TECHNOLOGICAL ADOPTION AND ITS IMPACT ON RICE PRODUCTION: CASE STUDIES OF FOGERA WEREDA– SOUTH GONDAR ZONE, AMHARA NATIONAL REGIONAL STATE, ETHIOPIA

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Declaration

I hereby declare that the MSc. thesis entitled "Technological adoption and its Impact on Rice Production (a Case Study of Fogera Woreda –South Gondar Zone, Amhara National Regional State of Ethiopia.)" has been carried out by me under the guidance of Muhdin Muhamedhussen (Assistant professor) and Sisay Tolla (MSc.).

The thesis is original and has not been submitted for the award of any degree, diploma or certificate.

By: Getaye Gizaw Date --------------- Signature ---------------

CERTIFICATE

This is to certify that the thesis entities "Technological adoption and its Impact on Rice Production: A Case Study of Fogera Woreda – South Gondar Zone, Amhara National Regional State of Ethiopia", Submitted to Jimma University for the award of the Degree of Master in Economic policy analysis and is a record of Valuable research work carried out by Mr. Getaye Gizaw, under our guidance and supervision.

Therefore we hereby declare that no part of this thesis has been submitted to any other university or institutions for the award of any degree or diploma.

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ABBREVIATION

ADLI	Agricultural development leads industrialization
ATA	Agricultural transformation agency
ATC	Average total control group
ATE	Average total effect
ATT	Average total treatment group
CIA	Conditional independence assumption
CSAE	Central statistical agency of Ethiopia
EEA	Ethiopian economic association
ESE	Ethiopia seed enterprises
FAO	Food and agricultural office
FOOARD	Fogera office of agriculture and rural development
FWARDO	Fogera wereda agricultural and rural development office
HA	Hectare
KBM	Kernel based matching
KM	Kilometers
MM	Millimeter
MOARD	Minister of agriculture and rural development
NNM	Nearest neighbor matching
PSM	Propensity score matching
RM	Radius based matching

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Abstract

Rice was introduced in Ethiopia in the 1970s and has since been cultivated in different parts of the countries and also has a great potential to contribute to food self-sufficiency and security in Ethiopia. This study was designed to assess the adoption and impact of rice production technology on household rice production in Fogera Woreda using cross sectional data obtained from 191 rice farmers selected from four kebeles to represent major rice producers. The study used binary logistic regression model to identify factors affecting adoption of rice production technology and propensity score matching to assess impact of adoption of rice production technology on household production levels. The results of binary logistic regression indicated that age of household head, family size of household head, participated labor force of household head, level of education of household head, size of cultivated land of household head and extension services significantly affected adoption of rice production technology. The propensity score matching showed adoption of rice production technology has a robust and positive effect on farmers' rice production in quintal per hectare. The average treatment effect on the treated (ATT) was about 9.48 quintal yield per-hectare increase for adopters as compared to non-adopters which indicate that efforts to disseminate existing rice production technology will highly contribute to increase rice production among farm households. The result of sensitivity analysis also shows that the significance level is unaffected even if the gamma values are relaxed in any desirable level even up to 100% percent. This shows that average treatment effect on treated is not sensitive to external change. Complementary agricultural technology adoption best yield results when they are taken up as a complete package together, rather than in the individual elements to give high rice yield.

Keywords: *Adoption of Rice production technology, propensities score matching, average treatment effect on the treated, Sensitivity analysis.*

CHAPTER ONE

INTRODUCTION

1.1 Background of the study

The study of how individuals are able to escape poverty is a central issue of economic development theory. Of the poor people worldwide (those who consume less than a 1 dollar-a-day), 75 per cent work and live in rural areas and projections suggest that over 60 percent will continue to do so up to 2025 (Mendola, 2007). These are good reasons to emphasize research on rural poverty reduction, and to redirect attention and expenditure towards agricultural development.

Food insecurity is a manifestation of poverty confronting many developing countries, especially those found in Sub-Saharan Africa and South Asia. For instance, about one third of the people in SSA are food insecure (Graaff, et al 2011). Agricultural growth is seen as a best-bet strategy for achieving food security because of the fact that agriculture is central to the livelihood of more than half of the world's population. Growth in agricultural production can reduce food insecurity by increasing the amount 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 technology is among the most revolutionary and impactful areas of modern technology, driven by the fundamental need for food and for feeding an ever-growing population. It has opened an era in which powered machinery does the work formerly performed by people and animals (such as oxen and horses). These machines have massively increased farm output and dramatically changed the way people are employed and produce food worldwide. A well-known example of agricultural machinery is the tractor. Currently, mechanized agriculture also involves the use of airplanes and helicopters (FAO, 2010).

The agricultural technology 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 technology could stimulate overall economic growth through inter sectorial linkages while conserving natural resources (Abdulai, et al 2005). Given the close link between food insecurity, farming and environmental degradation the impact of cultivation practices has received significant attention in the last two decades. New cultivation techniques have been introduced in many countries to enhance production in the agriculture sector (Graaff, et al 2011).

Adoption refers to the decision to use a new technology, method, practice, etc. by a firm, farmer or consumer. Adoption of the farm level (individual adoption) reflects the farmer's decisions to incorporate a new technology into the production process. On the other hand, aggregate adoption is the process of spread or diffusion of a new technology within a region or population. Therefore, a distinction exists between adoption at the individual farm level and aggregate adoption, within a targeted region or within a given geographical area (Feder et al., 1985).

Adoption of technological innovations in agriculture has attracted considerable attention among development economists because the majority of the population of less developed countries derives their livelihood from agricultural production and a new technology, which apparently offers opportunities to increase production and production (Feder et al., 1985). Agriculture progresses technologically as farmers adopt innovations. The extent to which farmers adopt available innovations and the speed by which they do so determines the impact of innovations in terms of production growth (Diederen et al., 2003).

Ethiopia is an agrarian country where more than 80% of the total population depends directly or indirectly on agriculture. Agriculture contributes for about half of the GDP (gross domestic product) and for more than 90% of foreign exchange earnings (EEA report, 2011). While agricultural productions are still taking place using traditional methods, efforts have been made by the Ethiopian governments to improve situations through dissemination of improved agricultural technology to farmers. Agriculture is Ethiopia's most important sector, the engine for the country's Agriculture Development

Led Industrialization (ADLI) strategy. The sector is the largest contributor to the overall economy and is fundamental to Ethiopia's overall development. Despite the dominance of traditional smallholder farmers in the sector, a new type of dynamism has begun to emerge. Over the past decade, production and production have consistently grown at near double-digit rates. Increased engagement with mid and large-scale private sector partners has also brought new technology and improved market linkages (ATA, 2014).

Accelerating agricultural growth in Ethiopia has wide-ranging impacts beyond smallholder farmers and rural development. Proactively including women will have significant impact on household nutritional status and increase women's contribution to the country's overall development. Increased agricultural production and commercialization and in particular the increase in related upstream and downstream economic activities that are part of this development can also provide employment opportunities for Ethiopia's youth as well as drive Industrialization and create export growth (ATA, 2014). In spite of its enormous agricultural potential, Ethiopia's history, however, is punctuated by food insecurity and famine due to climatic variability and the poor performance of the agricultural sector. In mindful of these problems, the government of Ethiopia launched policies and strategies that set out agriculture as a primary stimulus to generate increased output, employment, income and agricultural production.

Rice was introduced in Ethiopia in the 1970s and has since been cultivated in different parts of the countries. Rice has a great potential to contribute to food self-sufficiency and security in Ethiopia. In the country, four rice ecosystems are identified and these are upland rice, hydro orphic (rain fed lowland) rice, irrigated lowland rice and paddy rice (with or without irrigation). In Amhara region, rice cultivation was started in Fogera Woreda in 1993. According to Fogera Woreda Agricultural and Rural Development Office (2008), about 256 HHs in the woreda cultivated rice in area of 65 ha and produced 1625 quintals of rice. After five years, in 1999, 16383 HHs cultivated rice in an area of 6775.5 ha and 313921 quintals was produced in Amhara region. This indicates a tremendous increase in the response from the part of farmers to produce rice in Ethiopia. According to Getachew (2000), the discovery of wild rice in Fogera plain led to the initiation of rice cultivation in Amhara Region.

Availability and the use of high yielding and adaptable rice varieties; Introduction and utilization of improved farm mechanization technology; Adoption of various promotion approaches, such as, community based seed multiplication, pre-scaling up of technology, and on- farm demos, rice spacing and transplanting, where the seed rate is reduced and more space between seedlings is given, use of high yield variety of seeds, pesticides and irrigation have been shown to achieve important yield improvements over traditional broadcasting sowing because these technology allow for better weeding, diminish competition between seedlings, and allow for better branching out and nutrient uptake of the plants (Astatke et al., 2002). To gain more approaching in how the adoption of improved and new rice production technology can possibly increase rice production in the study area, the researcher assessed rice production technology adoption and its impact on rice production.

1.2 Statement of the problem

Several adoption research findings have pointed to the fact that the use of new agricultural technology, such as high yielding varieties that kick-started the Green Revolution in Asia, could lead to significant increase in agricultural production in Africa and stimulate the transition from low production subsistence agriculture to a high production agro-industrial economy (World Bank, 2008). This implies that agricultural production growth will not be possible without developing and disseminating cost effective yield-increasing technology, since it is no longer possible to meet the needs of increasing numbers of people by expanding the area under cultivation or relying on irrigation (Datt and Ravallion, 1996; Hossain, 1989).

Bola et al. (2012), used a local average treatment effect (LATE) method to examine the impact of improved agricultural technology adoption on rural farmers‟ welfare in Nigeria; using a cross sectional data of 481 rice producers stated that the decision of small farm households to adopt improved rice varieties were determined by the different socio-economic /demographic and institutional variables such as number of years of residence in the village, access to media, mobile phone, vocational training, livestock ownership, access to improved seed, and income from other crop production significantly increased the probability of adoption. As a result, adopters received more 3.6 quintals of rice additions per hectare.

Mamudu, et al. (2012) made a research entitled adoption of modern agricultural production technology by farm households in Ghana using logit model as a tool over 300 farmers who found that, plot size, expected returns from technology adoption, access to credit, and extension services are the factors that significantly affect technology adoption decisions of small farm households in the west district area of that country. Debela, (2011), agricultural growth can be achieved through better small farm management practices and increased adoption of improved agricultural technology such as chemical fertilizers, improved seed varieties, pesticides, and organic minerals. Among other important variables age of the household head, family size, number of oxen, access to credit, and off-farm activities positively affect the probability of participation in an agricultural extension program. Of which age, education level, and access to credit, affects significantly.

Ibrahim, (2013) on his constraints to agricultural technology adoption in Uganda panel data using probit model, shows that small farm heads with low educational level and small land holdings are less likely to adopt improved seed and fertilizer technology. (Tsegaye et al. , (2012) conducted a study on the „impacts of adoption of improved wheat technology on households‟ food consumption in South eastern Ethiopia‟ using a propensity score matching (PSM) over randomly selected 200 farmers stated that improved wheat seed varieties grew based on a recommended planting space (row) which had a robust and positive impact on small farm household level of food consumption. The average treatment effect on the treated (ATT) revealed that 377.37 to 603.16 calories per day increment came on the adopters of row planting method thereby improving household's income. Variables like age, education, farm experience, off-farm activities, access to credit, extension contact, and livestock holding affected adoption of wheat technology.

Lastly, these reviewed literatures aforementioned have helped for this research to design the potential socioeconomic and demographic factors related to the good quality consideration that support to explain the impact of rice production technology adoption on farm households rice yield. Despite their importance for agricultural policy analysis in general and rice production in particular, all the aforementioned adoption studies however, assessed the impact of technology adoption by simply examining the differences in mean outcomes of adopters and non-adopters or by using simple regression procedures that include the adoption status variables among the set of explanatory variables. Such simple procedures are flawed because they fail to deal appropriately with the self-selection bias and selection on unobservable attached to observational data collected through household surveys, and hence fail to identify the causal effect of adoption.

Despite the significance of rice in the livelihood of many farmers and income generating crop in the study area, it is only recently that few studies have been done on rice. However, most of these studies have focused on marketing and were limited to a specific area and production aspects. Systematic and adequate information on the process of adoption of rice production technology not well identified. Furthermore, its impacts on rice production have not yet been studied. Hence, this study was conducted to assess the determinants of adoption of rice production technology adoption in Fogera Wereda and also provide a consistent estimate of the impact of adoption on rice production and welfare of the farming households using estimation techniques.

1.3 Objectives of the study

1.3.1 General objectives

The general objective of this study was to identify factors that affect rice production technology adoption and to analyze its impact on rice production in study area.

1.3.2 Specific objectives

- To identify the factor that affect rice production technology adoption in the study area.

- To evaluate the impact of adoption of rice production technology on rice production (yield) in the study area.

1.4 Research Questions

- What are the factors that affect adoption of rice production technology in the study area?
- Does the practice of rice production technology adoption have significant impact on rice production?

1.5 Significance of the Study

The information generated by this study is expected to contribute for successful promotion of rice production technology adoption in the study area through improving farmer’s access to improved and new rice production technology. This study is designed to fill the information gap on impact of adoption of rice production technology on rice yield in the study area. It provide information of new agricultural technology effectiveness to our farmers who live in the study area as well as useful insight for those who design various planning and policies that are addressing the ways to improve production and income through targeting adoption of new rice production technology. In addition, the output of the study is believed to serve as a guideline and an input for future empirical studies which will target the impacts of adoption of agricultural production technology on rice and others crop production.

1.6 Scope and limitation of the Study

This study was conducted in Amhara regional state of Ethiopia, south Gondar zone, Fogera wereda which is one of the major rice producing districts in ANRS (Amhara National Regional state). Since it is not possible to cover the whole woredas of south Gondar Zone with the available time and resources, the researcher limits the study size and the scope of the problem to a manageable size. Hence, this study focused on the representative sites in fogera woreda. The study considers farmers who are participating in adoption of rice production technology (like use of irrigation, use of pesticides, row planting of rice, use of fertilizers and uses of high yield variety of rice seed) and who are not participating. Significant qualitative and quantitative information is gathered from agricultural production office like; total number of rice producer households, rice production in quintal per hectare, the different aspects of rice production technology adopted, problems related with the technology involvement and reason not to adopt by non-users of the technology.

1.7 Organization of the thesis

The thesis is organized in five main chapters. The introduction part describing background of the study, the problem statement, objectives, research question, significance of the study, scope and limitation of the study and organization of the thesis are presented in this first chapter. Subsequent to the introduction, relevant literature and conceptual framework of the study are reviewed in chapter two. Definition and description of basic concepts of high value in the study are described. Chapter three deals with description of the study area and discusses the methodology employed for data collection, sampling design and methods of data analysis. Main findings of the study are presented and discussed in chapter four. The first section of the chapter is devoted to describing the actors in rice production technology adoption, their role and linkage mechanisms. The different factors that influence the adoption rice production technology in the study area are presented and discussed in the second section. The last section in this chapter mainly deals with the impact of adoption of rice production technology on rice yield in the study area. Finally, chapter five presents the conclusions and recommendations based on the results of the study.

CHAPTER TWO

2. RELATED LITERATURE REVIEW AND CONCEPTUAL FRAMEWORK

2.1 Theoretical literature review

2.1.1 Rice production in Ethiopia

Rice is the staple food more than 60% of the world's population; it is a staple food for most of eastern Asia. About 50% of all rice grown in the world is produced and consumed in the Asian region. Rice runs a close second to wheat in its importance as a cereal in the human diet. It has high calorie food with protein content less than wheat (ENCU, 2006). Rice was introduced in Ethiopia in the 1970s and has since been cultivated in small pockets of the country. Rice has a great potential to contribute to food self-sufficiency and food security in Ethiopia. In the country, four rice ecosystems are identified and these are: upland rice, hydro orphic (rain fed lowland) rice, irrigated lowland ecosystem, paddy rice (with or without irrigation). Rice production has brought a significant change in the livelihood of farmers and created job opportunities for a number of citizens in different areas of the country. The demand for improved rice technology is increasing from time to time from different stakeholders (MoARD, 2010).

In Ethiopia, rice is among the target commodities that have received due emphasis in promotion of agricultural production, and as such it is considered as the "millennium crop" expected to contribute to ensuring food security in the country. Currently, mainly small-scale farmers grow rice in different parts of the country, but it is also produced by large-scale farms in few places mainly in lowlands of the country.

In spite of the huge potential of the country to produce different rice types, the crop is not under cultivation in many parts of the country. Now a days, rice cultivation is concentrated only in few areas such as Pawe, Gambella, Fogera, Libo Kemkem, Dera, Denbia, Alfetakusa Woreda, Mizan Tefri, Jimma (Gojeb area), Melkaworrer, Arbaminch, North Shewa, South Wollo (Chefa), Dangila-Jewi, Bichena, Quora, Metema and Armachiho (Welelaw, 2005). The estimated area, production and yield by rice producing region in Ethiopia are as follows. From 11.5 thousand hectares, 345 thousand quintals of rice have been estimated from four rice producing regions (Amhara, Oromiya, Tigray and Ethiopian Somale) in 2007/2008. This quantity has also accounted for 0.23 and 1.09 percent of the total area and production respectively, which was under cereal crop. Rice is highly productive crop in Ethiopia next to tef, wheat and maize. Its average production in 2006/2007 was 28.3 quintal per hectare. Amhara region is the leading rice producer in the country. It contributed the largest share in an area coverage (78.5%) and volume of production (85.5%) as well as high yield (19qt/ha). The Amhara region accounted for 0.28% and 0.48% of the total areas allotted and production of cereal produced in the region respectively (Eshetu, 2008).

Table 1: Area under rice during different seasons at national level

Season	Area(ha)
2007/2008	24434
2008/2009	32685
For 2009/2010 plan	100,000

Source: CSA abstract reports 2007

Table 2: production and production of rice at national level

Season	Production(qt)	Yield (qt/ha)
2006/07	1124443	18
2007/08	713160	29
2008/09	944000	29
Plan 2009/10	5000000	50

Source CSA abstract reports, 2006

Rice remains as a minor crop in Ethiopian Agriculture

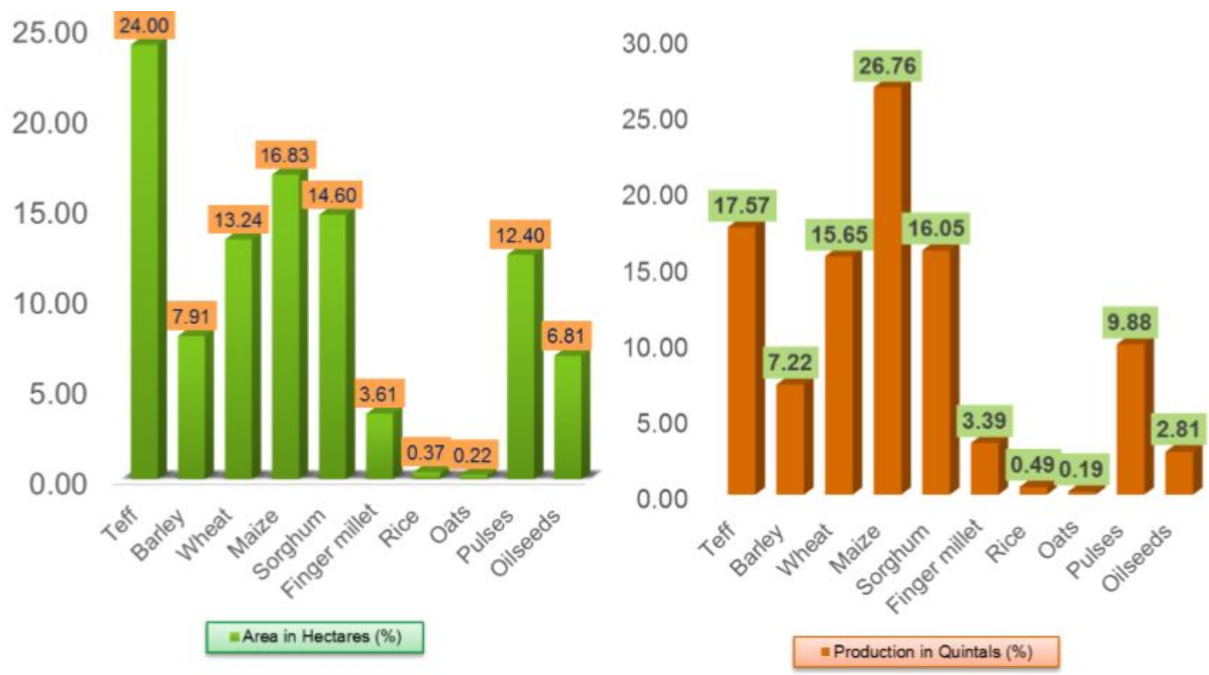


Figure 1: Percentage Distribution of Area and Production under Major Crops (2015/16 Main Season)

Source: Ethiopian institute of agricultural research (2016)

2.1.2 Adoption of new agricultural technology

Adoption is defined as the degree of use of a new technology in long-run equilibrium when a farmer has all the information about the new technology and it's potential. Adoption refers to the decision to use a new technology, method, practice, etc. by a firm, farmer or consumer. Adoption of the farm level (individual adoption) reflects the farmer's decisions to incorporate a new technology into the production process. On the other hand, aggregate adoption is the process of spread or diffusion of a new technology within a region or population. Therefore, a distinction exists between adoption at the individual farm level and aggregate adoption, within a targeted region or within a given geographical area (Feder et al., 1985).

Adoption of technological innovations in agriculture has attracted considerable attention among development economists because the majority of the population of less developed countries derives their livelihood from agricultural production and a new technology, which apparently offers opportunities to increase production and production (Feder et al., 1985). Agriculture progresses technologically as farmers adopt innovations. The extent to which farmers adopt available innovations and the speed by which they do so determines the impact of innovations in terms of production growth (Diederen *et al*., 2003). According to (Sunding el at., 2000), measures of adoption may indicate both the timing and extent of new technology utilization by individuals. Adoption behavior may be depicted by more than one variable. It may be depicted by a discrete choice, whether or not to utilize an innovation, or by a continuous variable that indicates to what extent a divisible innovation is used.
Rogers (1995) describes as follows: technology is a design for instrumental action that reduces the uncertainty in the cause effect relationships involved in achieving a desired outcome. (Enos, et al (1988) defined technology as the general knowledge or information that permits some tasks to be accomplished, some service rendered, or some products manufactured. Rogers (1995) conceptualized that diffusion is the process by which an innovation is communicated through certain channels over time among the members of a social system provided that decisions are not authoritative or collective, each member of the social system faces his or her own innovation decision following a five stage processes. The innovation decision process is the process through which an individual (other decision making unit) passes from first knowledge of an innovation forming an attitude toward the innovation, to a decision of adopt or reject, to implementation of the new idea, and to confirmation of this decision (Rogers, 1995). New technology adoption takes place within the mind of an individual or other decision making unit, however, diffusion occurs among the units in a social system.

2.1.3 Main stages in new technology adoption process

Rogers (1995) stated five main stages in new technology adoption process:

1. Knowledge: A decision making individual becomes aware of an innovation and has some idea of how it works is the main idea of this stage. As decision making persons first exposed to an innovation, however; lack information about the innovation and even have no desire to find extra information about the innovation.

2. Persuasion: This stage takes place when an individual decision unit creates a favorable or unfavorable attitude toward the innovation. Individual decision unit become interested in innovation and actively seeks information regarding to the new technology.

3. Decision: In this stage an individual typically is attracted to seek innovation-evaluation information, which is the reduction in uncertainty about an innovation's expected out comes. Questions like innovation's consequences, advantages and disadvantages be in my situation are usually answered by most individuals from their peers whose subjective opinion of the innovation is most convincing. Though this stage is most difficult to endorse by empirical evidence, individuals focus in activities that lead to a choice either to adopt or reject the innovation in weighing the advantages and disadvantages of adopting the innovation.

4. Implementation: Takes place when persons put an innovation in to use. Injunction to that an individual determines the usefulness of innovation as well. When that adopted new technology give utility to him/her will continue to use the innovation and otherwise.

5. Confirmation: A person evaluates the results of an innovation-decision already made. As a result, individual decision unit decided to use the innovation even up to the fullest capacity.

2.1.4 Types of adopters in new technology adoption process

Rogers (1995) conducted a research on „innovation adoption‟ stated that in the new technology adoption process there are five adopter categories. These are:

1. Innovators (Venture some): This category of adopters is very eager to try new ideas and leads them out of a local circle of peer networks and into more modern social relationships. Generally, the adopters of the innovation category are risk takers, under youngest age brackets, have higher social status, nearest to scientific sources, and interact with other technology innovators.

2. Early adopters (Respectable): Characterized by greatest degree of opinion leadership in most social systems, younger in age, have more financial variability, have higher social status, advanced education, greater social relationships, and greater exposure to different mass- media channels.

3. Early majority (Deliberate): Adopt new ideas before the average number of a social system. Similarly, they interact repeatedly with their peers and sometimes hold leadership positions. The innovation–decision period of early majority adopter is relatively longer as compared to innovator and the early adopter.

4. Late majority (Skeptical): Individual decision unit in late majority category characterized by adopting an innovation after the average member of the society adopts the innovation because these are with high degree of skepticism.

5. Laggards (Traditional): Laggards or individual decision unit who falls behind peers are the last category to adopt an innovation. Furthermore, laggards behave as they do have more isolated in social networks, lowest social status, and lowest financial changeability up to the extent little opinion leadership over the average number of a social system (Rogers, 1995).

2.1.5 Technology development and agricultural transformation

Despite various attempts to transform agriculture by the developing countries, the sector has still remained in its traditional state. The reason behind the low level of agricultural development is introverted policies followed by the governments of these countries over the years. Development strategies of the 1950s and early 1960s gave priority to promote the industrial sector for which agriculture was neglected. The rapid population growth, on the one hand, and the widening gap between the demand for and the supply of food production, on the other, has brought an impetus for agriculture to receive increased attention in the late 1960s (Yonas, 2013)

Therefore in order to reap the benefits that agriculture can provide to the mass of the rural poor in particular and to the national development at large, it is necessary to transform the traditional agriculture into a productive sector (Schultz et al., 2004) or what Mosher (1966) termed as "getting agriculture moving." Agricultural transformation, therefore, requires appropriate public policy intervention (Yotopoulos, 1967); (Halcraw, 1984) so as to generate the surplus produce. Further the formulation of agricultural policy in turn requires a consideration of various interacting factors that include, among others, organization of agriculture, natural factors, institutional arrangements, product characteristics, and factor and product markets (Halcrow, 1984). One of the basic factors in the transformation of agriculture is 'technological change. Hailu, (2008) described that adoption of new technology, on a regular basis, among others, encourage a dynamic growth process that enable the agricultural sector to produce food cheaply, and releasing labor to the non-agricultural sector. Agricultural technology, hence, refers to innovations of new ideas, methods, practices or techniques of production that provide the means of achieving sustained increase in farm production (Abate et al., 1989).

Anderson et al., (2013) pointed out that adoption of a new technology not previously used in the production process implies technological change, adoption being defined as the act of incorporating something into the production process. It is important to note that the generation of new technology is not suffice by itself but the degree of its diffusion does so. In this regard, Anderson stated that the adoption of technology must be preceded by technology diffusion where the latter term implies the act of making technology available to potential adopters and is then a link between R&D and adoption. Moser et al., (2006) emphasized that new technology adoption and diffusion alone is not enough to get agriculture moving and thus changes in the institutional, infrastructural, and cultural factors must occur in the process of transformation. Similarly Nerlove, (1993) noted the following: Technology, it seems that plays a crucial in agricultural modernization, but the process cannot be understood solely in terms of technology. The interactions of technology with a number of social and economic factors have to be taken into account.

The need for technology adoption in agriculture, in addition increasing factors' efficiency, is to cope with natural hazards faced by the sector. Experiences of many countries showed that sizable proportion of agricultural technology is commodity specific (improved seeds and animal breeds) that are suited only for limited and usually most favorable ecological environments (Anderson et al., 2013). Therefore, areas with poor environments may not have a chance of adopting due to their poor response to the technology in question. Agricultural technology includes not only biological and chemical types but also mechanical and management technology. It is within this given framework that agricultural technology should have to be perceived. These technology can help increasing efficiency in a number of ways.

According to Anderson et al. (2013), described that agricultural technology increase efficiency through increasing production for a given country of one or more resources, or a reduction in the use of resources with constant production, and efficient utilization of other agricultural resources used in the production process. It can be deduced that technological change in agriculture, its diffusion and adoption can substantially induce growth to agricultural production. Agricultural research and extension are the basis for such a process to advance further.

2.1.6 Adoption and Impact of Improved Agricultural Technology

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

Adoption is a mental process through which an individual passes from hearing about an innovation to its adoption that follows awareness, interest, evaluation, trial, and adoption stages (Bahadur, et al 2004). It can be considered 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.

Several studies in Africa show that adoptions of improved agricultural technology, though variably and incompletely, had positive impacts on income, food security and poverty reduction (Wanyama, et al 2010). Using the number of months that grains stay in store as a proxy to food security, Wanyama et al (2005) showed that soil management technology had a positive impact on the food security of the farming community within the soil management project area and its neighborhood in Kenya.

Setotaw, et al (2003) found that adoption of improved agricultural technology (improved varieties and agronomic practices) have positively and significantly affected household's food security in Ethiopia. Solomon, et al (2010) examined the impacts of adoption of chickpea varieties on the level of commercialization of smallholder farmers in Ethiopia. They found that adoption of improved chickpea varieties has a positive and robust effect on marketed surplus which reduces food insecurity in adopter households. A study by Adekambi et al, (2009) on the impact of agricultural technology adoption on poverty in Benin indicates the increase in production of rice farmers, following the adoption of NERICA (new rice in Africa) varieties. These results suggest that the promotion of NERICA cultivation can contribute to improving expenditure/income of farmers and consequently to poverty reduction. Studies conducted in Asia also reveal similar results. Using a propensity score matching method, Mendola (2007) examined the impacts of agricultural technology adoption on poverty reduction in rural Bangladesh. Findings show a robust and positive impact of agricultural technology adoption on farm households' well-being. Similarly, (Wu, et al 2010) conducted an impact study rural China and found that adoption of agricultural technology had a positive impact on farmers' well-being thereby improving household income.

2.1.7 Rice Production Practices

Rice variety: Many efforts are put in place to make sure farmers are using the recommended varieties which are economically viable. Such verities are like TXD 306 and NERICA (New Rice for Africa). NERICA is an upland rice variety which is result of the Asiatic type of rice, Oryza sativa and the African rice O. glaberrima. As reported by Mghase, et al. (2010), NERICA combines the high yield potential, responsiveness to improved and short structure for lodging resistance from sativa and the resistance to diseases, and drought resistance has potential for high yield, matures early 30-50 days earlier than the other upland varieties and is resistant to common environmental stresses of upland rice such as low moisture stress.

Fertilizers: Fertilizer is very important input for intensive rice production. Common fertilizers used particularly in rice fields range from organic to inorganic. The organic fertilizers are farm yard manure and compost which are found locally and not very widely used. Inorganic fertilizers such as Urea, Triple Super Phosphate (TSP), Di-Ammonium Phosphate (DAP), Sulphate of Ammonium (SA) and Calcium Ammonium Nitrate (CAN) are widely recommended.

Spacing: To avoid nutrient competition sufficient spacing between plants and rows is vital to get maximum yield in given plot of land. Appropriate spacing enables the farmer to keep appropriate plant population in his field. Hence, a farmer can avoid over and less population in a given plot of land which has negative effect on yield (Baloch, et al. 2002).

Weed control: Weeds are the most important biological barriers in rice production in a way that a noticeable part of the Production costs are allocated to them and are among the most important inhibiting factors with regards to increasing rice production (Mudge, 2004).

Weeds also serve as alternative hosts for many plant diseases and animal pests that attack crops; they also harbor various bacterial and fungal diseases (Akobundu, 1980). Losses caused by weeds exceed the losses from any category of agricultural pests.

2.2 Empirical literature review

Mendola (2006) used the Propensity Score Matching (PSM) methods to assess the impact of agricultural technology adoption on poverty in Bangladesh and observes that the adoption of high yielding improved varieties has a positive effect on household wellbeing in Bangladesh. In the same vein, Kijima, et al., (2008) conducted a study on the impact of New Rice for Africa (NERICA) in Uganda and found that NERICA adoption reduces poverty without deteriorating the income distribution. Diagne, et al., (2009) also assess the impact of NERICA adoption on rice yield in Cote d'Ivoire. The results show a positive and significant increase in yield particularly on the female farmers. More recently, Dontsop-Nguezet, et al. (20110 also examine the impact of NERICA adoption on farmers welfare in Nigeria. The result of the study shows that adoption of NERICA varieties has a positive and significant impact on farm household income and welfare measured by the per capita expenditure and poverty reduction in rural Nigeria.

Wolelaw (2005) identifies the main determinants of rice supply at farm level. The study uses Cobb Douglas production function model to estimate the limiting factors. The result that identified were, the current price, one year lagged price, actual consumption in the household, total production of rice in the farm, distant to the market and weather variables were significant to influence the supply of rice. A similar study on production part, Moses et al., (2007), examined the factors determining rain fed rice production in Adamawa state (Nigeria). Production function analysis was used to analyze the factors. The result shows that two of the variables used (farm size and seed) were significantly affect the production. Also resource production analysis revealed that seed was over utilized, while land and herbicide were underutilized. Decreasing the quantity of seed use and increasing the size of land and quantity of herbicide respectively could increase efficiency.

Christiaensen et al., (2011) also discovered that despite a good history of development of varieties of millet, sorghum, maize, rice and cowpea, most Malian farmers still retained their own seed or exchanged with nearby farmers; few used improved high yield varieties. Longley et al., (2002) discovered that studies of seed security in most disaster situations increasingly indicated that good quality seed was locally available in many emergencies and that often the problem was that some farmers lacked access to quality seed (Diederen et al., 2003)

Kiptot et al., (2004) on their studies of sharing seed and knowledge; farmer to farmer dissemination of agro forestry technology in western Kenya, the results confirmed that informal social networks such as relatives, friends and groups are important avenues for spreading new technology. This implies that family linkages indicate a potential for sharing within and between villages and thereby expanding a network of seed and knowledge sharing. Furthermore, as noted by seck (2008) one of the biggest constraints to the successive adoption of improved varieties is the availabilities of seed. Meanwhile, access to seed is a necessary condition for improved seed adoption (Dontsop-Nguezet, 2011) and the adoption of improved seed is an important component of agricultural production, food security and sustainable economic growth (Faltermeier, 2007)

Asfaw et *al.*, (2010) in Bako area, reported that participation of farmers in extension activities (which is represented by farmers attendance at the field days) is the only variable which is found to significantly influence the acceptance of improved maize variety. The same study showed that the acceptance of fertilizer technology in maize production is influenced positively and significantly by the farmers' use of credit and by the level of formal education of farm household.

According to Alemu *et al. (*1998), many variables can influence farmers' awareness and adoption of new varieties: human capital variables such as literacy; farm size; information sources such as agricultural extension or the research station; and distance from seed sources. Farmers with more land had a higher probability of adoption, probably because they are wealthier and have more land to experiment with improved wheat varieties. Extension visits also resulted in a higher probability of adoption by raising farmers' awareness of new wheat varieties and providing information about agricultural practices to accompany them. Oxen ownership increased the probability that farmers would adopt improved wheat varieties. Oxen owners usually participate more frequently in a demonstration, which gives them access to information on new technology. Distance is a major obstacle for adoption of technology in developing countries. The impediment posed by distance is likely to decline with the spread of wireless communication technology.

It is a greater challenge to adopt technology across different latitudes and varying ecological conditions (Sunding *et al*., 2000). Farmers with some education attainment are likely to adopting one or more of the technology choices: the marginal effect of the education variable is significantly positive for the probability of adoption. More educated households are commonly well informed and receptive, which translates to a higher likelihood of engaging in new technology. This finding is in line with several previous studies which point out innovation is positively related to farmers' abilities to decipher and analyze information (Ersado et al., 2003).

A study conducted by (Degnet Abebaw and Kassa B., 2001) on factors influencing the adoption of high yielding maize varieties in Southwestern Ethiopia underlined those factors such as age of farmers, frequency of contact with extension workers, annual on farm income level and farmers knowledge of fertilizer use and its application rates significantly affected farmers decision to produce these varieties.

2.3 Conceptual framework

The conceptual framework of the study (Figure 2) is formulated following review of related literatures reviewed in chapter two and based on the hypothesis that adoption of rice production technology is influenced by personal, psychological, institutional and economic factors. Therefore, this study will try to identify the influence of independent variables on the dependent variable.

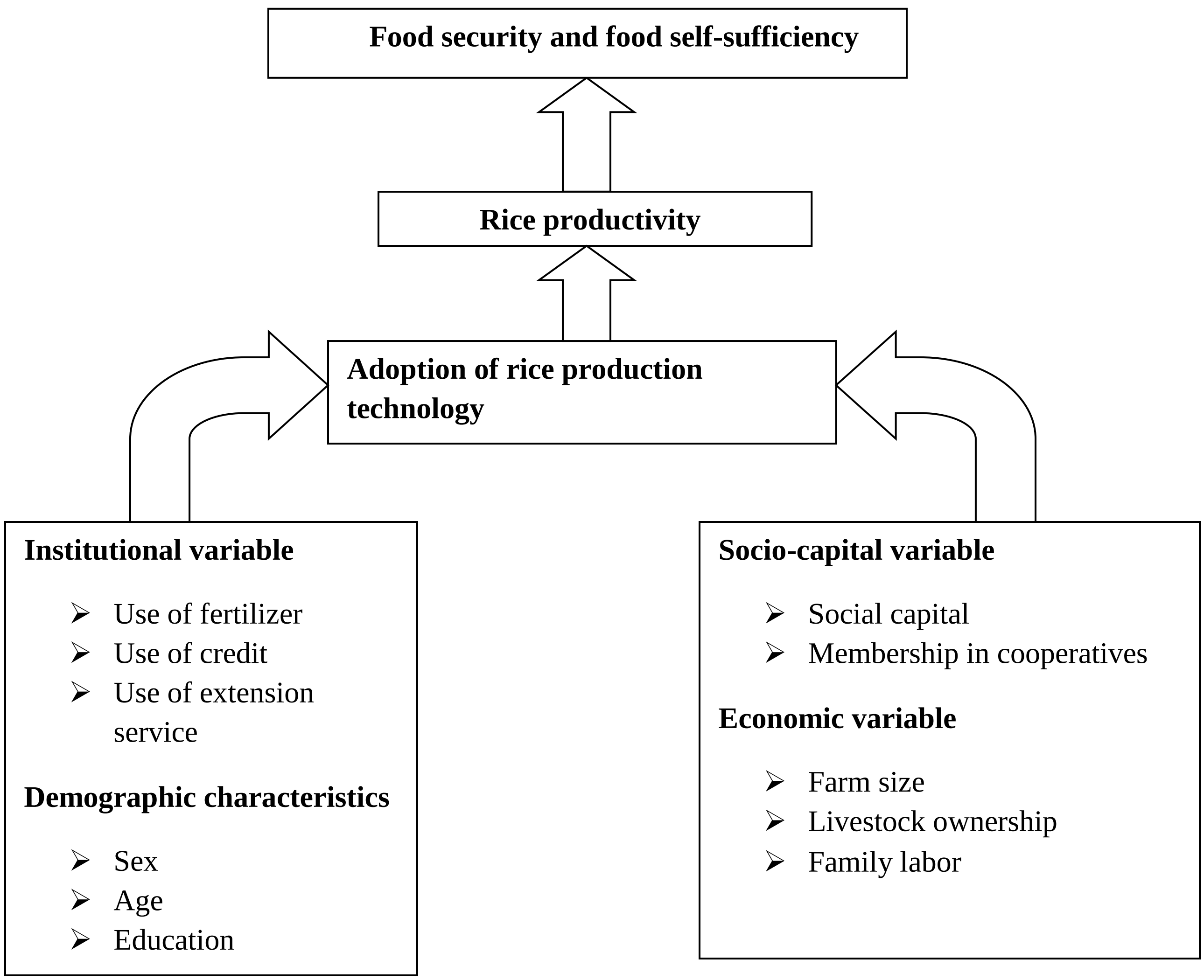


Figure 2: conceptual framework of the study

Source: own computation (2017)

CHAPTER THREE

3. RESEARCH METHODOLOGY

3.1 Description of the study area

Fogera wereda is one of the 106 wereda of Amhara national regional state and found in South Gondar zone. It is situated at $11^{0}58$ latitudes and $37^{0}41$ longitudes. The district is bordered on the south by Dera, on the west by Lake Tana, on the north by the Rib River which separates it from Kemkem, on the north east by Ebinat, and on the east by Farta. Wereta is the capital of the wereda and is found 625 km from Addis Ababa and 55 km from the Regional capital Bahir Dar. Wereta and Alem ber are two major towns in the wereda. The wereda is divided in to 25 rural peasant associations and 5 urban kebeles (FOOARD, 2009).

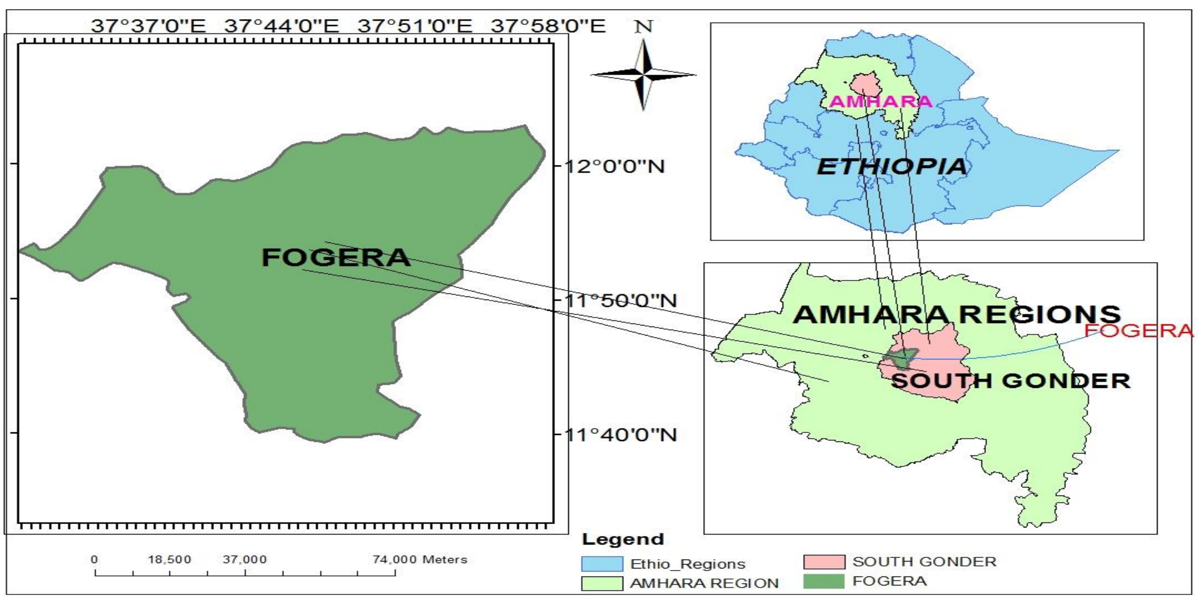


Figure 3: map of the study area

Source: own computation (2017)

The total land area of the wereda is 117.405ha. Flat land accounts for 76%, mountain and hill accounts 11% and valley bottom 13%. Average land holding is about 1.4 hectare with a minimum and maximum hectare of 0.5 and 3.0 hectares respectively. The dominant soil type in the Fogera plain is black clay soil (ferric vertisols), while the med and high altitude areas are orthic luvisols. The total human population of the wereda is 233,529.the rural population is estimated at 206,717 (CSA, 2007). The population has held steady in a split of about 51% of male and 49% of female. The number of agricultural household is 42,746. The mean annual rainfall is 1216.8 mm and ranges from 1106 to 1336 mm. Belg and Meher are two cropping seasons, with short and long rainy periods respectively. Farmers depend on Meher season rain for crop production.

Rivers in fogera wereda include the Gumara and Rib, both of which drain in to Lake Tana. A survey of land in fogera wereda shows that 44.2% is arable or cultivated and another 20% is irrigated, 22.9% is used for pasture, 1.8% has forests or shurblands, 3.7% is covered with waters and the remaining 7.4% is considered as degraded and other some 490 square kilometers of land adjacent to Lake Tana is subject to regular and severe flooding. The flooded plain is the major rice production areas. In addition, two Rivers are of great economic importance to the wereda because they are used for irrigating vegetables during the dry season. Both rivers cross many of the kebeles before entering in to Lake Tana (FWARDO, 2008).

Tef, corn, sorghum, cotton and sesame are important cash crop and rice is also the most important cereal crop of the wereda. Fogera is also known for its cattle breeding, which has a large frame and one of the best native milk cows in Ethiopia. In fogera wereda there are 16 cooperatives, 9 of which are multipurpose, 4 irrigation and 3 financial cooperatives. The multipurpose cooperatives provide milling services, sell basic household goods, and distribute agricultural input in collaboration with the agricultural input supply corporations and the Ambasel and Merkeb union cooperatives. Also located in this wereda is the community of Awra Amba, an Ethiopian grass-roots experiment in egalitarian living (FWARDO, 2008).

3.2 Research method and data sources

3.2.1 Data source and data collection techniques

The data for this study was collected from both primary and secondary sources. The primary data was collected from samples of respondents through questionnaires, interviews and observations. The data that are collected through a questionnaire survey includes; data on adoption of rice production technology, quantity of input used, labor force participation, livestock ownership, land holding, contact to extension service, credit access and family size. The primary data also include household demographic and socioeconomic characteristics.

In addition to primary data on the above issue, secondary data like; population number, agricultural input and output, land use pattern and agro ecology was collected from different sources. Secondary data was collected from wereda office of agriculture rural development, research center, cooperatives at different levels, Ethiopian seed enterprise (ESE) and other bureaus, different publications, research studies and websites.

3.2.2 Sampling method and sample size determination

For this study a multi-stage sampling technique was employed. In fogera wereda there are 5 urban and 29 rural kebeles. Out of 29 rural kebeles with a population size 44,168 only 15 kebeles with a population size of 12,165 cultivate both upland and low land rice's. In the first stage: four kebeles (shaga, kidist hana, kokit and wegetera) are selected purposively in order to get adequate information about the impact of technological adoption on rice production. This selection is based on agro-ecological zone. That is kokit and kidist hana kebele are dega and shaga and wegetera kebele are woina dega. The total number of households in the four selected kebele is 3244. That is shaga kebele has a total of 837 households, kidist hana kebele has a total of 829 households, kokit kebele has a total of 793 households and wegetera kebele has a total of785 households.

A simplified formula for proportion of total sample size selection:

Yeman T. (1967) Provide a simplified formula to calculate sample sizes. This formula was used to calculate sample size at 95% confidence level that is 0.05 degree of variability and e=0.07 level of precision.

$$n = \frac{N}{1+e2\ (N)}$$

Where n is sample size,

N is the population size.

N = the total number of households in the selected kebeles (3244hhs)

e = acceptable error margin (0.07)

Then the total sample size can be calculated by using the above formulas.

$$n = \frac{\mathrm{N}}{1+\mathrm{e}2\ (\mathrm{N})}$$

$$n = \frac{3244}{1+0.07*0.07\ (3244)}$$

$$n = \frac{3244}{17}$$

$$n = 191$$

Therefore in this study the number of sample households is 191.

In the second stage: after determining the total number of sample respondents in the study area, the next was to proportionally divide the sample to representative kebeles and then determining sample respondents in each of the four selected kebeles by using simple random sampling techniques. Then sample of respondents that cultivate rice and adopt modern rice production technology was selected randomly proportional to their population size. The formula is as follow;

$$ni = \frac{Ni}{N * n}$$

Where, ni = sample size of i^{th} kebele,

Ni = total household of i^{th} kebele, and

N = total number of household in the selected kebele and

n = total sample size.

For shaga kebele, $\frac{837}{3244} * 191 = 49$

For kidist hana kebele, $\frac{829}{3244} * 191 = 49$

For kokit kebele, $\frac{793}{3244} * 191 = 47$

For wegetera kebele, $\frac{785}{3244} * 191 = 46$

Therefore, the total respondent of the four kebele is the sum of the above sample that is 49+49+47+46=191.

In the third stage: The required sample size is 191 and to select adopters and non-adopters from each stratum groups, the study used proportionate selecting producers and selected 100 non adopter of rice production technology and 91 adopters of rice production technology. How it would be selected in proportionally farm household sample size from each stratum group stated in the table below as follows:-

Table 3: Stratified and proportionately selected sample

Kebeles	Farmer's type	Total number of HH	Sample household (ni)
Shaga	Adopter	399	24
	Non adopter	438	25
	Total	837	49
Kidist hana	Adopter	395	23
	Non adopter	434	26
	Total	829	49
Kokit	Adopter	378	22
	Non adopter	415	25
	Total	793	47
Wegetera	Adopter	374	22
	Non adopter	411	24
	Total	785	46
Total		3244	191

Source: kebeles administrative office and own computation (2017)

3.2.3 Method of data presentation and analysis

The data for this study is presented by using tables, graphs and figures. The study employed both descriptive and econometric data analysis techniques. The descriptive analysis was applied to discuss the situation of technological adoption on rice production in the study area by using mean, frequencies, percentages and maximum and minimum values while the econometric analysis was applied to identify variables that affect rice production and to analyze the impact of technology adoption on rice production. The study used MS-Excel, SPSS, and STATA latest software for data analysis purpose.

3.3 Model specification

3.3.1 Binary logistic regression model

Binary logistic regression was incorporated to analyze relationships between a dichotomous dependent variable and independent variables. Logistic regression combines the independent variables to estimate the probability that a particular event will occur that is a subject will be a member of one of the groups defined by the dichotomous dependent variable. The logistic regression was fitted using method of rice production technology adoption as dependent variable and the listed demographic and socioeconomic variables as explanatory variables which is assumed to determine practice of adoption of rice production technology and the outcome variable, rice production. The response variable is binary, taking values of one if the farmer adopts and zero otherwise. However, the independent variables are categorical, continuous and dummy.

The justification for using logit is its simplicity of calculation and that its probability lies between 0 and 1. Moreover, its probability approaches zero at a slower rate as the value of explanatory variable gets smaller and smaller, and the probability approaches 1 at a slower and slower rate as the value of the explanatory variable gets larger and larger (Gujarati, 2003). The function form of model is specified as follows:-

$$P = E(Y=1/Xi) = \frac{1}{1+e^{-(Bo+BiXi)}} \quad (1)$$

This will be writing as follows, z_i is equal to Bo + Bi Xi

$$Pi = \frac{1}{1+e^{-zi}} \quad (2)$$

$$1-Pi = \frac{1}{1+e^{zi}} \quad (3)$$

The probability that a given household is rice production technology adopter is expressed in equation (2), while the probability for non-adopters of rice production technology is expressed in equation (3).

Therefore, we can write as

$$\frac{Pi}{1-Pi} = \frac{1/1+e^{-zi}}{1/1+e^{zi}} = \frac{1+e^{zi}}{1+e^{-zi}} = e^{zi} \ldots\ldots\ldots\ldots \quad (4)$$

The ratio of probability that household is rice production technology adopter to the probability of that it is non-adopters of rice production technology.

$$Li = \ln \frac{Pi}{(1-Pi)} = z_i = B_o + B_1X_1 + B_2X_2 + \ldots\ldots\ldots + B_nX_n \ldots\ldots\ldots\ldots \quad (5)$$

Where, Zi= function of explanatory variables (X).

Bo= an intercept, B1, B2, B3…… Bn are slope of the equation in model

Li = log of the odds ratio = Zi

Xi= vector of relevant characteristic or independent variables.

3.3.2 Propensity score matching (PSM)

In this study, PSM was used to construct a group for comparisons based on probability model of adoption of rice cultivation technology. Members who adopted the technology are matched to non-adopters on the basis of the probability [or propensity scores, (PS)]. After matching the individuals with similar characteristics in both the adopter (treatment) and non-adopter (control) groups, the real effect of rice production technology adoption can then be calculated as the mean difference in rice output per hectare between the adopters and non-adopters. In addition to assessing the effect of adoption on rice output, the method of PSM allows us to examine the probability of a farmer adopting a technology.

By adjusting covariates between the treated and control groups, the PSM allows to construct counterfactuals using observational data. Second, miss-specified econometric models using observational data sometimes produce biased estimators. One source of such bias is that the two samples lack distribution overlap, and regression analysis cannot tell researchers the distribution overlap between two samples. Third, linear or logistic models have been used to adjust for confounding covariates, but such models rely on assumptions regarding functional form.

The basis of the PSM is that it helps in comparing the observed output of technology adopters to the output of counterfactual non-adopters based on the predicted propensity of adopting at least one technology (Rosenbaum and Rubin, 1983; Heckman *et al.,* 1998; Smith and Todd, 2005; Wooldridge, 2005). After estimating the propensity scores using the logit or probit model, the next task is to estimate an average treatment effect (ATE) of adoption on rice output. The ATE is estimated as the mean difference in rice output between adopters, denoted by Y (1) and matched control group, denoted by Y (0). Symbolically, equation (1) represents the model for estimation of the ATE.

$$ATE = E[Y\ (1)\ Y\ (0)] = E[Y\ (1)]\ E[Y\ (0)] \ldots\ldots\ldots\ldots\ldots \ (1)$$

Where, ATE = average total effect

E[Y (1) = Average outcomes for individual, with treatment, if he/she would adopters (Di=1)

E[Y (0) = Average outcome of untreated, when he/she would non adopters, or absence of treatment (Di=0)

The ATE model compares the rice output of farmers who adopted rice production technology with that of non-adopters or control for farmers that are similar in terms of observable characteristics and also partially control for non-random selection of participants in the rice production technology adoption program. The ATE as calculated in equation (1) could be interpreted as the effect of the rice production technology adoption on rice output. Apart from the ATE, an average treatment effect on the treated (ATT or ATET) is also estimated. The ATT model measures the effect of adoption on output for only farmers who actually adopted the rice production technology rather than across all rice farmers who could potentially adopt this technology. ATT is calculated using the expression in equation (2) as follows:

$$ATT = E\,[Y\,(1)\ Y\,(0)\ D = 1] = E[Y\,(1)\ D = 1]\ E[Y\,(0)\ D = 1] \ldots\ldots\ldots\ldots\ldots\ldots.. (2)$$

Where D is a dummy or indicator for treatment (D = 1 for adopters, 0 for non-adopters). Again, one could also estimate the average treatment effect on the untreated or control groups (ATC), which measures what the effect of adoption on output would be for farmers who did not adopt the rice production technology at all. The model for measuring such a parameter is expressed by equation (3) below.

$$ATC = E[Y\,(1)\ Y\,(0)\ D{=}0] = E[Y\,(1)\ D{=}0]\ E[Y\,(0)\ D{=}\ 0] \ldots\ldots\ldots\ldots\ldots\ldots (3)$$

According to Rosenbaum and Rubin (1983), the effectiveness of matching estimators as a feasible estimator for impact evaluation depends on two fundamental assumptions, namely:

Assumption 1: Conditional Independence Assumption (CIA):

It states that treatment assignment (Di) conditional on attributes, X is independent of the post program outcome [Y (1), Y (0)]. In formal notation, this assumption corresponds to:

$$[Y\,(1) - Y\,(0)] \perp [D \mid Xi] \ldots\ldots\ldots\ldots\ldots.. (4)$$

This assumption imposes a restriction that choosing to participate in a program is purely random for similar individuals. As a consequence, this assumption excludes the familiar dependence between outcomes and participation that lead to a self-selection problem (Heckman et al, 1998).

The conditional average effect of treatment on the treated has a problem, if the number of the set of conditioning variables (X's) is high, and thus the degree of complexity for finding identical households both from program users and non- users becomes difficult. To reduce the dimensionality problem in computing the conditional expectation, Rosenbaum and Rubin (1983) showed that instead of matching on the base of X's one can equivalently match treated and control units on the basis of the "propensity score" defined as the conditional probability of receiving the treatment given the values of X's, notational expressed as P (Xi) = Pr (Di=1|Xi)

Where Pr is the probability or the logistic cumulative distribution, Di = 1 if the subject was treated, Xi is a vector of pre- treatment characteristics. In estimating the propensity scores, all variables that simultaneously affect participation in the program and outcome variables were included. Thus, the average treatment effect on the treated conditional on propensity scores P(X).

Assumption 2: Assumption of common support:

$0 < P(X) < 1$ …………………………………………………………………………………….. *(5)*

The assumption is that P(x) lies between 0 and 1. This restriction implies that the test of the balancing property is performed only on the observations whose propensity score belongs to the common support region of the propensity score of treated and control groups (Becker et al., 2002). Individuals that fall outside the common support region were excluded in the treatment effect estimation. This is an important condition to guarantee improving the quality of the matching used to estimate the ATT. Moreover, implementing the common support condition ensures that a person with the same X values (explanatory variables) have a positive probability of being both participant and non-participants (Heckman et al, 1999). This implies that a match may not be found for every individual sample. Rosenbaum and Rubin (1983) describe assumption one and two together as strong ignore ability assumption. According to (Caliendo et al., 2008), there are steps in implementing PSM. These are estimation of the propensity scores, choosing a matching algorithm, checking the common support condition, and testing the matching quality.

3.3.3 Choosing a Matching Algorithm

The four commonly used matching algorithms, namely nearest neighbor matching, radius matching, caliper matching and kernel-based matching, has been employed to assess the impact of rice production technology on farmers' rice production. The nearest neighbor matching (NNM) method matches each farmer from the adopter group with the farmer from the non-adopter group having the closest propensity score. The matching can be done with or without replacement of observations.

NNM faces the risk of bad matches if the closest neighbor is far away. This risk can be reduced by using a radius matching (RM) method, which imposes a maximum tolerance on the difference in propensity scores. However, some treated units may not be matched if the dimension of the neighborhood (i.e. the radius) is too small to contain control units. The caliper matching method used to estimate the effect of an exposure in which subjects are selected for matching and the maximum permitted difference between matched subjects. The kernel-based matching (KM) method uses a weighted average of all farmers in the adopter group to construct a counterfactual. The major advantage of the KBM method is that it produces ATT estimates with lower variance since it utilizes greater information; its limitation is that some of the observations used may be poor.

3.4 Definitions of variable

3.4.1 Dependent variable

Impact analysis refers to the analysis of the distributional change of adoption of new technology on the well-being or welfare or income of the beneficiary (World Bank, 2008). Adoption of new technology aims at impacts or changes that are intermediate to livelihood outcomes and that relate more to the income of the user to the policies and structure in the sustainable livelihood framework (Asres, 2003). The dependent variable for the binary logit model is adoption of rice production technology. This variable is a dummy variable (given a value of 1 if the household is adopter and 0 if the household is non-adopter) and for the PSM (propensity score matching) model household rice crops production is a continuous variable measured in quintal per hectare and used rice production in order to whether the same impact on production is there or not.

3.4.2 Independent variable

The explanatory variables in this study are those variables, which are consideration to have influence on adoption of rice production technology and hence, on rice production. These included household personal and demographic variables, socioeconomic variables, household socio-capital variables and institution variables. These explanatory variables are listed as follows:-

1. Age of households head (AGHH): it is measured in terms of year and in most rural area of

Ethiopia household head is responsible member of a household to contribute labor for farm production. In this study age of the household head is used as indicator of experience of household head who started farming. It is categorical variable and expected to be affecting negatively because when age of farmers approach to old, able to adopt of new rice technology will be weak.

2. Sex of households head (SEXHH): it hypothesized that male-headed households are in a better position to pull labor force than the female headed ones. Christina et al., (2011) stated that women farmers may need a long adjustment period to diversify their income sources fully and to participate in institutions. This variable is entered the model as dummy variable (takes a value of 1 if the household head is male and 0 otherwise) and expected to have a positive relationship with adoption of rice production technology and rice crop production.

3. Family size of household head (FSHH): it refers to the number of family members in household which is measured in number. The existence of a large household size positively influences adoption of technology (Mulugeta, 2002), cited in Yonas (2013). It is a continuous variable.

4. Education level of households (EDUHH): it is categorical which helps household to increase production, through promoting awareness on the possible advantages of modernizing agriculture and improve way and adoption technological inputs. Hence, this variable is categorical and expected to have a positive relationship with adoption of rice production technology and rice crop production.

5. Size of cultivated land (SICL): this variable is continuous that stands for the total amount of cultivated land area of rice crop which is measured in hectare. (Ayele, 2013) identified that size of cultivated land has positive impact on household row planting of wheat crop production that farmers who have larger cultivated land are more likely to be row planter than those with smaller area and to participate in row planting because to reduce risk of row planting. So that it is hypothesized that positive relationship is expected between land and adoption of rice production technology.

6. Livestock ownership (LIVOW): This refers to the total number of animals possessed by the household measured in tropical livestock unit (TLU). Livestock is considered as another capital. Moreover, livestock used for plowing, threshing, transporting and etc. hence increase production thereby household income. Therefore, this variable will be hypothesized to have a positive impact on adoption of rice production technology and rice production.

7. Use of credit services USECRIDS): the variable is entered the model as a dummy variable (it takes a value 1 if the household use credit service and 0 otherwise). It is hypothesized that accesses to credit and adopting of rice production technology and household production will have positive relationship.

8. Labor force participation (PARLFOR): labor force is the number of workers in an economy. The farm labor force participation and adopting of rice production technology will have positive relationship because; it is a primary factor of rice production. The variable would be entered the model as a continuous variable that stands for the number of labor force participated in adoption of rice production technology.

9. Extension services (EXTEN): a dummy variable for extension contact: 1 if the household is contacted by an extension worker in the last years; 0 otherwise. Farmers having extension contact knows the source and possible benefit of adoption rice crop production technology and hence expected to be better adopters of technology. Therefore, it will be affect adoption of technology positively.

10. Attending training at FTC (ATFTC): this is also a dummy variable that can make the decision equation better off. Attend training households to the FTC is expected to determine both the household's participation in technology adoption and improving household rice crop production. This variable is dummy variable 1 if the households attend training at FTC and 0 otherwise. It is expected to be positive impact on adoption of rice production technology.

Table 4: variable definition

Code	Definition	Scale measurement	Type	Expected sign
ARPT(dependent variable)	A household head who has adopted rice production technology last year	Adopter=1 Non adopter=0	Dummy	
AGHH	Age of household head	In year	Categorical	-
SEXHH	Sex of household head	Male=1 female=0	Dummy	+
FSHH	Family size of households	In number	Continuous	+
EDUHH	Education level of households	In years of schooling (Illiteracy=1primary=2 secondary=3)	Categorical	+

SICL	Size of cultivated land	In hectare	Continuous	+
LIVOW	Livestock ownership	TLU	Continuous	+
USECRIDS	Use of credit services	Yes=1 no=0	Dummy	+
PARTLFOR	Participation of farm labor force	In number	Continuous	+
EXTEN	Extension services	Yes=1 no=0	Dummy	+
ATFTC	Attending training at farmer training center	Yes=1 no=0	Dummy	+

Source: Own computation (2017)

CHAPTER FOUR

4. RESULT AND DISCUSSION

4.1 Socio-economic background of the respondents

4.1.1 Age of household head

It is the number of years that the head of the household has completed at the time of the survey. The average age of the sample household head was found to be 42.57 years for both adopter and non-adopter where the minimum is 18 and the maximum is 66 (table 5). As the table below reveals that from the total of 91 adopters of rice production technology 20 (10.47%) of households were found between the age of 18-32 and 41(21.47%) of households were found between the age of 33-49 and the remaining 30(15.71%) of households were found between the age of 50-66. And also the table below reveals that from the total of 100 non-adopters of rice production technology 15 (7.85%) of households were found between the age of 18-32 and 61(31.94%) of households were found between the age of 33-49 and the remaining 24(12.57%) of households were found between the age of 50-66. Older farmers may have more experience, resources, or authority that can allow them more possibilities for trying recommended production practices (CIMMYT, 1993). Age of the adopter and non-adopter exhibits as there exists a relationship with the probability of adoption of the rice production technology and therefore, age of the household head is considered as a proxy for experience.

Table 5: ages of sample household head

Age	Adopter		Non adopter	
	Frequency	%	Frequency	%
18-32	20	10.47	15	7.85
33-49	41	21.47	61	31.94

50-66	30	15.71	24	12.57
Total	91	47.65	100	52.35

Pearson chi2 (2) = 4.8893   Pr = 0.087,

Source: Own survey based on data (2017)

4.1.2 Sex of household head

These demographic characteristics of the farmers by rice production adoption technology status were presented in (table 6). Based on the result, about 30.89% of the sample households were headed by females and the remaining 69.11% were headed by males. Besides, out of the 47.64% adopter household heads, 13.09% were female headed unlike to 34.55% male headed households. The corresponding figure for non-participants male and female households are about 34.55% and 17.80% respectively. As the table (table 6) reveals that in terms of adoption status for both adopter and non-adopter male households have more probability of adoption than female households. Non adopters' respondents said that, rice production technology adoption requires more labors, and it takes time and is not easy to access agricultural inputs. Thus mentioned problems as their expressions affect them not to participate in adoption of rice production technology.

Table 6: Sex of sample household head

Sex	Adopter		Non adopter	
	Frequency	%	Frequency	%
Male	66	34.55	66	34.55
Female	25	13.09	34	17.80
Total	91	47.65	100	52.35

Pearson chi2 (1) = 0.9509   Pr = 0.329,

Source: Own survey based on data (2017)

4.1.3 Family size of household head

Table 7 indicated that in the study area the average family size of both adopters and non-adopters are 6.11 and 5 people per household respectively, while the minimum is 1 and the maximum are 11 and 9 families. But there was a wide variation in family members among households. From the data non-adopter households have less family size than adopter households. The larger the farm size the farmer has, the better he/she is initiated to involve in adoption of rice production technology. Therefore, adopter households have more probability of adopting rice production technology than non-adopter households and family size of households is directly associated with adoption of rice production technology.

Table 7: Family size of sample household head

Fshh	Mean	Minimum	Maximum	Total sample
Adopter	6.11	1	11	91
Non adopter	5	1	9	100

Pearson chi2 (10) = 52.8378   Pr = 0.000,

Sources: Own survey based on data (2017)

4.1.4. Participated labor force of household head

It was assumed that the existence of large number of active age family members will increase the demand of adoption of rice production technology. This is because rice production is labor intensive activity particularly on technology adoption.

The average labor force available was 3 man equivalents. In (table 8), the data result reveals that, the mean labor force participation is 3.07 with the minimum labor force participated is 1 and the maximum labor force participated is 7. According to the data result, about 47.64% of adopters and 52.36 % of non-adopters have farm labor. The remaining both adopter and non-adopters farmer‘s express they do not have availability of farm labor. The reasons are having their own work, preferring work and by lack of demand to work farm activity.

Table 8: Participated labor force of sample household head

Parlfor	Mean	Minimum	Maximum	Total
Adopter	3.07	1	7	91
Non adopter	3.07	1	7	100

Pearson chi2 (6) = 9.9472 Pr = 0.072,

Source: Own survey based on data (2017)

4.1.5 Level of education of the household head

Definitely, education plays a great role in adoption of rice production technology and other technology. It assists both adopter and non-adopters as a crucial way of collecting information with regard to rice production technology as well. About 42.66% of the respondents were literates; this figure is greater than the national figure for adult literacy (36%) indicating that the area is better off in terms of education.

As (table 9), reveals out of the total of rice production technology adopter households about 34(17.80%) of household heads were illiterate, 31(16.23%) of household heads attained primary school and the other 26(13.61) of household heads attained secondary school. And also out of the total of rice production technology non-adopter households about 57(29.84%) of household heads were illiterate, 28(14.66%) of household heads attained primary school and the other 15(7.85%) of household heads attained secondary school. Comparisons by the level of rice production technology adoption participation reveal that 57 (29.84% participants) and 43 (22.51% non-participants) were found educated and non-educated, respectively.

Table 9 : Education level of sample households head

Eduhh	Adopter		Non adopter	
	Frequency	%	Frequency	%
Illiterate	34	17.80	57	29.84
Primary	31	16.23	28	14.66
Secondary	26	13.61	15	7.85

Total	91	47.65	100	53.35

Pearson chi2 (2) = 8.5118   Pr = 0.004,

Source: Own survey based on data (2017)

4.1.6 Size of cultivated land

Farmers with large area of land are more likely to introduce new agricultural technology than those with smaller area of land. The landholding of the sample households ranges from 0.5 ha to 3 ha with an average figure of 1.066 hectares. As (table 10) stated, the land holding of the sample household varies from 0.125 hectare to 3 hectare. It is quite true that in normal circumstances land size and land production are directly and positively related. Taking this into consideration the finding also confirmed that soil type and size of cultivated has its own influence on adoption of rice crop production technology in case of this study and statistical significant.

Table 10: Cultivated land size sample household heads

Sicl	Mean	Minimum	Maximum	Total sample
Adopter	1.066	0.125	3	91
Non adopter	1.066	0.125	1.75	100

Pearson chi2 (13) = 32.6732   Pr = 0.012,

Source: survey based on data (2017)

4.1.7 Livestock ownership of household head

The average livestock (including cattle, sheep, goats, pack animals, and poultry) was 4.46 TLU with the minimum and the maximum holdings of 0.7 TLU and 17.8 TLU respectively.

In the communities where both agriculture and pasturing are the main source of economic activity, TLU has a significant influence on their agricultural production and on total amount of income received. As respondents responds if they have a number of oxen, they will use to tillage and to get income from selling. They said that livestock's, especially oxen are multidimensional purpose for them.

Table 11: Livestock holding sample household heads

Livow	Mean	Minimum	Maximum	Total sample
Adopter	4.46	0.7	17.8	91
Non adopter	4.46	0.7	17.8	100

Pearson chi2 (39) = 57.4844   Pr = 0.128,

Source: Own survey based on data (2017)

4.1.8 Use of credit service

The main source of credit in the study area is Fogera Woreda "ACSI" microfinance and richer individuals. Table 12 showed that out of the total of adopters 37.17% of households were credit users while 10.47% did not want to take credit. And also showed that out of the total of non-adopters 29.84% of households were credit users while 22.51% did not want to take credit due to various reasons which are food consumptions rather than farm inputs consumption and unexpected expenditure, existing of high interest rate and by having enough money to buy agricultural inputs. About 67.02% had access to institutional credit.

Table 12: Credit user of sample household heads

Usecredis	Adopter	%	Non adopter	%
User	71	37.17	57	29.84
Non user	20	10.47	43	22.51
Total	91	47.65	100	52.35

Pearson chi2 (1) =   9.5251   Pr = 0.432,

Source: Own survey based on data (2017)

4.1.9 Access to extension service

As result of (table 13), about 27.75% of the adopters sample household and 17.28% of non-adopters sample household get extension service around their villages while 19.90% of adopters sample household and 35.08% of non-adopters sample household did not get extension support respectively.

When we compare to adopters with non-adopters, adopter households get support from extension agents more and more than non-adopter households and therefore, there is significant difference between adopter and non-adopter regarding to access of extension services. Extension service here refers to advice, demonstration and distribution of input.

Table 13: Extension services user sample household heads

Exten	Adopter	%	Non adopter	%
Access	53	27.75	33	17.28
Not access	38	19.90	67	35.08
Total	91	47.65	100	52.35

Pearson chi2 (1) = 12.2638 Pr = 0.027,

Source: Own survey based on data (2017)

4.10 Attending at farmers training center

According to the data result (Table 14), 18.32% of adopters and about 17.28% of non-adopters were attending farmers training center while 29.32% of adopters and 35.08% of non-adopters were not attending farmers training at farmers training center because of the reason that their home is far from their farmers training center (FTC). About 64.4% of households did not get a chance to participate farmers training at farmers training and keeps them away from gaining best agricultural practices

Table 14: Attending of farmers training center of sample household head

Atftc	Adopter	%	Non adopter	%
Attained	35	18.32	33	17.28

Not attained	56	29.32	67	35.08
Total	91	47.65	100	52.35

Pearson chi2 (1) = 0.6199 Pr = 0.431,

Source: Own survey based on data (2017)

4.11 Production output of rice by respondents (in quintal/hectare)

Production output of rice is the total number of rice yields in quintal per hectare of each respondents and it is an outcome variable for impact analysis of this study.

As table (table 15) reveals that out of the total of 47.64% household adopters of rice production technology, 10.47% of households produce 5-15 quintal per hectare of rice and 16.23% of households produce 15-30 quintal per hectare of rice and also 16.23% of households produce 31-50 quintal per hectare of rice and 4.71% of households produce 51-65 quintal per hectare of rice in year 2008/2009. Out of the total of 53.36% non-adopters of rice production technology households, 22.51% of households produce 5-15 quintal per hectare of rice and 25.65% of households produce 15-30 quintal per hectare of rice and also 3.14% of households produce 31-50 quintal per hectare of rice and 1.05% of households produce 51-65 quintal per hectare of rice in year 2008/2009.

Table 15: Production Output of Rice by Respondents (in quintal per hectare) (n = 191)

Rice Production Output (in quintal per hectare)	Adopter		Non-adopter	
	Frequency	%	Frequency	**%**
5-15	20	10.47	43	22.51
16-30	31	16.23	49	25.65
31-50	31	16.23	6	3.14
51-65	9	4.71	2	1.05

Total	91	47.64	100	53.36

Pearson chi2 (3) = 10.0827 Pr = 0.018,

Source: Own survey based on data (2017)

4.2 Determinants of rice production technology adoption

4.2.1 Binary logistic regression model result

Binary logistic regression model was used to estimate and identify determinant factors of that affect adoption of rice production technology and propensity score matching model was used to analyze impact of adoption of rice production technology on rice production. Before fitting both models, it is essential to check whether there is or not high degree of association among and between both discrete and continuous explanatory variables. In logistic regression contained a binary outcome and discreet or continuous explanatory variables. For each explanatory variable in model there would be an associated parameter. The Wald test by (Angrest et al., 1995) is used to test whether the parameter associated with an explanatory variable is zero or not. If the parameter of explanatory variable is significantly differ from zero then associated variable should be included in the model. Therefore, all explanatory coefficients were greater than zero. The goodness fit of model for binary logistic regression model, an intuitively appealing way to summarize the result of fitted logistic model is via a classification table. This cross-classification is the result of cross-classification of the outcome variable ‘y” with a dichotomous variable whose values are derived from the estimated logistic probabilities. With regard to the predictive efficiency of the models out of 191 sample household include in the model, 147 (77%) were correctly predicted. The sensitivity and specificity indicate that 76% of adopter of rice production technology and 78% of non-adopters of rice production technology households were correctly predicted in their categories respectively.

With regard to the error rates committed in the classification table, the false positive rate (number error where the household is predicted to be adopter, but is in fact non adopter) is 24.18% while the false negative rate (the number of error where the false household is predicted to be non-adopter, but is in fact adopter) is 22%. This result is thought to provide evidence that the model fits (appendix table 22).

4.2.2 Main factors affecting adoption of Rice production technology

The adoption process of agricultural technology depends primarily on access to information and on the willingness and ability of farmers to use information channels available to them. The role of information in decision-making process is to reduce risks and uncertainties to enable farm households to make the right decision on adoption of improved agricultural technology.

In this sub section, we treat results concerning adoption at household level as well as the socio economic, demographic and other factors that affect the adoption of rice production technology. This study employed logistic regression model to estimate and to figure out factors having a certain sort of relationship to the rice production technology adoption. The output of the logistic regression model showed that six variables determine the probability of participating in adoption of rice production technology. These are age of household head, family size of the household head, participated labor force of household, education level of household head, size of cultivated land of household head and access to extension services.

Age of household head: this variable influences rice production technology adoption negatively and significant at 10% level of significant (p=.073) between adopters and non-adopters of rice production technology (table 16). The marginal effect (-.010) shows that keeping other explanatory variables constant, a 1 year increase in the age of the household head, decreases households probability of adopting rice production technology by 1% (table 16).

Family size of household head: this variable is significant at 1% of significance level (p=.000) between adopters and non-adopters of rice production technology (table 16). The marginal effect (.1134) also reveals keeping all other explanatory variables constant, a 1% increases in family size increases household probability of adopting rice production technology by 11%. This suggests that family size is among the major variable in influencing decisions of households to participate in adoption of rice production technology.

Participated labor force of household head: In this study participated family labor force is found to be significantly different at 10% significant level (p=.072) between the adopters and non-adopters (table 16). This means that it had positively and significantly influenced farmers' decision to adopt rice production technology. The odds ratio (1.28) reveals a household heads that has more family labor is about 1.3 times more likely to participate in rice technology adoption as compared to those who has not available family labor. Due to the fact that rice production is challenging particularly to adopt new technology, which needs high family labor is the possible explanation to the test result. The finding of this study is consistent with Chilot (1994) study conducted on new wheat technology adoption in Wolmera and Addis Alem.

Education level of household head: It is a variable positively correlated with both adopters of rice production technology and non-adopters and significantly influence the adoption of rice production technology 1% level of significance (p=.003). The marginal effect (0.179) means that keeping other factor variables constant, a year increase in level of education increases probability of adopting rice production technology by 17.9% (table 16).

Education helped farmers to develop perception on production of rice through time which contributes for the adopters of rice production technology. The finding of the present study is in line with the findings of (Shiyani, et al 2000).

Size of cultivated land of household head: Farmers with large area of land are more likely to introduce new agricultural technology than those with smaller area of land. This variable is significant at 5% significant level (p=.035) for adoption of rice production technology. It has positive relationship with rice production technology. The implication is that the result is expected since cultivated land is one of the major factors of rice production. The marginal effect (0.156) implies that keeping other factor constant, a unit increase in size of cultivated land increases the probability of households adopting of rice production technology by 15.6%.

Access to extension services: it is positively related with adoption rice production technology. This variable is significant at 5% (p=.014) probability level (table 16). Farmers need to be equipped with knowledge and skill about specific technology to be effective in agricultural production. The marginal effect of this variable is (0.2318) reveals that keeping other factor constant, a unit increase in access to credit services increase the probability of adopting rice production technology by 23.18% (table 16).

Estimation results of binary logit model

Table 16: Estimation result of Rice production technology adoption binary logit model

Variables	Robust coefficient	Odds ratio	P>[Z]	S.E	Marginal effect
Aghh	-.0428465	.9580584	0.073*	.0239402	-.0106925
Sexhh	.1493449	1.161073	0.715	.4087765	.0371999
Fshh	.4546282	1.575587	0.000***	.0963557	.1134539
Parlfor	.247736	1.281122	0.072*	.1377916	.0618233
Eduhh	.7201111	2.054661	0.003***	.2393349	.179706
Sicl	.626748	1.871514	0.035**	.2970068	.156407
Livow	.0484799	1.049674	0.530	.0772038	.0120983
Usecrids	.2935556	1.341188	0.475	.4110474	.0729286
Exten	.9447838	2.572257	0.014**	.382531	.2318219
Atftc	.3070263	1.359377	0.420	.381093	.0765751
_cons	-4.768916	.0084896	0.000***	1.194781	----------

Where, * significant level at 10%, ** significant level at 5% and *** significant level at 1%.

Number of obs = 191

LR chi2 (10) = 79.00

Prob > chi2 = 0.0000

Log likelihood = -92.677508 Pseudo R2 = 0.2988

Source: own computation based on data (2017)

4.2.3 The impact of technology adoption on rice production

Estimating the propensity score is important for two things. The first one is to estimate the average treatment effect on the treated (ATT); and second, to obtain matched treated and non-treated farming households. Logistic regression is used to estimate the propensity scores. Thus, Propensity score methods allow the researcher to directly address the question of what can be earned from adopters and the loss of being non-adopters.

According to (Grilli, et al 2011) the necessary steps when implementing propensity score matching are: Propensity Score estimation, Choose matching algorithm, Check overlap/common support. Hence, to analyze the impact of adoption of rice production technology on households rice production, propensity score matching with different matching algorithms namely: nearest neighbors, nearest radius, caliper matching and kernel matching was employed.

Matching of adopter and non-adopter households were carried out to determine the common support region. The basic criterion for determining the common support region is to delete all observations whose propensity score is smaller than the minimum propensity scores of participants and larger than the maximum in the control group (Caliendo and Kopeining, 2008).

The summary statistics of propensity scores of farmers (Table 17), the predicted propensity scores range from 0.148124 to 0.9963699 with mean value of 0.6616371 and standard deviation 0.2408404 for the rice technology adopter farmers, while it ranges from 0.150809 to 0.9759661 with mean value of 0.3056574 and standard deviation 0.2208784 for those non-adopter farmers.

Accordingly, the common support region was satisfied in the range of 0.9759661 to 0.148124 by deleting 6 observations from those adopters only.

Table 17: Predict propensity score common support region

Observations	Mean	Std. dev	Min	Max
Adopters	0.6616371	0,2408404	0.148124	0.9963699
Non-adopters	0.3056574	0.2208784	0.150809	0.9759661
Total	0.4752602	0.2909859	0.148124	0.9963699

Source: Own survey based on data (2017)

Before computing the ATT, the similarity of the subsample of control cases that are directly compared with the treated cases should be tested using the so-called "pstest". This test helps to balance information for propensity scores and for each covariate before and after matching. The standardized bias difference between treatment and control samples was used as a convenient way to quantify the bias between treatment and control samples. In almost all cases, it is evident that sample differences in the raw data (unmatched data) significantly exceed those in the samples of matched cases. The process of matching thus creates a high degree of covariate balance between the treatment and control samples that are used in the estimation procedure.

Table 18 showed the values of Pseudo R-square and LR chi-square before and after matching which can be used as indices for the fulfillment of the balancing requirement. The pseudo *R*-square indicates how well the regressors *X* explain the participation probability, meaning all the explanatory (independent) important variables included in the model do exactly explains the probability of households rice production technology adoption. After matching there should be no systematic differences in the distribution of covariates between both groups and therefore the pseudo R-square should be fairly low. Then, low value of pseudo R-square and the insignificant LR Chi-square reported in row one and columns two that both groups have the same distribution in covariates after matching. These results clearly show that the matching procedure is able to balance the characteristics in the treated and the control groups. We therefore used these results to evaluate the effect of adoption of rice production technology among groups of households having similar observed characteristics.

Table 18: pstest balance score matching

Matching	before matching			after matching		
Algorithm	Ps R^2	LR chi square	P-value	Ps R^2	LR chi square	P-value
Neighbor (1)	0.313	82.64	-000	0.024	5.70	0.969
(3)	0.313	82.64	-000	0.027	6.29	0.856
(5)	0.313	82.64	-000	**0.021**	**5.06**	**0.708**
Kernel (.1)	0.313	82.64	-000	0.032	7.51	0.875
(.25)	0.313	82.64	-000	0.023	5.37	0.191
(.5)	0.313	82.64	-000	0.071	16.32	0.000
Caliper (.1)	0.313	82.64	-000	0.024	5.70	0.969
(.25)	0.313	82.64	-000	0.04	5.70	0.969
(.5)	0.313	82.64	-000	0.024	5.70	0.969
Radius (.01)	0.313	82.64	-000	0.311	51.72	0.000
(.1)	0.313	82.64	-000	0.311	51.72	0.000
(.5)	0.313	82.64	-000	0.311	51.72	0.000

Source: own survey (2017)

4.2.4 Estimation of treatment effect: matching algorithms

Choice of matching algorithm was carried out from nearest neighbor, radius, caliper and kernel methods. The choice of estimator based on three criteria; namely, balancing test, Pseudo R-square and matched sample size. The matching estimator which balances more independent variables, has low pseudo R-square value and results in large matched sample was chosen as being the best estimator of the data. Accordingly, nearest neighbor matching method with 5 was found to be the best estimator of the data of rice production (Table 18 & 19). As depicted in the table, relatively, this estimator resulted in least pseudo R-square (0.021), large number of matched sample size (185) by discarding unmatched households from total of 191 households. And balancing test after matching percent of bias is below five percent and also its LR chi square is insignificant.

As showed (Table 19), the Average Treatment effect on the Treated (ATT) was computed based on the three alternative matching methods. Outcome variables are rice production which is measured in quintal per hectare. The impact of adoption of rice production technology on household rice production was based on sample of matched treated and control groups, the estimated average treatment effect (ATT) significant effect on rice production of participant farmers with significant t - statistic (3.48) at 1 percent significance level ($p< 0.001$). The average production of rice crop of adopters of rice production technology household was higher by 9.48 quintal per hectare in a given product year when compared with the average production of non-adopter households. So it is concluded in this analysis that the rice production technology adoption has positive production effect on the farm households of the study area. Hence adoption of rice production technology has positive impact on the life of the adopters indicating positive welfare effect or reduction of poverty level on the side of the adopters.

Table 19: Propensity score, NN matching, kernel matching, caliper matching and radius matching results

Outcome variable	Algorithm	Number of adopter	Number of non-adopter	ATT	SE	t-value
Rice production in quintal per hectare	Neighbor (1)	85	100	9.07	2.96	3.06
	(3)	85	100	9.64	2.49	3.87
	(5)	**85**	**100**	**9.48**	**2.72**	**3.48**
	Kernel (.01)	85	100	6.72	2.35	2.86
	(.25) (.5)	85	100	9.85	2.27	4.32
		85	100	9.21	2.02	4.56
	Caliper (.01)	85	100	6.40	2.48	2.58
	(.1)	85	100	9.07	2.96	3.06
	(.25)	85	100	9.07	2.96	3.06
	Radius (.01)	85	100	9.96	1.63	6.08
	(.1)	85	100	9.96	1.63	6.08
	Where ATT, average treatment effect on treated and SE, standard error					

Source: Own survey data (2017)

Table 20: average treatment effect on treated (ATT)

Sample	Treated	Control	Difference	S.E.	T-stat
ATT	27.5411765	18.0611765	9.48	2.72138172	3.48

Source: Own computation (2017)

4.2.5 Sensitivity test for average treatment effect on the treated

Caliendo and Kopeing (2008) contend that PSM only controls the observed variables, included in the propensity score, to match both the treated and control groups of the households. Un observable characteristics are left out of consideration. As cited in

(Menale, et al 2010) it was stated that before interpreting the base line estimates as evidences of a true causal effect of the treatment, testing the presence of unobserved variable is of great importance, which can be done using a sensitivity analysis. Sensitivity analysis is applicable mainly to check whether and to what extent the estimated average treatment effects are robust to possible deviations from the conditional independence assumption (CIA) (Ichino, et al 2008). Although, the CIA is a basic assumption to identify the true treatment effect in the ATT estimation strategy, the validity of the CIA cannot be tested using non-experimental data (Crino, 2011). One of the prime assumptions of the sensitivity analysis is that assignment to treatment may be confounded provided that the set of observable variables, that is, the common support assumption (CSA) no longer holds. But, it is assumed that the CIA is uncompounded given observed X and an unobserved binary variable, U.

Sensitivity analysis is a strong identifying assumption and must be justified. According to (Grilli and Rampichini, 2011) sensitivity analysis is the final diagnostic that must be performed to check the sensitivity of the estimated treatment effect to small changes in the specification of the propensity score. In table 21, result was reported, based on this concept of the sensitivity analysis shows that the significance level is unaffected even if the gamma values are relaxed in any desirable level even up to 100% percent. This shows that average treatment effect on treated is not sensitive to external change. Hence there are no external variables which affect the result above calculated for ATT result.

Table 21: Sensitivity test of external effect on ATT

Gamma	Q-mh+	Q-mh-	P-mh+	P-MH-
1	12.2069	12.2069	0	0
1.05	12.0948	12.4007	0	0
1.1	11.9516	12.5493	0	0
1.15	11.8164	12.693	0	0
1.2	11.6885	12.8321	0	0
1.25	11.567	12.9671	0	0

1.3	11.4515	13.0981	0	0
1.35	11.3415	13.2255	0	0
1.4	11.2365	13.3494	0	0
1.45	11.136	13.4702	0	0
1.5	11.0399	13.5879	0	0

NB. Gamma : odds of differential assignment due to unobserved factors

Q_mh+ : Mantel-Haenszel statistic (assumption: overestimation of treatment effect)

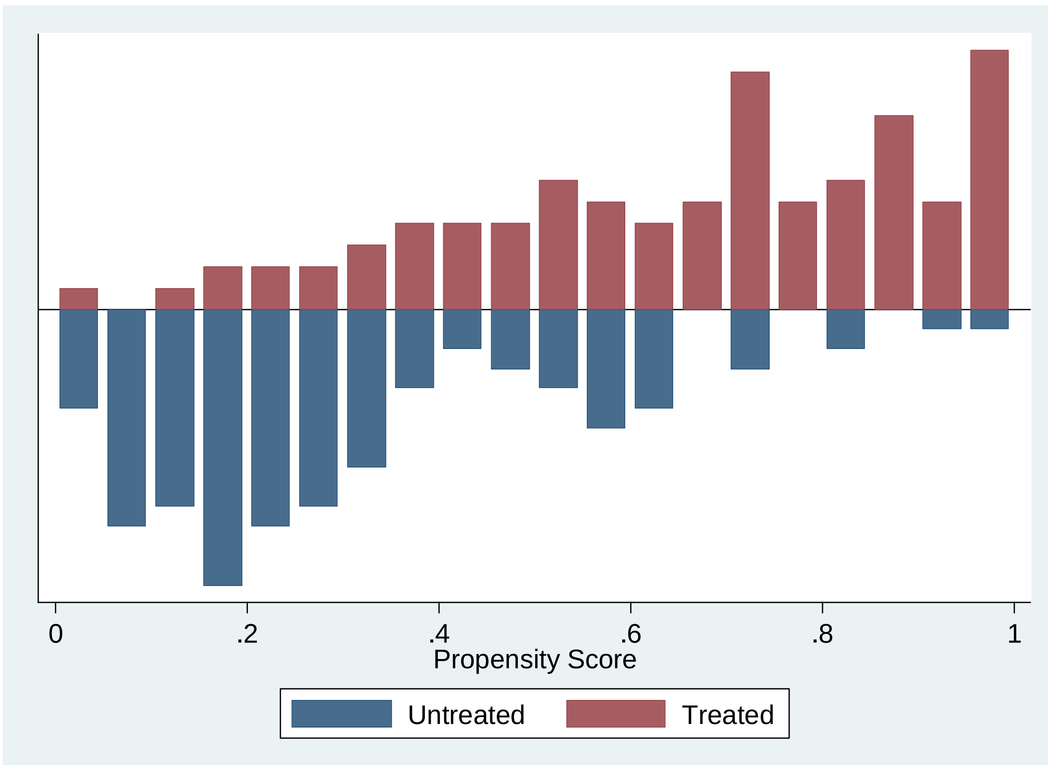
Q_mh- : Mantel-Haenszel statistic (assumption: underestimation of treatment effect)

p_mh+ : significance level (assumption: overestimation of treatment effect)

p_mh- : significance level (assumption: underestimation of treatment effect)

Sources: own survey based on data (2017)

Figure 4: Propensity score distribution of matched sample



Source: own survey based data (2017)

CHAPTER FIVE

5 CONCLUSION AND RECOMMENDATION

5.1 Conclusion

New agricultural technology play a key role in increasing agricultural production. Since rural households are basically entitled to food through own production, higher agricultural production can easily translate to a better food security condition among these households which could be manifested by higher consumptions. Though adoptions of agricultural technology may enhance food security among the adopters, impact figures actually vary across different agro ecologies, socioeconomic contexts, and features of the improved technology signifying the role of empirical studies. As a result, a number of studies have tried to measure the impact of new agricultural technology on different outcome indicators such as poverty, income and yields (production).

This study tried to assess the contribution of rice production technology adoption on rice production by using propensity score matching method which helps in separating the true impact of adoption of rice production technology. The objective of this study was to evaluate the factor that affect rice production technology adoption and the impact of rice production technology adoption on production yield of smallholder farmers in selected districts of Fogera wereda. Propensity score matching (PSM), binary logit, and cross-sectional survey data were used to attain the objective of the study. The study employed cross sectional household level data collected in 2016/2017 cropping season from 191 sample farming households.

A propensity score matching approach was used to compare adopter households with non-adopters in terms of their rice production levels as measured in quintal per hectare. The results show that rice production technology had a robust and positive impact on farmers' rice production levels. In the mean time we could identify factors affecting adoption of improved rice technology; age, family size of households, participated labor forces, education, size of cultivated land and access extension services were found to be important variables to determine farmers' propensity to adopt. The nearest neighbors matching, radius matching, capelir matching and kernel matching methods were employed to assess impact of adoption of rice production technology on household production of rice. From used algorithms nearest neighbor matching (5) was choices as best estimator of data based on balancing test, pseudo R2 and sample size.

The sensitivity analysis also showed that the estimates are almost free from unobserved covariates. In addition the Rosenbaum bounds procedure was used to check the sensitivity of the estimated effect to unobserved selection bias. Consequently, it can be concluded that, the overall the results are remarkably robust and the analysis support the robustness of the matching estimates. The implication of the findings is straight forward; even if the adoption of rice production technology is quite low in Fogera Woreda, those households who could use the technology could improve their production. Hence, scaling up the best practices of the adopters to other farmers can be considered as one option to enhance production in the area while introducing new practices and technology is another option.

5.2 Recommendations

Understanding the factors that influence or hinder adoption of agricultural technology is essential in planning and executing technology related programs for meeting the challenges of agricultural production in our country. Therefore to enhance rice production technology adoption by farmers, it's important for policy makers and planners of new technology to understand farmers need as well as their ability to adopt technology in order to come up with technology that will suit them. It is better to encourage rice technology adoption because the results of this study signified that application of rice production technology increase the production of adopters.

Based on the key findings of this study the following actions are recommended:

The most important problem in practicing adoption of rice crop technology is its labor requirement and the associated costs. Even if the promoted agronomic technology would be superior, an important benchmark for farmers' adoption is increased labor production rather than land production (Moser and Barrett, 2006). In the case of the labor intensive agricultural technology, this seems to be a valid concern as a large number of farmers complained about the workload required for employing these new technology. The availability of larger family labor for agriculture affects the likelihood of participation in improved rice production technology adoption highly significantly and positively, as expected. This is because perhaps in rural areas; large households provide labor on the farm as such it is likely that farmers who have large families would provide the necessary labor to adopt improved rice production technology. It further suggested that, households with economically active labor size improved their decision behavior on improved rice production technology adoption since rice is considered as labor intensive where households with more family labor could produce more outputs. It is therefore, while disseminating improved rice production technology priority should be given to households with large family size to enhance technology adoption and dissemination.

Changing the attitudes of farmers is a crucial factor in adopting rice production technology. If farmers have awareness about the long run benefit of adopting modern rice production technology, they do not need only immediate economic advantages from their product. In case of production, household heads with very limited education encounter in successfully managing, fertilizer and pesticide applications, and also what to produce in line with taste and preference of consumers demand, especially in the presence of ineffective farmer's training services. So stakeholders' and Agricultural and Rural Development Offices have to create awareness about the long run benefits of adopting rice production technology. Continuous education and training on adoption and production will have a positive impact on their attitudes. This implies that interventions to speed up rice production technology adoption and dissemination must be targeted at improving farmers' knowledge and skills by capacitating and supporting FTCs focused especially on aspects of rice production technology adoption and production.

Technology adoption is not appropriate to the poor with fragmented landholding and small labor support because of risk of crop failure. Farmers are working under limited plots of land by natural as well as socio-economic factors. Land is a constraining factor of production in agriculture. A total land holding is positive and significant influences technology participation. Thus, intervention aimed at improving the fertility status and would enhance technology adoption. Moreover, improved varieties distribution must be targeted at households with large land holding size to improve rice technology dissemination and adoptions.

The improved access to diversified and qualified agricultural extension services still remains critically important. Therefore, local government with together regional should supply improved farm inputs on the time for farmers through creating awareness on recommended amounts.

The agricultural research and extension activities need to consider additional agronomic practices along with the rice production technology adoption method in order to increase rice production, and for the successful promotion, adoption and scaling up of good agronomic practices and extension should contact farmers individually as well as in group to be awarded in terms of rice production technology adoption is suitable to improve household production. Improved awareness creation on rice production technology adoption should be provided through extension services supported by provision of inputs including credit facilities.

The introduction of the above measures into the picture of technology adoption, therefore, could enhance the number of adopters and the cropped area under rice with production technology. Hence, expansion in the level of technology adoption would consequently result in substantial rice production and income on a sustainable basis.

Therefore, the research recommended that adopting rice production technology as a package (row and spacing, improved seed, fertilizer rates and or compost, early hand weeding and hoeing, tilling repeatedly) is vital as a policy in enhancing rice yield on the marginal farm lands. Complementary agricultural technology adoption best yield results when they are taken up as a complete package together, rather than in the individual elements to give high rice yield.

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APPENDIX: QUESTIONNAIRES

TITLE: TECHNOLOGICAL ADOPTION AND ITS IMPACT ON RICE PRODUCTION IN FOGERA WEREDA-SOUTH GONDAR ZONE, AMHARA NATIONAL REGIONAL STATE OF ETHIOPIA

JIMMA UNIVERSITY

COLLEGE OF BUSINESS AND ECONOMICS

DEPARTMENT OF ECONOMICS

ECONOMIC POLICY ANALYSIS MSC PROGRAM

Questionnaire

Questionnaire numbers_________________ Interviewer's________________

Date of interviews _____________________signature______________

Dear Respondents:

I, Getaye Gizaw, am prospective graduate of Masters of Science in Economics policy analysis in Jimma University, College of Business and Economics, dealing Master's thesis. Therefore I would like to assure you that questionnaire is used only for the academic purposes. Thank you for your cooperation.

Instructions to Enumerators

1. Make brief introduction to the respondent before starting the interview (greet them, tell your name, get her/his name, and make clear the purpose and objective of the study that you are undertaking).

2. Please ask the question clearly and patiently until the respondent understands.

3. During the process put the answers of each respondent both on the space provided and encircle the choice or tick mark as require

I: General information

1.1 Kebele---

1.2 Name of household head------------------------------

1.3 Age of household head (in year)?

I. 18-33 years

II. 33-49 years

III. 49-66 years

1.4 Sex of household head: Male □ Female □

1.5 Education level of household head (in years of schooling)?

I. Primary

II. Secondary

III. tertiary

II: Demography characteristics of household head

2 About family information

2.1 How many family members live in your home**? (**In number)

2.2 Are all they participating in household farm activity?

Yes □ No □

2.3 If No #2.2, how many are they participating in household farm activity? ________

2.4 Do you face labor shortage to practice agricultural technology?

Yes □ No □

2.5 If yes #2.4, how do you solve labor shortage problem?

By hiring □ all □

Asking for cooperation □ others (Specify) --------------?

3 About both rice technology and broadcast of rice information

3.1 How long have you been in rice production? …………….. Years

3.2 Did you adopt rice production technology in year 2008E.C?

Yes □ No □

3.3 If No #3.2, why did not adopt rice technology?

It requires more labor □ It is low productive than traditional production □

It takes time when plowing and sowing □ other specifies ___________?

3.4 Did you have ever information about rice production technology in the past time?

Yes □ No □

3.5 If Yes #3.4, where did you get that information?

Extension agent's □ at farmers training center □

Friends and families □ others (please specify) _____________?

3.6 If yes #3.2, which rice crop production technology you used?

Row planting □ high yield seed □

Fertilizer □ irrigation □

Pesticides □ none □ if other specify _______?

3.7 Which of these improved technology have you adopted on large scale and on a continuous basis?

Row planting □ high yield seed □

Fertilizer □ irrigation □

Pesticides □ none □ if other specify _______?

3.8 If yes # 3.2 what are impact on rice production?

Increase household income □ all □

Reduce input consumption □ other specify_________?

3.9 If yes # 3.2, what was the area under rice production? ____________________Ha

3.10 If yes#3.2 how many you produced from each rice production technology?

Types of technology	Cultivated land in hectare	Used fertilizer per quintal	Total production in quintal	Used labor
Row planting				
Fertilizer				
Irrigation				
High yield seed				

3.11 How do you perceive the effectiveness of adoption of rice production technology on the improvement of rice crop production?

1=very good □ 2=good □

3=poor □ 4=if other, specify _____?

3.12 Describe the benefits and drawbacks you have encountered on the application of rice production technology on rice production?

Advantages____

____

____

Disadvantages____

____

____

3.13 What are the problems facing you in the adoption of the improved rice processing technology in your area?

No working capital □ No enough equipment □ No good market □

No good leadership in the group □ No selling price difference with conventional method □

Any other reason ………?

4 About farm land size and production information

4.1 How many hectare of farm land do you have?

4.2 If do you have farm land, how did you get?

Types of farm land	Remark(x)	In hectare
By own		
By share by		

Rent		
By gift		

4.3 Does farm land size increase as well as production of rice increase?

Yes □ No.□

4.4 If yes #4.3, how many quintals do you get per hectare?

5 About livestock holding

5.1 Do you have livestock's and their products?

Yes □ No.□

5.2 If yes #5.1, how many do you have and get income from it, year 2008 E.C?

Types of livestock		Total owned	Tropical livestock unit (TLU)
Cattle	Oxen		
	Cow		
	Heifer		
	Calve		
	Bull		
	Total		
Marine	Mules		
	Horses		
	Donkey		
	Total		

5.3 What do you use to farming? Oxen or others specify _______________________?

5.4 Do you have change in your rice production when number of oxen increase?

Yes □ No □

5.5 If yes #5.4 how can it increase production of rice crop?

It uses to farming than others □

It uses to cover input cost of rice product due to price more than others □

If other specify ……………?

6 Membership local organization and access to credit information

6.1 Do you have access to credit? Yes ( ) No ( )

6.2 If no, how do you finance your rice production? …………………………………

6.3 If yes, state sources and amount of credit received in 2008

No	Source	Amount
1		
2		

6.4 If yes #6.3, for what purpose do you use?

For food consumption □

For farm input consumption □

Others specify--------------------------------?

6.5 Did you return the credit after the agreed period?

Yes □ No □

6.6 If no, please give reasons for not returning the credit ………………….

6.7 Do you belong to any social group?

Yes □ No □

6.8 If yes, how many groups: …………………?

6.9 If your answer is yes to #6.7, in which social group?

Equb □ Edir □

Social network □ farmers cooperatives □ other specify …………………?

7 About extension services information

7.1 Have you had any visit by extension agents in 2008?

Yes □ No □

7.2 If yes, how many times were you visited by the extension agents with information on improved rice production technology in 2008? …………

7.3 Are you satisfied with the visits?

Yes □ No □

7.4 If yes, give reasons …………………………………………………………..

7.5 If no, give reasons: ……………………………………………………………

7.6 Do you attend the farmers training center (FTC)?

Yes □ No □

7.7 If no #7.3, why do not you attend FTC?

Far from your home □

They did not give good training and advices □

Other reasons ----------------------------

8 About using recommended technology input information.

8.1 How did you use agricultural input for rice crop production in 2008 E.C? Mark (x)

Types of input		Full user recommended (1)	Half user recommended (2)	None user recommended (3)
Fertilizer	DAP			
	UREA			
	Compose			
Improved seed				
Chemical	Herbicides			
	Insecticides			
	Fungicides			
	Other			

Codes: 1= for non-user of recommended amount of inputs

2= for half user of recommended amount of inputs

3= for full user of recommended amount of inputs

8.2 If you did not apply the above agricultural input for rice crop production, what is your reason?

--?

Thank you for your cooperation

Appendix Table 22: logit and marginal result

```
. logit arpt aghh sexhh fshh parlfor eduhh sicl livow usecrids exten atftc, or

Iteration 0:   log likelihood = -132.17899
Iteration 1:   log likelihood = -92.869685
Iteration 2:   log likelihood = -92.678049
Iteration 3:   log likelihood = -92.677508
Iteration 4:   log likelihood = -92.677508

Logistic regression                               Number of obs   =        191
                                                  LR chi2(10)     =      79.00
                                                  Prob > chi2     =     0.0000
Log likelihood = -92.677508                       Pseudo R2       =     0.2988
```

arpt	Odds Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
aghh	.9580584	.0229361	-1.79	0.073	.9141428	1.004084
sexhh	1.161073	.4746195	0.37	0.715	.5210849	2.587086
fshh	1.575587	.1518169	4.72	0.000	1.304441	1.903096
parlfor	1.281122	.1765278	1.80	0.072	.977917	1.678336
eduhh	2.054661	.4917523	3.01	0.003	1.28534	3.284449
sicl	1.871514	.5558525	2.11	0.035	1.045636	3.349699
livow	1.049674	.0810389	0.63	0.530	.9022742	1.221154
usecrids	1.341188	.5512918	0.71	0.475	.5992463	3.001745
exten	2.572257	.9839681	2.47	0.014	1.215356	5.444091
atftc	1.359377	.5180489	0.81	0.420	.6440994	2.868975
_cons	.0084896	.0101432	-3.99	0.000	.0008164	.0882847

```
. logit arpt aghh sexhh fshh parlfor eduhh sicl livow usecrids exten atftc, ro

Iteration 0:   log pseudolikelihood = -132.17899
Iteration 1:   log pseudolikelihood = -92.869685
Iteration 2:   log pseudolikelihood = -92.678049
Iteration 3:   log pseudolikelihood = -92.677508
Iteration 4:   log pseudolikelihood = -92.677508

Logistic regression                               Number of obs   =        191
                                                  Wald chi2(10)   =      36.96
                                                  Prob > chi2     =     0.0001
Log pseudolikelihood = -92.677508                 Pseudo R2       =     0.2988
```

arpt	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
aghh	-.0428465	.0243837	-1.76	0.079	-.0906376	.0049446
sexhh	.1493449	.4231591	0.35	0.724	-.6800317	.9787215
fshh	.4546282	.10711	4.24	0.000	.2446965	.66456
parlfor	.247736	.1355774	1.83	0.068	-.0179908	.5134628
eduhh	.7201111	.2675725	2.69	0.007	.1956787	1.244543
sicl	.626748	.2511042	2.50	0.013	.1345929	1.118903
livow	.0484799	.0602737	0.80	0.421	-.0696545	.1666143
usecrids	.2935556	.4066891	0.72	0.470	-.5035403	1.090652
exten	.9447838	.3788099	2.49	0.013	.2023302	1.687238
atftc	.3070263	.3794111	0.81	0.418	-.4366058	1.050659
_cons	-4.768916	1.426441	-3.34	0.001	-7.564689	-1.973143

```
. mfx

Marginal effects after logit
      y  = Pr(arpt) (predict)
         =  .47886233
```

variable	dy/dx	Std. Err.	z	P>|z|	[95% C.I.	]	X
aghh	-.0106925	.0061	-1.75	0.080	-.022644	.00126	42.7016
sexhh*	.0371999	.10505	0.35	0.723	-.168702	.243101	.691099
fshh	.1134539	.02686	4.22	0.000	.060803	.166105	6.11518
parlfor	.0618233	.03385	1.83	0.068	-.00453	.128176	3.07853
eduhh	.179706	.0669	2.69	0.007	.048593	.310819	1.73822
sicl	.156407	.06259	2.50	0.012	.033725	.279089	1.06615
livow	.0120983	.01504	0.80	0.421	-.017383	.04158	4.46702
usecrids*	.0729286	.10023	0.73	0.467	-.123527	.269384	.670157
exten*	.2318219	.08974	2.58	0.010	.055937	.407707	.450262
atftc*	.0765751	.09433	0.81	0.417	-.108306	.261457	.356021

(*) dy/dx is for discrete change of dummy variable from 0 to 1

```
. correlate $xlist
(obs=191)
```

	aghh	sexhh	fshh	parlfor	eduhh	sicl	livow	usecrids	exten	atftc
aghh	1.0000									
sexhh	0.0276	1.0000								
fshh	0.2097	0.1216	1.0000							
parlfor	0.3432	0.0973	0.2490	1.0000						
eduhh	-0.0613	-0.0495	0.0822	-0.0680	1.0000					
sicl	0.1769	-0.0684	0.2562	0.0513	0.0465	1.0000				
livow	0.2616	-0.0368	0.3152	0.2243	0.0510	0.2764	1.0000			
usecrids	0.1056	0.0371	0.3023	-0.0307	0.0777	0.2327	0.1702	1.0000		
exten	0.0580	0.0129	0.1624	0.0018	-0.0465	0.2439	0.1601	0.1425	1.0000	
atftc	0.0871	0.0001	0.0235	0.2055	-0.0582	-0.0473	-0.0902	0.0100	0.0084	1.0000

```
. reg arpt fshh parlfor sicl livow

      Source |       SS       df       MS              Number of obs =     191
-------------+------------------------------           F(  4,   186) =   17.34
       Model |  12.9399818     4  3.23499545           Prob > F      =  0.0000
    Residual |  34.7039972   186   .18658063           R-squared     =  0.2716
-------------+------------------------------           Adj R-squared =  0.2559
       Total |  47.6439791   190  .250757785           Root MSE      =  .43195

------------------------------------------------------------------------------
        arpt |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        fshh |   .0860615   .0142261     6.05   0.000     .0579962    .1141268
     parlfor |   .0212895   .0222324     0.96   0.340    -.0225706    .0651496
        sicl |   .1165083   .0460306     2.53   0.012     .0256991    .2073176
       livow |   .0074468   .0118639     0.63   0.531    -.0159582    .0308519
       _cons |  -.2728635    .101999    -2.68   0.008    -.4740872   -.0716398
------------------------------------------------------------------------------

. vif

    Variable |       VIF       1/VIF
-------------+----------------------
        fshh |      1.20    0.835478
       livow |      1.20    0.836205
        sicl |      1.12    0.889708
     parlfor |      1.10    0.912179
-------------+----------------------
    Mean VIF |      1.15
```

```
. estat gof, group (10)

Logistic model for arpt, goodness-of-fit test

  (Table collapsed on quantiles of estimated probabilities)

       number of observations =       191
             number of groups =        10
      Hosmer-Lemeshow chi2(8) =         5.49
                  Prob > chi2 =         0.7045

. estat classification

Logistic model for arpt

              -------- True --------
Classified |         D            ~D  |      Total
-----------+--------------------------+-----------
     +     |        69            22  |         91
     -     |        22            78  |        100
-----------+--------------------------+-----------
   Total   |        91           100  |        191

Classified + if predicted Pr(D) >= .5
True D defined as arpt != 0
--------------------------------------------------
Sensitivity                     Pr( +| D)   75.82%
Specificity                     Pr( -|~D)   78.00%
Positive predictive value       Pr( D| +)   75.82%
Negative predictive value       Pr(~D| -)   78.00%
--------------------------------------------------
False + rate for true ~D        Pr( +|~D)   22.00%
False - rate for true D         Pr( -| D)   24.18%
False + rate for classified +   Pr(~D| +)   24.18%
False - rate for classified -   Pr( D| -)   22.00%
--------------------------------------------------
Correctly classified                        76.96%
--------------------------------------------------

.
```

Appendix Table 23: participation production

```
.
. tab arpt, sum (pro)
```

arpt	Summary of pro Mean	Std. Dev.	Freq.
0	17.58	9.1760888	100
1	27.835165	14.451654	91
Total	22.465969	13.006684	191

```
.
```

Appendix Table 24: summary of propensity score participation

```
.
. *summary of ps
.
. sum _pscore
```

Variable	Obs	Mean	Std. Dev.	Min	Max
_pscore	191	.4752602	.2909859	.0148124	.9963699

```
. sum   _pscore if   arpt==1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
_pscore	91	.6616371	.2408404	.0148124	.9963699

```
. sum   _pscore if   arpt==0
```

Variable	Obs	Mean	Std. Dev.	Min	Max
_pscore	100	.3056574	.2208784	.0150809	.9759661

Appendix Table 25: result of ATT using propensity score matching

```
. psmatch2  ($ylist $xlist), outcome(pro) neighbor(1) common  logit
```

Logistic regression — Number of obs = 191; LR chi2(10) = 79.00; Prob > chi2 = 0.0000; Pseudo R2 = 0.2988

Log likelihood = -92.677508

arpt	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
aghh	-.0428465	.0239402	-1.79	0.073	-.0897685	.0040755
sexhh	.1493449	.4087765	0.37	0.715	-.6518423	.9505322
fshh	.4546282	.0963557	4.72	0.000	.2657745	.643482
parlfor	.247736	.1377916	1.80	0.072	-.0223305	.5178026
eduhh	.7201111	.2393349	3.01	0.003	.2510232	1.189199
sicl	.626748	.2970068	2.11	0.035	.0446254	1.208871
livow	.0484799	.0772038	0.63	0.530	-.1028368	.1997966
usecrids	.2935556	.4110474	0.71	0.475	-.5120825	1.099194
exten	.9447838	.382531	2.47	0.014	.1950369	1.694531
atftc	.3070263	.381093	0.81	0.420	-.4399021	1.053955
_cons	-4.768916	1.194781	-3.99	0.000	-7.110643	-2.427188

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
pro	Unmatched	27.8351648	17.58	10.2551648	1.7358376	5.91
	ATT	27.5411765	18.4705882	9.07058824	2.96806089	3.06

Note: S.E. does not take into account that the propensity score is estimated.

psmatch2: Treatment assignment	psmatch2: Common support Off suppo	On suppor	Total
Untreated	0	100	100
Treated	6	85	91
Total	6	185	191

```
.
. psmatch2  ($ylist $xlist), outcome(pro) neighbor(3) common  logit
```

```
Logistic regression                               Number of obs   =        191
                                                  LR chi2(10)     =      79.00
                                                  Prob > chi2     =     0.0000
Log likelihood = -92.677508                       Pseudo R2       =     0.2988
```

arpt	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
aghh	-.0428465	.0239402	-1.79	0.073	-.0897685	.0040755
sexhh	.1493449	.4087765	0.37	0.715	-.6518423	.9505322
fshh	.4546282	.0963557	4.72	0.000	.2657745	.643482
parlfor	.247736	.1377916	1.80	0.072	-.0223305	.5178026
eduhh	.7201111	.2393349	3.01	0.003	.2510232	1.189199
sicl	.626748	.2970068	2.11	0.035	.0446254	1.208871
livow	.0484799	.0772038	0.63	0.530	-.1028368	.1997966
usecrids	.2935556	.4110474	0.71	0.475	-.5120825	1.099194
exten	.9447838	.382531	2.47	0.014	.1950369	1.694531
atftc	.3070263	.381093	0.81	0.420	-.4399021	1.053955
_cons	-4.768916	1.194781	-3.99	0.000	-7.110643	-2.427188

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
pro	Unmatched	27.8351648	17.58	10.2551648	1.7358376	5.91
	ATT	27.5411765	17.8941176	9.64705882	2.49258503	3.87

Note: S.E. does not take into account that the propensity score is estimated.

psmatch2: Treatment assignment	psmatch2: Common support Off suppo	On suppor	Total
Untreated	0	100	100
Treated	6	85	91
Total	6	185	191

.

```
. psmatch2  ($ylist $xlist), outcome(pro) neighbor(5) common  logit
```

Logistic regression		Number of obs = 191
	LR chi2(10) = 79.00
	Prob > chi2 = 0.0000
Log likelihood = -92.677508		Pseudo R2 = 0.2988

arpt	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
aghh	-.0428465	.0239402	-1.79	0.073	-.0897685	.0040755
sexhh	.1493449	.4087765	0.37	0.715	-.6518423	.9505322
fshh	.4546282	.0963557	4.72	0.000	.2657745	.643482
parlfor	.247736	.1377916	1.80	0.072	-.0223305	.5178026
eduhh	.7201111	.2393349	3.01	0.003	.2510232	1.189199
sicl	.626748	.2970068	2.11	0.035	.0446254	1.208871
livow	.0484799	.0772038	0.63	0.530	-.1028368	.1997966
usecrids	.2935556	.4110474	0.71	0.475	-.5120825	1.099194
exten	.9447838	.382531	2.47	0.014	.1950369	1.694531
atftc	.3070263	.381093	0.81	0.420	-.4399021	1.053955
_cons	-4.768916	1.194781	-3.99	0.000	-7.110643	-2.427188

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
pro	Unmatched	27.8351648	17.58	10.2551648	1.7358376	5.91
	ATT	27.5411765	18.0611765	9.48	2.72138172	3.48

Note: S.E. does not take into account that the propensity score is estimated.

psmatch2: Treatment assignment	psmatch2: Common support Off suppo	On suppor	Total
Untreated	0	100	100
Treated	6	85	91
Total	6	185	191

```
.
. psmatch2 ($ylist $xlist), kernel outcome(pro)bwidth(0.1)common  logit ate
```

Logistic regression		Number of obs	=	191
		LR chi2(10)	=	79.00
		Prob > chi2	=	0.0000
Log likelihood = -92.677508		Pseudo R2	=	0.2988

arpt	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
aghh	-.0428465	.0239402	-1.79	0.073	-.0897685	.0040755
sexhh	.1493449	.4087765	0.37	0.715	-.6518423	.9505322
fshh	.4546282	.0963557	4.72	0.000	.2657745	.643482
parlfor	.247736	.1377916	1.80	0.072	-.0223305	.5178026
eduhh	.7201111	.2393349	3.01	0.003	.2510232	1.189199
sicl	.626748	.2970068	2.11	0.035	.0446254	1.208871
livow	.0484799	.0772038	0.63	0.530	-.1028368	.1997966
usecrids	.2935556	.4110474	0.71	0.475	-.5120825	1.099194
exten	.9447838	.382531	2.47	0.014	.1950369	1.694531
atftc	.3070263	.381093	0.81	0.420	-.4399021	1.053955
_cons	-4.768916	1.194781	-3.99	0.000	-7.110643	-2.427188

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
pro	Unmatched	27.8351648	17.58	10.2551648	1.7358376	5.91
	ATT	27.5411765	17.7247011	9.8164754	2.52613739	3.89
	ATU	17.58	21.7741768	4.19417681	.	.
	ATE			6.77739508	.	.

Note: S.E. does not take into account that the propensity score is estimated.

psmatch2: Treatment assignment	psmatch2: Common support Off suppo	On suppor	Total
Untreated	0	100	100
Treated	6	85	91
Total	6	185	191

```
.
. psmatch2 ($ylist $xlist), kernel outcome(pro)bwidth(0.25)common  logit

Logistic regression                             Number of obs   =        191
                                                LR chi2(10)     =      79.00
                                                Prob > chi2     =     0.0000
Log likelihood = -92.677508                     Pseudo R2       =     0.2988
```

arpt	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
aghh	-.0428465	.0239402	-1.79	0.073	-.0897685	.0040755
sexhh	.1493449	.4087765	0.37	0.715	-.6518423	.9505322
fshh	.4546282	.0963557	4.72	0.000	.2657745	.643482
parlfor	.247736	.1377916	1.80	0.072	-.0223305	.5178026
eduhh	.7201111	.2393349	3.01	0.003	.2510232	1.189199
sicl	.626748	.2970068	2.11	0.035	.0446254	1.208871
livow	.0484799	.0772038	0.63	0.530	-.1028368	.1997966
usecrids	.2935556	.4110474	0.71	0.475	-.5120825	1.099194
exten	.9447838	.382531	2.47	0.014	.1950369	1.694531
atftc	.3070263	.381093	0.81	0.420	-.4399021	1.053955
_cons	-4.768916	1.194781	-3.99	0.000	-7.110643	-2.427188

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
pro	Unmatched	27.8351648	17.58	10.2551648	1.7358376	5.91
	ATT	27.5411765	17.6843324	9.85684409	2.27974808	4.32

Note: S.E. does not take into account that the propensity score is estimated.

psmatch2: Treatment assignment	psmatch2: Common support Off suppo	On suppor	Total
Untreated	0	100	100
Treated	6	85	91
Total	6	185	191

```
.
. psmatch2 ($ylist $xlist), kernel outcome(pro)bwidth(0.5)common  logit

Logistic regression                               Number of obs   =        191
                                                  LR chi2(10)     =      79.00
                                                  Prob > chi2     =     0.0000
Log likelihood = -92.677508                       Pseudo R2       =     0.2988
```

arpt	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
aghh	-.0428465	.0239402	-1.79	0.073	-.0897685	.0040755
sexhh	.1493449	.4087765	0.37	0.715	-.6518423	.9505322
fshh	.4546282	.0963557	4.72	0.000	.2657745	.643482
parlfor	.247736	.1377916	1.80	0.072	-.0223305	.5178026
eduhh	.7201111	.2393349	3.01	0.003	.2510232	1.189199
sicl	.626748	.2970068	2.11	0.035	.0446254	1.208871
livow	.0484799	.0772038	0.63	0.530	-.1028368	.1997966
usecrids	.2935556	.4110474	0.71	0.475	-.5120825	1.099194
exten	.9447838	.382531	2.47	0.014	.1950369	1.694531
atftc	.3070263	.381093	0.81	0.420	-.4399021	1.053955
_cons	-4.768916	1.194781	-3.99	0.000	-7.110643	-2.427188

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
pro	Unmatched	27.8351648	17.58	10.2551648	1.7358376	5.91
	ATT	27.5411765	18.3280951	9.21308141	2.01841202	4.56

Note: S.E. does not take into account that the propensity score is estimated.

psmatch2: Treatment assignment	psmatch2: Common support Off suppo	On suppor	Total
Untreated	0	100	100
Treated	6	85	91
Total	6	185	191

```
.
. psmatch2 ($ylist $xlist), caliper(0.1) outcome(pro) common  logit ate

Logistic regression                             Number of obs   =        191
                                                LR chi2(10)     =      79.00
                                                Prob > chi2     =     0.0000
Log likelihood = -92.677508                     Pseudo R2       =     0.2988
```

arpt	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
aghh	-.0428465	.0239402	-1.79	0.073	-.0897685	.0040755
sexhh	.1493449	.4087765	0.37	0.715	-.6518423	.9505322
fshh	.4546282	.0963557	4.72	0.000	.2657745	.643482
parlfor	.247736	.1377916	1.80	0.072	-.0223305	.5178026
eduhh	.7201111	.2393349	3.01	0.003	.2510232	1.189199
sicl	.626748	.2970068	2.11	0.035	.0446254	1.208871
livow	.0484799	.0772038	0.63	0.530	-.1028368	.1997966
usecrids	.2935556	.4110474	0.71	0.475	-.5120825	1.099194
exten	.9447838	.382531	2.47	0.014	.1950369	1.694531
atftc	.3070263	.381093	0.81	0.420	-.4399021	1.053955
_cons	-4.768916	1.194781	-3.99	0.000	-7.110643	-2.427188

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
pro	Unmatched	27.8351648	17.58	10.2551648	1.7358376	5.91
	ATT	27.5411765	18.4705882	9.07058824	2.96806089	3.06
	ATU	17.58	21.74	4.16	.	.
	ATE			6.41621622	.	.

Note: S.E. does not take into account that the propensity score is estimated.

psmatch2: Treatment assignment	psmatch2: Common support Off suppo	On suppor	Total
Untreated	0	100	100
Treated	6	85	91
Total	6	185	191

```
.
. psmatch2 ($ylist $xlist), caliper(0.5) outcome(pro) common  logit

Logistic regression                             Number of obs   =        191
                                                LR chi2(10)     =      79.00
                                                Prob > chi2     =     0.0000
Log likelihood = -92.677508                     Pseudo R2       =     0.2988
```

arpt	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
aghh	-.0428465	.0239402	-1.79	0.073	-.0897685	.0040755
sexhh	.1493449	.4087765	0.37	0.715	-.6518423	.9505322
fshh	.4546282	.0963557	4.72	0.000	.2657745	.643482
parlfor	.247736	.1377916	1.80	0.072	-.0223305	.5178026
eduhh	.7201111	.2393349	3.01	0.003	.2510232	1.189199
sicl	.626748	.2970068	2.11	0.035	.0446254	1.208871
livow	.0484799	.0772038	0.63	0.530	-.1028368	.1997966
usecrids	.2935556	.4110474	0.71	0.475	-.5120825	1.099194
exten	.9447838	.382531	2.47	0.014	.1950369	1.694531
atftc	.3070263	.381093	0.81	0.420	-.4399021	1.053955
_cons	-4.768916	1.194781	-3.99	0.000	-7.110643	-2.427188

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
pro	Unmatched	27.8351648	17.58	10.2551648	1.7358376	5.91
	ATT	27.5411765	18.4705882	9.07058824	2.96806089	3.06

Note: S.E. does not take into account that the propensity score is estimated.

psmatch2: Treatment assignment	psmatch2: Common support		
	Off suppo	On suppor	Total
Untreated	0	100	100
Treated	6	85	91
Total	6	185	191

```
.
. psmatch2 ($ylist $xlist), caliper(0.25) outcome(pro) common  logit
```

Logistic regression		Number of obs	=	191
		LR chi2(10)	=	79.00
		Prob > chi2	=	0.0000
Log likelihood = -92.677508		Pseudo R2	=	0.2988

arpt	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
aghh	-.0428465	.0239402	-1.79	0.073	-.0897685	.0040755
sexhh	.1493449	.4087765	0.37	0.715	-.6518423	.9505322
fshh	.4546282	.0963557	4.72	0.000	.2657745	.643482
parlfor	.247736	.1377916	1.80	0.072	-.0223305	.5178026
eduhh	.7201111	.2393349	3.01	0.003	.2510232	1.189199
sicl	.626748	.2970068	2.11	0.035	.0446254	1.208871
livow	.0484799	.0772038	0.63	0.530	-.1028368	.1997966
usecrids	.2935556	.4110474	0.71	0.475	-.5120825	1.099194
exten	.9447838	.382531	2.47	0.014	.1950369	1.694531
atftc	.3070263	.381093	0.81	0.420	-.4399021	1.053955
_cons	-4.768916	1.194781	-3.99	0.000	-7.110643	-2.427188

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
pro	Unmatched	27.8351648	17.58	10.2551648	1.7358376	5.91
	ATT	27.5411765	18.4705882	9.07058824	2.96806089	3.06

Note: S.E. does not take into account that the propensity score is estimated.

psmatch2: Treatment assignment	psmatch2: Common support Off suppo	On suppor	Total
Untreated	0	100	100
Treated	6	85	91
Total	6	185	191

.

```
. psmatch2 ($ylist $xlist), radius bw(0.01) outcome(pro) common  logit ate
```

Logistic regression		Number of obs	=	191
		LR chi2(10)	=	79.00
		Prob > chi2	=	0.0000
Log likelihood = -92.677508		Pseudo R2	=	0.2988

arpt	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
aghh	-.0428465	.0239402	-1.79	0.073	-.0897685	.0040755
sexhh	.1493449	.4087765	0.37	0.715	-.6518423	.9505322
fshh	.4546282	.0963557	4.72	0.000	.2657745	.643482
parlfor	.247736	.1377916	1.80	0.072	-.0223305	.5178026
eduhh	.7201111	.2393349	3.01	0.003	.2510232	1.189199
sicl	.626748	.2970068	2.11	0.035	.0446254	1.208871
livow	.0484799	.0772038	0.63	0.530	-.1028368	.1997966
usecrids	.2935556	.4110474	0.71	0.475	-.5120825	1.099194
exten	.9447838	.382531	2.47	0.014	.1950369	1.694531
atftc	.3070263	.381093	0.81	0.420	-.4399021	1.053955
_cons	-4.768916	1.194781	-3.99	0.000	-7.110643	-2.427188

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
pro	Unmatched	27.8351648	17.58	10.2551648	1.7358376	5.91
	ATT	27.5411765	17.58	9.96117647	1.88159402	5.29
	ATU	17.58	27.5411765	9.96117647	.	.
	ATE			9.96117647	.	.

Note: S.E. does not take into account that the propensity score is estimated.

psmatch2: Treatment assignment	psmatch2: Common support		
	Off suppo	On suppor	Total
Untreated	0	100	100
Treated	6	85	91
Total	6	185	191

```
.
. psmatch2 ($ylist $xlist), radius bw(0.1) outcome(pro) common  logit

Logistic regression                               Number of obs   =        191
                                                  LR chi2(10)     =      79.00
                                                  Prob > chi2     =     0.0000
Log likelihood = -92.677508                       Pseudo R2       =     0.2988
```

arpt	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
aghh	-.0428465	.0239402	-1.79	0.073	-.0897685	.0040755
sexhh	.1493449	.4087765	0.37	0.715	-.6518423	.9505322
fshh	.4546282	.0963557	4.72	0.000	.2657745	.643482
parlfor	.247736	.1377916	1.80	0.072	-.0223305	.5178026
eduhh	.7201111	.2393349	3.01	0.003	.2510232	1.189199
sicl	.626748	.2970068	2.11	0.035	.0446254	1.208871
livow	.0484799	.0772038	0.63	0.530	-.1028368	.1997966
usecrids	.2935556	.4110474	0.71	0.475	-.5120825	1.099194
exten	.9447838	.382531	2.47	0.014	.1950369	1.694531
atftc	.3070263	.381093	0.81	0.420	-.4399021	1.053955
_cons	-4.768916	1.194781	-3.99	0.000	-7.110643	-2.427188

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
pro	Unmatched	27.8351648	17.58	10.2551648	1.7358376	5.91
	ATT	27.5411765	17.58	9.96117647	1.63915434	6.08

Note: S.E. does not take into account that the propensity score is estimated.

psmatch2: Treatment assignment	psmatch2: Common support Off suppo	On suppor	Total
Untreated	0	100	100
Treated	6	85	91
Total	6	185	191

```
. psmatch2 ($ylist $xlist), radius bw(0.5) outcome(pro) common  logit
```

Logistic regression		Number of obs	=	191
		LR chi2(10)	=	79.00
		Prob > chi2	=	0.0000
Log likelihood = -92.677508		Pseudo R2	=	0.2988

arpt	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
aghh	-.0428465	.0239402	-1.79	0.073	-.0897685	.0040755
sexhh	.1493449	.4087765	0.37	0.715	-.6518423	.9505322
fshh	.4546282	.0963557	4.72	0.000	.2657745	.643482
parlfor	.247736	.1377916	1.80	0.072	-.0223305	.5178026
eduhh	.7201111	.2393349	3.01	0.003	.2510232	1.189199
sicl	.626748	.2970068	2.11	0.035	.0446254	1.208871
livow	.0484799	.0772038	0.63	0.530	-.1028368	.1997966
usecrids	.2935556	.4110474	0.71	0.475	-.5120825	1.099194
exten	.9447838	.382531	2.47	0.014	.1950369	1.694531
atftc	.3070263	.381093	0.81	0.420	-.4399021	1.053955
_cons	-4.768916	1.194781	-3.99	0.000	-7.110643	-2.427188

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
pro	Unmatched	27.8351648	17.58	10.2551648	1.7358376	5.91
	ATT	27.5411765	17.58	9.96117647	1.63915434	6.08

Note: S.E. does not take into account that the propensity score is estimated.

psmatch2: Treatment assignment	psmatch2: Common support Off suppo	On suppor	Total
Untreated	0	100	100
Treated	6	85	91
Total	6	185	191

Appendix Table 26: propensity score matching test

```
.
. *To balance propensity score and covariates
.      *before matching
.
. pstest   _pscore $xlist ,both sum
```

Variable	Unmatched Matched	Mean Treated	Mean Control	%bias	%reduct |bias|	t-test t	t-test p>|t|	V(T)/ V(C)
_pscore	U	.66164	.30566	154.1		10.66	0.000	1.19
	M	.66164	.65789	1.6	98.9	0.10	0.917	1.00
aghh	U	43.077	42.36	7.7		0.54	0.593	1.51
	M	43.077	44.824	-18.8	-143.7	-1.34	0.182	2.04*
sexhh	U	.72527	.66	14.1		0.97	0.332	.
	M	.72527	.68132	9.5	32.7	0.65	0.519	.
fshh	U	7.3407	5	110.5		7.65	0.000	1.28
	M	7.3407	7.6374	-14.0	87.3	-0.94	0.350	1.23
parlfor	U	3.3626	2.82	37.2		2.58	0.011	1.33
	M	3.3626	3.4066	-3.0	91.9	-0.20	0.845	1.14
eduhh	U	1.9121	1.58	42.7		2.96	0.004	1.20
	M	1.9121	2.0659	-19.8	53.7	-1.24	0.218	0.88
sicl	U	1.2843	.8676	59.2		4.15	0.000	5.28*
	M	1.2843	1.1223	23.0	61.1	1.60	0.111	8.49*
livow	U	5.1736	3.824	47.2		3.31	0.001	4.53*
	M	5.1736	4.8352	11.8	74.9	0.75	0.453	2.66*
usecrids	U	.78022	.57	45.8		3.15	0.002	.
	M	.78022	.72527	12.0	73.9	0.86	0.393	.
exten	U	.58242	.33	52.1		3.60	0.000	.
	M	.58242	.49451	18.1	65.2	1.19	0.237	.
atftc	U	.38462	.33	11.4		0.78	0.434	.
	M	.38462	.50549	-25.1	-121.3	-1.64	0.102	.

* if variance ratio outside [0.66; 1.52] for U and [0.66; 1.52] for M

Sample	Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
Unmatched	0.313	82.64	0.000	52.9	45.8	156.7*	1.10	29
Matched	0.055	13.87	0.240	14.3	14.0	56.2*	1.99	43

* if B>25%, R outside [0.5; 2]

Appendix Table 27: sensitivity test result

```
. mhbounds arpt, gamma (1(0.05)1.5)

Mantel-Haenszel (1959) bounds for variable arpt

Gamma         Q_mh+     Q_mh-     p_mh+     p_mh-
-------------------------------------------------
    1       12.2069   12.2069         0         0
 1.05       12.0948   12.4007         0         0
  1.1       11.9516   12.5493         0         0
 1.15       11.8164    12.693         0         0
  1.2       11.6885   12.8321         0         0
 1.25        11.567   12.9671         0         0
  1.3       11.4515   13.0981         0         0
 1.35       11.3415   13.2255         0         0
  1.4       11.2365   13.3494         0         0
 1.45        11.136   13.4702         0         0
  1.5       11.0399   13.5879         0         0

Gamma : odds of differential assignment due to unobserved factors
Q_mh+ : Mantel-Haenszel statistic (assumption: overestimation of treatment effect)
Q_mh- : Mantel-Haenszel statistic (assumption: underestimation of treatment effect)
p_mh+ : significance level (assumption: overestimation of treatment effect)
p_mh- : significance level (assumption: underestimation of treatment effect)
```

Appendix Table 28: Conversion estimation of livestock

Livestock categories	TLU
Oxen and cow	1
Calf	0.25
Heifer	0.75
Horse	1,1
Mule	0.75
Donkey	0.7
Goat and sheep	0.06
Chicken	0.013

Source: (Storck et al., 1991)