and livestock holding, higher family size and active family member, membership in farmers' cooperatives and contact with agricultural research center, closeness to agricultural extension office and main market characterize the adopters of improved food legume technologies.

The study also indicates that adoption of improved food legume technologies can motivate farmers to shift from the mono-cropping system, which increases infestation of disease and pests to a more diverse one. The adoption of improved food legume technologies provides farmers with higher income- as the legumes are grown essentially as cash crop and usually fetch higher prices than common cereals. Furthermore, they are the major source of protein for the household who cannot acquire it from animal products. However, the adoption of improved food legume technologies is highly constrained by labor-intensive nature of the production, lack of improved food legume technologies especially water logging tolerant varieties and market irregularities.

The determinants of adoption of improved food legume technologies were identified by using Probit and clog-log models. The results of the estimated limited dependent variable models revealed livestock holding, farm size, membership in farmer's cooperative and frequency of contact with agricultural research center are positively associated with adoption of improved food legume technologies. In contrary, being very old, distance from main market and agricultural extension office, and participation of household head in off farm activity were found to be negatively associated with the likelihood of adoption of the improved legume technologies.

In addition, PSM treatment effect model was estimated to evaluate impact of adoption of improved food legume varieties on the welfare of households by considering daily income, consumption expenditure and calorie intake per AE as welfare indicators. The results of PSM revealed the positive effect of improved food legume varieties on household income. This study also looked into intra-household differentials of the impact by developing clusters based on gender, age, and involvement in farming activities of household members. The intra household analysis indicated that households with productive labor force receive better treatment effect while households with economically dependents female members receive considerably lower treatment effects from adoption of improved food legume varieties.

Furthermore, to evaluate impact of intensity of adoption of improved food legume varieties on household welfare, this study employed GPS model. The results from GPS confirm the positive and significant impact of intensity of adoption of improved food legume varieties on income, consumption expenditure and daily calorie intake.

5.2. Conclusion and Policy Implication

As the finding of the study indicated, adoption of improved food legume technologies was quite low even if the study area has huge potential for production of food legumes. Thereby, there is a justifiable need to exert a stronger and targeted effort to improve the adoption of improved food legume technologies. Based on the finding of this study, the following recommendations are made.

1. The adoption of improved food legume technologies was facilitated by having more livestock. Therefore, stakeholders in the study area should give much emphasis to the improvement of the productivity of the livestock through disseminating improved breeds and improving feeding practice.

2. Membership in farmers' cooperative was positively correlated with adoption of improved food legume technologies. Thereby, to enhance adoption of improved food legume technologies, it is important to improve the capacity of cooperatives through providing resources like office to operate, giving training and creating a conducive (non-interference) policy environment

3. The frequency of contact with agricultural research center was found to increase the likelihood of adoption of food legume technologies. Therefore, stakeholders in the study area should give much emphasis to improving the provision and outreaching services of the research center through designing and implementing participatory research activities, capacity building, discussion forums and the like.

4. Distance from agricultural extension office and distance from main markets are important variables that adversely affect the adoption of improved food legume technologies. The district offices of agriculture should give emphasis on the accessibility of the agricultural extension service they are supposed to provide. Similarly, responsible ministries and their

grass-roots level branches need to make the necessary effort to establish markets in more accessible locations or increase farmers' access to markets through infrastructure development

5. Even if adoption of improved food legume varieties has promising welfare impact, it significantly differs among members due to age and sex differences. Therefore, researchers, policy makers and any other institution engaged in development and dissemination of improved food legume varieties should give special attention to the dynamics within the household.

Finally, this study strongly recommends further studies on the adoption of improved food legume technologies and their impact on household welfare using higher sample size and repeated measures to account for the heterogeneities that are crucial in such studies. Both spatial and temporal aspects of the adoption and impact dynamics need to be looked into to come up with precise and practical recommendations.

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7. APPENDIX

Appendix 1: Conversion factors to compute adult equivalents

	Conversion factor	
Age year	Male	Female
Under 1	0.33	0.33
1-1.99	0.46	0.46
2-2.99	0.54	0.54
3-4.99	0.62	0.62
5-6.99	0.74	0.7
7-9.99	0.84	0.72
10-11.99	0.88	0.78
12-13.99	0.96	0.84
14-15.99	1.06	0.86
16-17.99	1.14	0.86
18-29.99	1.04	0.8
30-59.99	1	0.82
60+	0.84	0.74

Source: WHO and FAO (1985).

Appendix 2: Energy content per grams of edible portions for selected foods

Food item	Kcal/gm		Kcal/gm
Drink Item		**Staple Food Item**	
Tea	1.19	Maize	3.65
Soft Drink	0.38	Green Maize	1.66
Juice	0.6	Wheat	2.47
Beer In Ml	4.3	Barely	3.54
Coffee Been	1.103	Rice	1.11
Fruit		Sorghum	3.805
Orange	0.47	Potato	0.77
Mango	0.6	Bean	3.29
Papaw	0.43	Fresh bean	1.04
Pineapple	0.5	Groundnut	5.67
Banana	0.89	Sweet potato	1.36
Apple	0.52	**Vegetable**	
Guava	0.68	Tomato	0.18
Sugarcane	0.32	Onion	0.4
Avocado	1.6	Head Cabbage	0.25
Cactus	0.75	Leaf Cabbage	0.37
Gista	0.48	Spinach	0.23
Animal Product		Beetroot	0.43
Beef	2.5	Carrot	0.41
Goat	1.43	Pumpkin	0.249
Sheep	2.94	Paper	1.493
Chicken	2.39	Garlic	1.49
Eggs(Unit)	61	**Fat, Oil, Snakes, Sweeter And Other**	
Milk	0.42	Cooking Oil	8.964
Cheese	0.98	Margarine	7.47
Butter	7.17	Biscuit	3.53
Yogurt	0.59	Popcorn	3.75
Honey	3.04	Sugar	3.87
		Chocolate	5.46
		Ginger	0.8

Source: CTA/ECSA (1987)

Appendix 3: Conversion factors to compute Tropical Livestock Unit (TLU)

Livestock Category	**TLU**
Calf	0.25
Heifer	0.75
Bull	1
Cow and Ox	1
Horse	1.1
Donkey	0.7
Mule	0.7
Sheep and goat(adult)	0.13
Chicken	0.013

Source: Storck *et al.,*1991

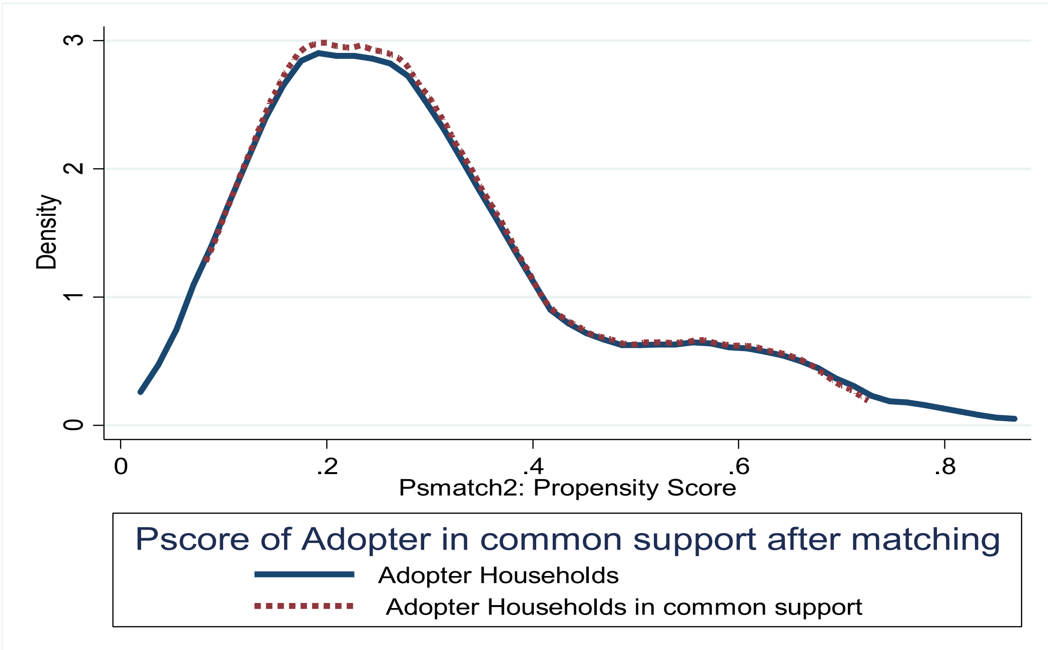
Appendix 4: Model quality test for estimation of adoption of improved food legume varieties

Econometric Model	df	AIC	BIC
Probit	16	563.7	633.2
Complementary clog-log	16	570.3	640.7

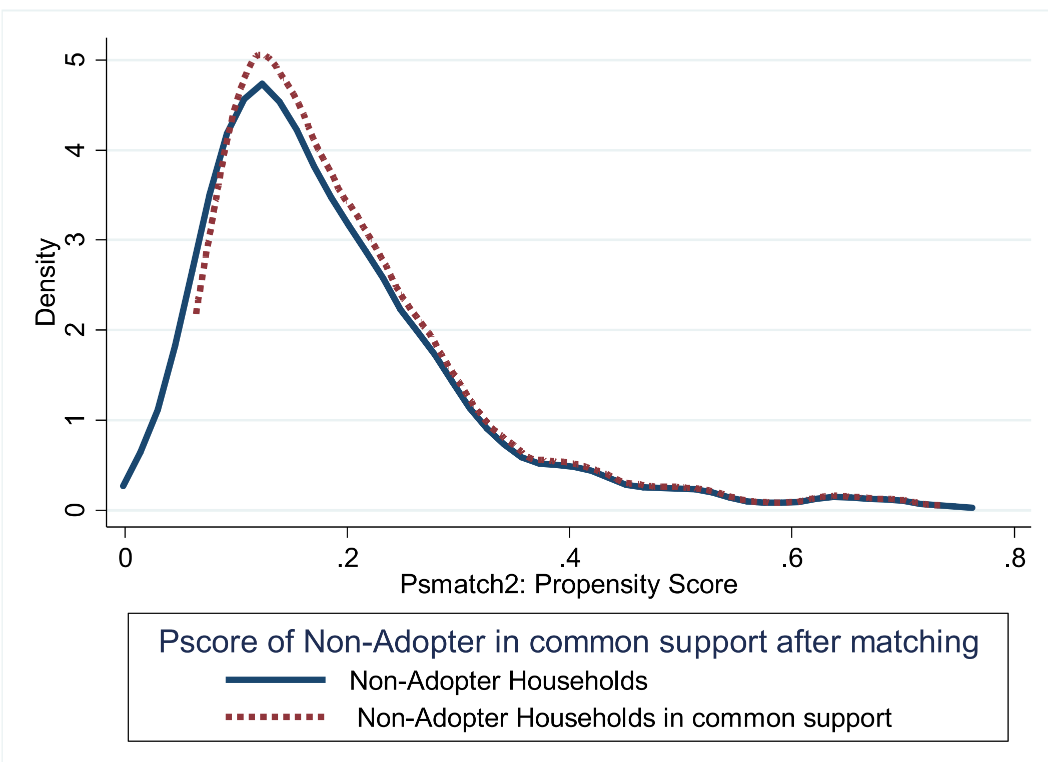
Appendix 5:Logistic regression results of household's propensity score to adopt

Covariate	**Coef.**	**Std. Err.**	**z-value**
Age	-0.007	0.009	-0.80
Education (Years)	0.009	0.031	0.29
No. hh member involve in farm	0.072	0.063	1.14
Livestock holding (TLU)	0.105	0.025	4.26***
Member in farmers Association	0.585	0.224	2.62***
Access to credit	-0.077	0.243	-0.32
Distance from (walking hour)			
Agri. extension office	-0.044	0.115	-0.38
Town	0.153	0.087	1.76*
Main market	-0.144	0.107	-1.35
Use fertilizer	1.004	0.256	3.91***
Off farm activity	-0.916	0.409	-2.24**
Constant	-2.441	0.521	-4.68***
Observation	600		
Wald $chi^2(15)$	63.32***		
Log pseudo likelihood	-268.89		
pseudo R- square	0.10		

Appendix 6: Kernel density of P-score with common (off) support regions adopter households



Appendix 7: Kernel density of P-score with common (off) support regions non-adopter households



Appendix 8: Propensity score and covariate balance

Covariates		Mean		% bias reduction		T-test	
	Sample	Treated	Control	%bias	bias	t	p>t
Age	U	43.82	42.94	6.9		0.65	0.518
	M	43.74	474.27	-4.2	39.2	-0.33	0.74
Education	U	5.47	4.95	14.4		1.43	0.153
	M	5.42	5.20	5.9	59.3	0.46	0.644
No. hh involve in farm	U	3.51	3.13	21.4		2.23**	0.026
	M	3.50	3.48	1.5	92.9	0.11	0.91
Livestock holding	U	9.20	6.59	58		6.01***	0.00
	M	8.98	8.79	4.2	92.8	0.31	0.759
Member in farm association	U	0.43	0.30	27.1		2.78***	0.006
	M	0.42	0.41	1.4	94.8	0.11	0.914
Access to credit	U	0.29	0.36	-15		-1.48	0.141
	M	0.30	0.29	0.4	97.4	0.03	0.975
Distance from town	U	1.82	1.72	6.3		0.68	0.499
	M	1.81	1.78	2	69.2	0.15	0.879
Use fertilizer and pesticide	U	0.31	0.13	44.5		4.91***	0.00
	M	0.30	0.27	7.5	83.2	0.53	0.596
Distance to agro ext office	U	0.67	0.69	-1.8		-0.19	0.847
	M	0.68	0.67	0.6	69.2	0.05	0.964
Off farm activity	U	0.07	0.14	-21.9		-2.03**	0.043
	M	0.06	0.05	3.1	86	0.31	0.757
Distance from main market	U	1.39	1.50	-8.1		-0.85	0.398
	M	1.40	1.41	-0.5	93.5	-0.04	0.966

***, and ** is Significant at 1% and 5% probability level

Source: Own estimation result

Appendix 9: Joint significance test (likelihood ratio test)

Matching estimate	sample	Pseudo R^2	LR chi^2	$p>chi^2$	MeanBias	MedBias
NNM						
	unmatched	0.104	64.49	0.000	20.5	15.0
NN(1)	matched	0.028	9.76	0.552	9.8	11.1
	unmatched	0.104	64.49	0.000	20.5	15.0
NN(2)	matched	0.012	4.03	0.969	6.3	4.9
	unmatched	0.104	64.49	0.000	20.5	15.0
NN(3)	matched	0.012	4.32	0.960	6.3	5.7
	unmatched	0.104	64.49	0.000	20.5	15.0
NN(4)	matched	0.009	3.26	0.987	5.8	5.4
	unmatched	0.104	64.49	0.000	20.5	15.0
NN(5)	matched	0.008	2.61	0.995	5.4	6.1
KM						
	unmatched	0.104	64.49	0.000	20.5	15.0
Band width 0.1	matched	0.002	0.78	1.000	2.8	2.0
	unmatched	0.104	64.49	0.000	20.5	15.0
Band width 0.25	matched	0.019	6.69	0.824	7.4	4.9
	unmatched	0.104	64.49	0.000	20.5	15.0
Band width 0.5	matched	0.068	23.65	0.014	13.5	10.8
CM						
	unmatched	0.104	64.49	0.000	20.5	15.0
0.01	matched	0.021	6.96	0.803	8.2	8.2
	unmatched	0.104	64.49	0.000	20.5	15.0
0.25	matched	0.028	9.76	0.552	9.8	11.1
	unmatched	0.104	64.49	0.000	20.5	15.0
0.5	matched	0.028	9.76	0.552	9.8	11.1

Appendix 10: Algorithm to estimate the generalized propensity score

Covariate	**Coef.**	**Robust std. Err.**	**Marginal effect**
Age	0.028	0.013	2.16**
Education	-0.022	0.031	-0.72
Livestock in TLU	0.066	0.023	2.85***
No. hh in farm activity	-0.043	0.074	-0.58
Use fertilizer and chem.	0.598	0.267	2.24**
Freq cont with research center	-0.122	0.091	-1.34
Access to credit	-0.561	0.275	-2.04**
Distance to agri ext office	-0.176	0.105	-1.68*
Distance to main market	0.020	0.082	0.25
Off farm activity	0.430	0.341	1.26
District	0.255	0.183	1.39
Constant	-4.001	0.684	-5.85***
Observation	127		
Residual df	115		
Log pseudo likelihood	-32.55		
AIC	.7803		
BIC	-536.3		

Appendix 11: Sample Survey Interview Schedule

Questionnaire for the study on Adoption and Welfare Impact of Improved Food Legume Technologies in Bale Highlands of Ethiopia: Intra and Inter-Household Empirical Analysis

SECTION 1: Prelude

1. Date ________________________ (DD/MM/YYYY)
2. Interviewer's name _____________________
3. Supervisor's name ______________________
4. Checked on __________________(DD/MM/YYYY)
5. District ___________Kebele ______Village __________ Household ID ________
6. Village altitude _______ latitude ________________ Longitude ____________
7. This respondent is the one randomly chosen for the study

   1 = Yes, SKIP to Section 2.

   2 = No.

8. Why was the individual in the original sample not interviewed?

   1 = Refused to be interviewed 2 = Head of the household (or his spouse) was not at home

   3 = Premises empty for the survey period 4 = Premises did not exist

   5 = Other (specify): ____

SECTION 2: Demographic characteristics of the household

	Let's discuss about each member of your household (all the people living in the same compound, eating from the same "pot or plate" and working to sustain the family						
	First name **(start with the respondent)**		Gender **0=F** **1=M**	Age **(Years)**	Literacy in **years** of education	Involves in agricultural activities? **1= Yes0=No**	Engaged in off-farm activities in the last 12 months? **1= Yes0=No**
1.	P1						
2.	P2						
3.	P3						
4.	P4						
5.	P5						
6.	P6						
7.	P7						
8.	P8						
9.	P9						
10.	P10						
11.	P11						
12.	P12						
13.	P13						
14.	P14						
15.	P15						

SECTION 3: Access to infrastructure and asset ownership

Let's discuss about community level infrastructures:				
		Km	Walking Distance (**minutes**)	Driving distance (**minutes**)
1.	How far is the village market from your residence?			
2.	How far is the nearest main market from your residence?			
3.	How far is the nearest source of seed from your residence?			
4.	How far is the nearest source of fertilizer from your residence?			
5.	How far is the nearest source of herbicides/pesticides from your residence?			
6.	How far is the nearest farmer cooperative from your residence?			
7.	How far is the nearest agricultural extension office from your residence?			
8.	How far is the nearest health center from your residence?			
9.	How far is the nearest school from your residence?			
10.	How far is the nearest town from your residence?			
11.	Does the household have ELECTRICITY?	1 = Yes 0 = No		
12.	Have you experienced any power failures in the past 12 months?	1 = Yes 0 = No		

	Ask about each of the following items and indicate how many of each is owned by the household. (EXCLUDE BROKEN OR OUT-OF-FUNCTION ITEMS)			
	Asset	How many […] do you have in the household?	How much did you purchase your […]? **(In Birr estimate)** *(if more than two items, take average price)*	What is the current market price of your […]? (**Birr**) *(if more than two items, take average price)*

13.	Animal scotch cart			
14.	Bicycle			
15.	Cars			
16.	Generator			
17.	Horse/mule cart			
18.	Mobile Phones			
19.	Motorbike			
20.	Grain mill			
21.	Ox-plough			
22.	Phone (land line)			
23.	Plowing oxen			
24.	Plowing donkey			
25.	Private water well			
26.	Private borehole			
27.	Radio, cassette or CD player			
28.	Refrigerator			
29.	Sewing machine			
30.	Television			
31.	Tractor			
32.	Water pump			
33.	Wheel barrow			
34.	Solar panels			
35.	Satellite dish			

SECTION 4: Social capital and Networking

	Let's discuss about whether any member of this household is member of any formal or informal institution.				
	Type of group/association	Is anyone in the family a member of [...]? **1=Yes0=No**	Who is the member? 1= Husband 3= Children 2= Wife 4= Husband and wife 5=All 6 = Other	Since when?	Will the member(s) continue membership? **1=Yes0=No**
1.	Producers' cooperative				
2.	Agricultural marketing cooperative				
3.	Local administration				
4.	Farmers' association				
5.	Women's association				
6.	Youth association				
7.	Religious groups/associations				
8.	Saving and credit group/association				
9.	Funeral association				
10.	Government team				
11.	Water users' association				
12.	HIV/AIDS support group/association				
13.	Garden groups				
14.	Other, specify…………….				
15.	For how many years have you lived in this village?				
16.	How many people are there in this village that you can rely on for critical support in times of need?		1= relatives _______ 2 = non-relatives____		

17.	How many people are there outside this village that you can rely on for critical support in times of need?	1= relatives _______ 2 = non-relatives_____	
18.	Are any of your friends or relatives active members in formal or informal institutions within and outside this village?	1 = yes 0 = No	
19.	How many traders do you know in this village who can buy your grain?		
20.	How many traders do you know outside this village who can buy your grain?		

SECTION 5: Land holding and faba bean/field pea production

	Sub section 5.1: Land holding (hectare) during the 2014/15 cropping season		
	Land category	Cultivated land size (vegetables +annual + permanent crops (e.g., wheat, faba bean, coffee)	Uncultivated land size (e.g. grazing, homestead etc)
1.	Own land used		
2.	Rented in land		
3.	Rented out land		
4.	Size of bought land during **2014/15** season		
5.	Size of sold land during**2014/15** season		
	Sub-section 5.2: Faba bean/field pea production and technology use		
	Let's discuss about Faba bean/field pea production now:		
6.	Have you ever planted any improved faba bean varieties during the last five years?	1 = Yes 0 = No	
7.	Do you remember when you planted improved faba bean varieties for the first time?	1 = Yes, when?______0 = No	
8.	Have you been growing improved faba bean continuously since	1 = Yes 0 = No	

	you first planted it?	
9.	Have you ever planted any improved field pea during the last five years?	1 = Yes 0 = No
10.	Do you remember when you planted improved field pea for the first time?	1 = Yes, when?______0 = No
11.	Have you been growing improved field pea continuously since you first planted it?	1 = Yes 0 = No

	Subsection 5.3: Input use						
12.	Have you purchased any seed of faba bean for the 2014/15 cropping season? 1. Yes 0. No (SKIP to Qn 17)						
	Please tell us about the seed of all faba bean and field pea varieties you purchased for the 2014/15 cropping season						
	Variety name	Quantity (Kg)	Is it improved? 1 = yes 0 = no	Is it local? 1 = yes 0 = no	Which market did you buy it from?	How much did it cost (Birr/kg)?	Will you recycle/replant the seed? 1 = yes 0 = no
13.	i.						
14.	ii.						
15.	iii.						
16.	iv.						
17.	Have you purchased any seed of field pea for the 2014/15 cropping season? 1. Yes 0. No (SKIP to Qn 22)						
	Variety name	Quantity (Kg)	Is it improved? 1 = yes0 = no	Is it local? 1 = yes 0 = no	Which market did you buy it from?	How much did it cost (Birr/kg)?	Will you recycle/replant the seed? 1 = yes 0 = no
18.	i.						
19.	ii.						
20.	iii.						
21.	iv.						
22.	How many plots of farmland do you have?			Number of plots:			

23.	Let's discuss about each of the plots:								
24.		Plot 1	Plot 2	Plot 3	Plot 4	Plot 5	Plot 6	Plot 7	Plot 8
25.	Size of plot (timad)								
26.	Form of ownership? Code A								
27.	Who manages the plot? Code B								
28.	How far is it from your residence to walk on foot? MINUTES								
29.	How fertile is it? Code C								
30.	What proportion is irrigated (%)								
	Code A 1.Own 2.Rented in 3. Sharecropped 4. Gift			Code B 1.Husband 2.Wife 3. Husband and wife 4. Children			Code C 1.Very fertile 2.Fertile 3.Infertile 4.Very infertile		

	5. Loaned for free 6. Other			5. Family 6. Other			5. I don't know		
		Plot 1	Plot 2	Plot 3	Plot 4	Plot 5	Plot 6	Plot 7	Plot 8
31.	Main crops on the plot(START with faba bean)	C1.	C1.	C1.	C1.	C1.	C1.	C1.	C1.
		C2.	C2.	C2.	C2.	C2.	C2.	C2.	C2.
		C3.	C3.	C3.	C3.	C3.	C3.	C3.	C3.
		C4.	C4.	C4.	C4.	C4.	C4.	C4.	C4.
29.	Area share (%) of faba bean on the plot								
30.	Area share (%) of field pea on the plot								
31.	Improved faba bean varieties grown on the plot	V1.	V1.	V1.	V1.	V1.	V1.	V1.	V1.
		V2.	V2.	V2.	V2.	V2.	V2.	V2.	V2.
32.	Yield of improved faba bean varieties (kg) on the plot	V1.	V1.	V1.	V1.	V1.	V1.	V1.	V1.
		V2.	V2.	V2.	V2.	V2.	V2.	V2.	V2.
33.	Local faba bean varieties grown on the plot	V1.	V1.	V1.	V1.	V1.	V1.	V1.	V1.
		V2.	V2.	V2.	V2.	V2.	V2.	V2.	V2.
34.	Yield of local faba bean varieties (kg) on the plot	V1.	V1.	V1.	V1.	V1.	V1.	V1.	V1.
		V2.	V2.	V2.	V2.	V2.	V2.	V2.	V2.
35.	Improved field pea	V1.	V1.	V1.	V1.	V1.	V1.	V1.	V1.

	varieties grown on the plot	V2.	V2.	V2.	V2.	V2.	V2.	V2.	V2.
36.	Yield of improved field pea varieties (kg) on the plot	V1. V2.	V1. V2.	V1. V2.	V1. V2.	V1. V2.	V1. V2.	V1. V2.	V1. V2.
37.	Local field pea varieties grown on the plot	V1. V2.	V1. V2.	V1. V2.	V1. V2.	V1. V2.	V1. V2.	V1. V2.	V1. V2.
38.	Yield of local field pea varieties (kg) on the plot	V1. V2.	V1. V2.	V1. V2.	V1. V2.	V1. V2.	V1. V2.	V1. V2.	V1. V2.
39.	Total yield for all faba bean varieties (kg) on the plot								
40.	Total yield for all field pea varieties (kg) on the plot								
41.	Yield (kg) of other crops on the plot	C3. C4.	C3. C4.	C3. C4.	C3. C4.	C3. C4.	C3. C4.	C3. C4.	C3. C4.

	Let's discuss about the quantity and cost of fertilizer and chemicals used in 2006/07for crop production per plot									
			Plot 1	**Plot 2**	**Plot 3**	**Plot 4**	**Plot 5**	**Plot 6**	**Plot 7**	**Plot 8**
	Fertilizer									
42.	Urea **(kg)**	Faba bean								
		Field pea								
		Other crops								
		Total								
43.	DAP **(kg)**	Faba bean								
		Field pea								
		Other crops								
		Total								
		Field pea								
		Other crops								
		Total								
44.	Manure **(kg)**	Faba bean								
		Field pea								
		Other crops								
		Total								
45.	Bio fertilizer	Faba bean								
		Field pea								
		Other crops								
		Total								
			Plot 1	**Plot 2**	**Plot 3**	**Plot 4**	**Plot 5**	**Plot 6**	**Plot 7**	**Plot 8**
	Chemicals									
46.	Herbicide (**kg/liter**)	Faba bean								
		Field pea								
		Other crops								
		Total								
47.	Pesticide (**kg/liter**)	Faba bean								
		Field pea								
		Other crops								
		Total								
48.	Fungicide (**kg/liter**)	Faba bean								
		Field pea								
		Other crops								
		Total								

SECTION 6: Livestock production and marketing

	Sub-section 6.1: Livestock ownership and estimated market value		
	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		

Sub - Section 6.2: 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)**
17.	Milking cows						
18.	Non milking cows (mature)						
19.	Trained oxen for plowing						
20.	Bulls						
21.	Heifers						
22.	Calves						
23.	Mature goats						
24.	Young goats						
25.	Mature sheep						
26.	Young sheep						
27.	Donkeys						
28.	Horses						
29.	Mules						
30.	Mature chicken						

31.	Traditional bee hives						
32.	Modern bee hives						
	Animal products						
33.	Milk and Yoghurt						
34.	Butter						
35.	Cheese						
36.	Eggs						
37.	Beef						
38.	Mutton						
39.	Honey						
40.	Hide						
41.	Skin						
42.	**Manure**						

SECTION 7: Access to agricultural services

	Subsection 7.1: Agricultural Extension				
	Let's discuss about the agriculture related interactions you have had over the last 12 months:				
	Source	How many times did you interact with […] in the last 12	How many field days did you attend in the last 12	Did you discuss about pulse crops with […] in the last 12 months? **1 = Yes**	How many farming related training organized by [...] did you attend in the last 12 months?

		months?	months organized by [...]?	**0=No**	
1.	Government extension service				
2.	Government research service				
3.	Farmer Cooperatives or groups				
4.	Neighbor farmers				
5.	Seed traders/Agro-dealers				
6.	NGOs				
7.	International research institutions				

Subsection 7.2: Market information access

	Commodity	Did you get market information before you decided to grow/raise [..]?		Did you get market information before you decided to sell [..]?		Have you ever taken […] to the market and been unable to sell?
		1= Yes **0 = No**	If **Yes**, Source? **CODE D**	**1= Yes** **0 = No**	If **Yes**, Source? **CODE D**	**1= Yes** **0 = No**
8.	Faba bean					
9.	Field pea					
10.	Other crops					
11.	Livestock					

Code D
1 = Government extension service 2 = Government research service
3 =Farmer Cooperatives or groups 4 = Neighbor farmers
5 = Seed traders/Agro-dealers 6 = NGOs

	7 = Private and international research institutions 8 = Markets 9 = Others					
Subsection 7.3: Rural Credit						
Let's discuss about the different facilities at your disposal within the Village/Community Please						
12.	Are there times you have critical shortage of available funds for agricultural activities?	1 =Yes 0 = No (SKIP to Qn 22)				
13.	In which months do you face critical fund shortages?	1 = January to March 2 = April to June 3 = July to September 4 = October to December				
14.	Did you receive any cash and/or input credit of any source in the last 12 months for crop or livestock production or household consumption?	1 =Yes 0 = No (SKIP to Sub-Section 7.4)				
Let's discuss about the types, quantity, and source of the credits you acquired						
		Have you ever received [..]? 1 = Yes 0 = No	From whom? CODE G	How much? (with unit)	Did you get the […] in time? 1 = Yes 0 = No	Will you be able to pay back the [..] in time? 1 = Yes 0 = No 3=Not applicable	Do you plan to continue taking [..]? 1 = Yes 0 = No
15.	Cash loan						
16.	Food loan						
17.	Seed loan						
18.	Fertilizer loan						
19.	Herbicide/pesticide loan						
20.	loan for farm implements						
21.	Loan for plowing animals						
22.	Loan for irrigation						
23.	loan for non-farm business						
24.	loan for						

	another debt repayment						
25.	Loan for utilities (water, education, etc)						
		CODE G: 1 = Bank 2= Local money lender 3= Neighbor farmers 4 = NGO 5 = government 6 = relatives 7 = Other					

SECTION 8: Coping with food insecurity

1.	Were there times in the last 12 months when the household was in any sort of food shortage?	1 = Yes 0 = No **(SKIP to Qn. 4)**
2.	If there were, why did they happen?	1 = Drought 2 = Poor harvest 3 = Lost job 4 = Death in the family 5 = Unreliable income 6 = Inflation 7 = Theft
		8 = Other, specify -
3.	How did the household recover from this?	1 = Relied on neighbors 2 = Relied on family to send food 3 = Took credit 3 = Relied on family to send money 5 = Remittances from abroad 6 = Sent children away 7 = Other
		8 = Other, specify -
4.	Do members of the household ever borrow food from other households?	1 = Yes 0 = No
5.	Does this household ever lend food to other households?	1 = Yes 0 = No
6.	Do you expect people to return what they borrowed?	1 = Yes 0 = No
7.	Do people in this household use credit to get food?	1 = Yes 0 = No

SECTION 9: Household Food consumption and expenditure

	Food consumption and its monthly expenditure			
		On average, how much […] does your household consume in a month?SPECIFY UNIT	On average, how many times do you purchase […] from the market in a month?	On average, how much do you spend on […] in a month? Birr
	Staple foods			
1.	Maize (dry)			
2.	Maize (green)			
3.	Wheat			
4.	Barley			
5.	Rice			
6.	Sorghum			
7.	Potatoes			
8.	Beans dry			
9.	Beans fresh			
10	Groundnut dry			
11	Sweet potatoes			
	Drinks			
12	Tea (leaves)			
13	Coffee leaves)			
14	Soft drinks			
15	Juices			
16	Local beer			
17	Bottled beer			
18	Wine			
19	Drinking water			
20	Coffee beans			

	Fruits			
21	Oranges			
22	Mangoes			
23	Pawpaws			
24	Pineapple			
25	Bananas (ripe)			
26	Apple			
27	Guava			
28	Sugar cane			
29	Cactus fruit			
30	Cherimoya			
31	Avocado			
	Meat and other animal products			
32	Beef			
33	Goat meat			
34	Sheep meat			
35	Chicken			
36	Eggs			
37	Milk			
38	Cheese			
39	Butter			
40	Yoghurt			
41	Honey			
	Vegetables			
42	Tomatoes			
43	Onions			
44	Cabbage			
45	Cabbage (local)			
46	Spinach			
47	Carrot			
48	Pumpkin			

49	Pepper			
50	Beetroot			
51	Garlic			
	Fats, oils, sweeteners, snacks and others			
52	Cookingoil			
53	Margarine			
54	Bread			
55	Biscuits			
56	Popcorn			
57	Sugar			
58	Salt			
59	Chocolate			
60	Ginger			

SECTION 10: Household economics and employment

1.	What is your – <u>the respondent</u> – main source of income currently?	1 = Farming 2 = Petty trading 3 = Daily wage labor 4 = Remittance 5 = No income 6= Other (Specify)		
2.	On average what is the minimum monthly income level that your household can survive on? _______Birr			
3.	On average what is the minimum monthly expenditure that your household has to make? ______ Birr			
	For each household member, tell me the most important activities they have done in the last 12 months in terms of earning money or goods for themselves or the household and to survive from day to day.			
	Family member	Activity description (START from THE RESPONDENT)	Is this member employed by anyone for this activity? 1 = Yes 0 = No	Monthly average income (Birr)

4.	P1	A1		
5.		A2		
6.	P2	A3		
7.		A4		
8.	P3	A5		
9.		A6		
10.	P4	A7		
11.		A8		
12.	P5	A9		
13.		A10		
14.	P6	A11		
15.		A12		
16.	P7	A13		
17.		A14		
18.	P8	A15		
19.		A16		
20.	P9	A17		
21.		A18		
22.	P10	A19		
23.		A20		
24.	P11	A21		
25.		A22		
26.	P12	A23		
27.		A24		
28.	P13	A25		
29.		A26		

30.	P14	A27		
31.		A28		
32.	P15	A29		
33.		A30		
34.	Taking all the livelihood activities together, which three activities are the most important for the household's economic survival (the general good of the family)?	1 = Most Important ______________________ 2 = Second most important________________ 3 = Third most important _________________		

Thank you so much!!