# AGRICULTURAL TECHNOLOGY, POVERTY AND INCOME DISTRIBUTION: AN ECONOMIC ANALYSIS IN AWI ZONE OF ETHIOPIA

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# DECLARATION

I, hereby, declare that the thesis work entitled "**Agricultural Technology, Poverty and Income Distribution: An Economic Analysis in Awi Zone of Ethiopia** " is my original work carried out under the supervision of Prof. Nand Kumar and Prof. Seema Singh. This thesis has been prepared in conformity with the rules and regulations of Delhi Technological University, Delhi. The research work presented and reported in the thesis has not been submitted either in part or full to any other university or institute for the award of any other degree or diploma.

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# CERTIFICATE

This is to certify that the thesis titled **"Agricultural Technology, Poverty and Income Distribution: An Economic Analysis in Awi Zone of Ethiopia"** submitted to the Delhi Technological University, Delhi, in fulfillment of the requirements for the award of the degree of Doctor of Philosophy in Economics embodies the original research work carried out by **Mr. Aynalem Shita Muluneh** under our supervision. This work has not been submitted in part or full for any degree or diploma of this or any other University.

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# ABSTRACT

*This study investigates the economic benefits of agricultural technology adoption and its impact on rural poverty and income distribution at Awi Administrative Zone, Ethiopia. To achieve its objectives primary data has been collected through structured questionnaire and in-depth interview during the agricultural production season of 2017/18. The results were estimated by using budgetary analysis technique, Blinder-Oaxaca (B-O) decomposition method, Logit model, Tobit model, Propensity Score Matching (PSM) technique and dose–response function. The results of budgetary analysis technique indicated that adoption of fertilizer increased profit of maize producers by 37.7% while it was estimated 58% for those farmers who adopted fertilizer and improved seeds simultaneously. Similarly, adoption of fertilizer in teff production increased profit of farmers by 90.9%. The B-O decomposition found the existence of significant productivity gap between adopters and non-adopters of technologies from 50-73% where 71.7-77.3% of the differences primarily resulted from adoption of technologies. The logit models revealed that adoption of agricultural technology is determined positively and significantly by education level, family size, access to extension service and access to credit while age of the household affects adoption negatively. As captured by the tobit model, intensity of fertilizer use was influenced by age, education, family size, extension service and accessibility of credit. The PSM technique estimated that annual consumption expenditure per adult equivalent and total household income of fertilizer adopters increased ranging from ETB 1542-1654 and 8369-10710 respectively as compared to non-adopters. Moreover, simultaneous adoption of fertilizer and improved seeds resulted in an increment in consumption expenditure of ETB 1700-1818 and total income of households range from ETB 11293 to 13667. On the other hand, while adoption of fertilizer resulted in a reduction in poverty measured by headcount index of 17.4-18.2%, simultaneous adoption of fertilizer and improved seeds reduced poverty by 18.8-20.0% depending on various matching algorithms. However, it simultaneously worsens distribution of income implying that large farmers were more benefited from adoption than the poor. After adoption of fertilizer, total income inequality measured by Gini coefficient increased ranging from 0.017 - 0.055. On the other hand, simultaneous adoption of fertilizer and improved seeds resulted in an increase in income inequality by about 0.047-0.087 depending on alternative matching algorithms. Generally, this study revealed that adoption of agricultural technologies* *improves agricultural productivity, increase consumption expenditure and reduce rural poverty. Hence, the government, financial institutions, and farmers' cooperatives should be coordinated to enhance farmers' adoption of agricultural technologies through expanding extension services, credit accessibility, and ensuring timely availability of technologies at an affordable price. Moreover, further efforts should be exerted to achieve balanced adoption of agricultural technologies since adoption of technology worsen distribution of income.*

***Keywords***: *Agriculture Technology; Economic Analysis; Poverty; Income Distribution; B-O Decomposition; Logit model; Tobit model; PSM ; Dose Response Function; Awi Zone; Ethiopia.*

# ABBREVIATIONS AND ACRONYMS

| | |
|---|---|
| ADLI | Agricultural Development-Led Industrialization |
| ACSI | Amhara Credit and Saving Institute |
| AGRA | Alliance for a Green Revolution in Africa |
| AMC | Agricultural Marketing Corporation |
| ATT | Average Treatment effect for the Treated |
| B-O | Blinder-Oaxaca |
| CBN | Cost of Basic Needs |
| CSA | Central Statistics Agency |
| DAP | Di-Ammonium Phosphate |
| DD | Difference in Differences |
| EPRDF | Ethiopian People's Revolutionary and Democratic Front |
| ESR | Endogenous Switching Regression |
| ETB | Ethiopian Birr |
| FAO | Food and Agriculture Organization |
| FEI | Food-Energy-Intake |
| FGT | Foster- Greer- Thorbecke |
| GDP | Gross Domestic Product |
| GPS | Generalized Propensity Score |
| GTP | Growth and Transformation Plan |
| HYVs | High Yield Varieties |
| IARI | Indian Agricultural Research Institute |
| IFPRI | International Food Policy Research Institute |
| IPBO | International Plant Biotechnology Outreach |
| IRD | Integrated Rural Development |
| IV | Instrumental variables |
| KBM | Kernel Based Matching |
| ML | Maximum Likelihood |
| MMP | Minimum Package Project |
| MoFED | Ministry of Finance and Economic Development |

| | |
|---|---|
| NBE | National Bank of Ethiopia |
| NEPAD | New Partnership for Africa's Development |
| NNM | Nearest Neighbor Matching |
| OLS | Ordinary Least Square |
| PADEP | Peasant Agricultural Development and Extension Program |
| PSM | Propensity Score Matching |
| SDPRP | Sustainable Development and Poverty Reduction Program |
| TAM | Technology Acceptance Model |
| TPB | Theory of Planned Behavior |
| TRA | Theory of Reasonable Action |
| UN | United Nations |
| UNDP | United Nation Development Program |
| USAID | United States Agency for International Development |
| UTAUT | Unified Theory of Acceptance and Use of Technology |

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# CHAPTER ONE

# INTRODUCTION

## 1.1 The State of Agriculture and Green Revolution

Though improvements have been registered, still more than 820 million (10.8 % of the total population) people in the world suffer from hunger (unable to acquire enough food to meet dietary energy requirements (FAO, 2019a). Development of the agriculture sector is, therefore, believed to be one of the most powerful strategies to end extreme hunger and poverty. Worldwide, more than 45% of the population still resides in rural areas where agriculture is their major means of livelihood (World Bank, 2018). Hence, promoting productivity in agriculture sector is vital, as the sector is a key source of income and employment for the poor and vulnerable population groups. It is particularly critically for Africa where nearly 59% of the population of Africa relies on agriculture (FAO, 2019b) and about 70% of farmers are smallholder farmers working on small parcels of less than 2 hectares (AGRA, 2017).

In Africa, agriculture significantly contributed towards the achievement of the main priorities of the continent, such as alleviation of hunger and poverty, enhancing intra-Africa investment and trade, rapid industrialization and economic diversification and employment creation among others (NEPAD, 2013). A special nature of African agriculture is that the sector creates employment opportunity for about 55% of the population (World Bank, 2018).

Even though agriculture is believed to be the major source of livelihood for African countries, assuring food security is becoming a critical problem for these countries (Owusu, Abdulai, & Abdul-Rahman, 2011). According to FAO (2019a), approximately 21.5% of the population of Africa is found to be food insecure.

Unlike the experience of Latin America and Asia where the growth of their agriculture sector was resulted from adoption of modern agricultural technologies such as machanisation, improved varieties, extensive use of fertilizer and irrigation, in Africa agricultural growth over the previous three decades was achieved by cultivating more land and by mobilizing a larger agricultural labor force (NEPAD, 2013). However, Africa is still producing too little food and value-added products due to low level of agricultural productivity (AGRA, 2018). Recently, since expanding of cultivation area is hardly possible, agricultural growth depends on improvement in productivity of smallholder farm via the adoption of agricultural technologies such as improved seeds and fertilizers (Nonvide, 2017).

The increment of productivity in developing countries resulted from the application of improved varieties of seeds, fertilizers and other chemical inputs occurred in the late 1960s is known as Green Revolution (Pinstrup-Andersen & Hazell, 1985). Green Revolution refers to the transformation of agriculture in many developing nations that lead to boost agricultural productivity resulted from agricultural research, infrastructural and extension development. It originated from Mexico and spread to India and other developing countries. In fact, India is the most successful country in the advent of Green Revolution which adopted it in the mid1960s and became food self-sufficient in short period of time (Rena, 2004). In India, Green Revolution witnessed in tremendous yield increment through the use of high yielding varieties of wheat and rice, fertilizers and irrigation during early 1970s (Singh, 2012).

According to Mcarthur and Mccord (2017), use of fertilizers, high yield variety of seeds and irrigation are considered to be the main essential factors of agricultural production. Nyangena and Juma (2014) found that use of fertilizers and improved seeds extensively raise maize productivity. Similarly a study by Matuschke, Mishra, and Qaim (2007) revealed that adoption of fertilizer, high yield varieties of seeds and irrigation improved productivity of wheat in India.

While Green Revolution has significantly increased productivity in many Asian and Latin America countries, in Africa, the level of adoption and its impact were not promising (Awotide, Awoyemi, Omonona, & Diagne, 2012; Mekonnen, 2017). In this regard, (Pinstrup-Andersen & Hazell, 1985) argued that in order to reap the benefits of Green Revolution, its implementation should be integrated into the development strategy and supported by proper public policy and institutional changes.

Evidences revealed that a substantial improvement in land productivity which was occurred during the Asian Green Revolution has been attributed to greater use of fertilizer (Druilhe & Barreiro-hurlé, 2012). Due to poor natural endowments of Africans soil, it necessitates substantial increase in the use of inorganic fertilizer so as improve agricultural productivity and to enhance sustainable food production (Martey, 2018).

The increased demand for food due to increment in population pressure requires sustained increase in agricultural production and productivity which calls upon the adoption of new agricultural technologies (Dadi et al., 2004; Kassie, Shiferaw, & Muricho, 2011). Many studies revealed that technological adoption in agriculture enhance productivity of land and resulted in substantial increment in agricultural output production (Akinola & Owombo, 2012; Awotide et al., 2012; Myint & Napasintuwong, 2016; Nyangena & Juma, 2014). Moreover, literatures indicate that use of technologies reduces poverty and enhances the welfare of the society through improvement in land productivity (Afolami, Obayelu, & Vaughan, 2015; Kassie et al., 2011; Mendola, 2007).

Even though improving agricultural productivity is considered as the pertinent strategy for improving the living standard of the people, the question of whether this change in income is fairly distributed among beneficiaries or not is far from clear. Some studies revealed that adoption of technology can worsen income distribution in which the improvement in income due to technology adoption benefited large-scale farmers than small scale farmers (Freebairn, 1995; Huang, Zeng, & Zhou, 2015; Sahoo, 2014). In contrary, some other studies revealed that the impact of technology adoption on increasing income is found to be better for smallholders than large farmers and hence reduces income inequality (Kilima et al., 2013; Matuschke et al., 2007; Ut, Hossain, & Janaiah, 2000; Warr & Coxhead, 1992). On the other hand, Lin (1999) and Wu, Ding, Pandey, and Tao (2010) conclude that the net impact of hybrid rice's adoption on income distribution is insignificant because of offsetting effect in production-mix adjustments and the existence of nearly the same rate of improved rice adoption between lower-income and large-income households.

## 1.2 Agricultural Development Strategies and their Performance in Ethiopia

In Ethiopia the agriculture sector has got greater attention and support by the government over years, though it was less than the expected level (Welteji, 2018). This section deals on agricultural policies and development plans in Ethiopia since 1950s. During this period Ethiopia has been under three political regimes; Imperial Regime, Derg regime and Ethiopian People Revolutionary Democratic Front (EPRDF) regime.

### 1.2.1 Imperial Regime

The political arena during this era was characterized by absolute monarchism. However, development policies emphasized on industrial development and less attention was given for the agricultural sector (Alemu, Oosthuizen, & Van Schalkwyk, 2002; Welteji, 2018). During the Imperial regime, three national development plans were implemented.

The First Five Year Development Plan (1957-1962) prioritizes on the improvement of foreign exchange earnings by enhancing cultivation of coffee. Likewise, the Second Five-Year Development plan (1963-1967) added to placed emphasis on the establishment of large-scale commercial farms. However, cereal production which was cultivated in more than 80% of the total crop area was ignored. Consequently, during the First and the Second Five-year Plan periods agriculture could not produce enough materials to meet the demand of the population (Khairo, Battese, & Mullen, 2005).

Due to the occurrence of food shortage, policy makers shifted their attention towards the agriculture sector in the late 1960s. As a result, in the Third Five Year Plan (1968-1973), though the overall growth strategy was not modified, agriculture sector has got a greater emphasis. In the Third Five Year Plan priority was given to modernize peasant agriculture through the allocation of financial and human resources towards the selected promising areas of production. In line with this five year plan, Integrated Rural Development (IRD) projects were launched. The project tried to familiarize peasants with a commercial market system, dissemination of improved seeds & fertilizer, credit provision and distribution of better implements among others. Since it was costly to widely replicate IRD projects, it evolved into Minimum Package Projects (MPP) in

1971 with the main objective of minimum services provision mainly on fertilizers and credit. However, in the mid-1970s, its implementation was discontinued due to the donors' dissatisfaction of the political system of the country (Alemu et al., 2002).

### 1.2.2 Derg Regime

Ethiopia was under the Derg Regime from 1974–1991. During this period, priorities were given for collective and state farms at the cost of individual farms. Due to political unrest and extensive villagization programmes along with distorted macroeconomic policies implemented by the government, the contribution of rural development policies were undermined (Welteji, 2018). During the Derg regime, the average growth rate of Ethiopian GDP was found to be about 1.7% which was lower than the Imperial period (Alemu et al., 2002).

Derg encouraged socialist methods of production. As a result, in 1975, land was nationalized by the socialist government and was distributed among peasant households (private farms). Moreover, state farms and producer cooperatives were established. In 1976, Agricultural Marketing Corporation (AMC), marketing parastatal of the government, was formed with the objective of gathering farm outputs from farmers at low prices. Producer cooperatives were used as agents of the AMC which sell farm inputs to peasants and buy grains from them.

Six annual development movements were conducted by Derg regime between 1978 and 1984. In addition, massive villagization and re-settlement programmes were carried out to promote collectivization though the results were not successful, unlike Russia, where it improved the lives of many farmers (Alemu et al., 2002). In 1981, MPP-II was launched by the World Bank. In contrast to MPP-I which used model farmers, MPP II was implemented through the peasant associations by using them as agents for the dissemination of green revolution inputs and credit.

Initiated by the 1983/84 drought, the government implemented, a "ten-year perspective plan" with the purpose of improving surplus extraction and achieving food self-sufficiency in production. Though efforts were exerted, the result was not promising; number of state farms and producer cooperatives were not expanded at the expected level and shortage of finance was the major bottleneck. Consequently, agricultural production was stagnated (Alemu et al., 2002).

Regarding to the objectives of food sufficiency, a new agricultural development program called the Peasant Agricultural Development and Extension Program (PADEP) was launched in 1985 by replacing MPP-II. At the end of the 1980s, PADEP reshuffled its targets towards addressing the problems of agricultural development in low potential areas. Due to various reasons, however, the performance PADEP was below its plan (Abrha, 2015).

A three-year plan (1987-1990) was established by revising the Ten Year Perspective Plan of the government which emphasized on main stable crops of the country such as maize, *teff*, barely, wheat and sorghum. However, the plan was discontinued due to the introduction of Mixed Economic Policy in March 1990. In line with the mixed economic policy, collectivized agriculture has died and collective farms were distributed to members.

### 1.2.3 EPRDF Regime

The Derg regime was replaced by the EPRDF in 1991. This regime adopterd more of Free market economic policy. Consequently, price and trade policies were liberalized; stabilization policies were introduced to correct macro price distortions; plans were set to privatize state farms (Abrha, 2015; Alemu et al., 2002). More importantly, the development strategy of the government was shifted from industry-led to agriculture-led in 1993 and Agricultural Development Led Industrialization (ADLI) strategy was introduced (Khairo et al., 2005; Welteji, 2018). In Ethiopia the agriculture sector has got a special attention in the development planning process of the government since the formulation of ADLI (Alemu et al., 2002; Khairo et al., 2005). One of the main objectives of this strategy was modernizing the Ethiopian agriculture through adoption and diffusion of new farm technologies (green revolution technologies) such as fertilizers and certified seeds.

Moreover, successive national plans of the government such as Sustainable Development and Poverty Reduction Program (SDPRP), Plan for Accelerated and Sustainable Development to End Poverty (PASDEP) and Growth and Transformation Plans (GTP I and GTP II) have given a strong emphasis on improving agricultural productivity through research-generated information and technologies, among others.

SDPRP was a three year plan (2002/03 –2004/05) which placed greater emphasis to the welfare of rural population. It also identified agricultural sector as the basis of economic development in other sectors and emphasized on capacity building and education, agricultural research, water harvesting and small scale irrigation so as to insure food security in the country (MoFED, 2002). Consequently, during the SDPRP period, agricultural value added has been growing with an annual average growth rate of 6.43% while real GDP has registered 6.4% rate of growth (MoFED, 2006)

When SDPRP comes to the end, the government of Ethiopia has started to implement PASDEP (2005/06-2009/10). In PASDEP, in addition to continue the implementation of important strategic directions under SDPRP such as food security, rural development, human development, and capacity-building, it primarily emphasized on private sector development, commercialization of agriculture, and promoting industry and urban development (MoFED, 2006). Moreover, PASDEP planned to increase the supply of modern agricultural inputs such as improved seeds, fertilizer and pesticides. During the PASDEP period, Ethiopian economy has realized high and sustainable growth (annual average of 11%). During this period, the supply and consumption of agricultural technologies such as fertilizer and improved seeds has been increased substantially. Consequently, average productivity of crops has been enhanced from 12.1 quintal/ha in 2004/05 to 17 quintal/ha 2009/10 (MoFED, 2010).

During GTP I (2010/11-2014/15) emphasis was given to agricultural and rural development, infrastructure, industry, social and human development among others. It was planned to double GDP and agricultural value added at the end of GTP-I compared to the values of 2009/10 (MoFED, 2010). In GTP-I Real GDP has been grown at an average rate of 10.1%, nearly 1% shortfall from what was planned (11%). Though GTP-I was expected to lay down the base for achieving transformation from agriculture to industry sector, at the end of the GTP-I the contribution of the industry sector was found to be only 15.1%. To increase agricultural productivity, various activities such as dissemination of modern technologies, natural resources conservation and irrigations were executed. As a result agricultural GDP has been increased by an annual average rate of 6.6% though it was below the planned growth rate of 8% (National Planning Commission, 2016).

Currently, the country is implementing GTP-II (2015/16-2019/20) which is serving as a milestone to achieve the country's vision of becoming a low middle-income country by 2025. GTP-II is planning to focus on ensuring rapid, sustainable & broad-based growth through enhancing productivity of agriculture and manufacturing, improving quality of production and stimulating competition in the economy. In GTP-II, agriculture is expected to continue as the major driver of the rapid economic growth and development in the country. To this end, in addition to enhancing production and productivity, emphasis is given to high value crops, industrial input and export commodities. According to the GTP-II document, priority is given, to address the constraints embedded in the development of agricultural and marketing systems (National Planning Commission, 2016).

## 1.3 Agriculture and Technology in Ethiopia

### 1.3.1 The Contribution of Agriculture Sector to the Ethiopian Economy

Ethiopia is the second most populous nation in Africa where agriculture sector is the backbone of the country's economy. For instance, during 2017/18, the sector accounts for 35% of GDP and source of livelihood for about 80% of the population who lives in the rural area (NBE, 2018). Moreover, agriculture is expected to continue as a dominant sector and an important source of economic growth during the GTP-II period, the current five year plan of the country (National Planning Commission, 2016).

As indicated in table 1.1, the average growth rate of the agriculture sector in Ethiopia was found to be 5.23% between 2012/13-2017/18 with ups and downs, which is much lower than the growth rate of the industry and service sector which has shown an average growth rate of 19% and 9.7% respectively for the same period (NBE, 2018). Moreover, even though the contribution of the sector to the total GDP is found to be 38.27%, on average, its contribution to the country's growth rate is appeared to be low (21.65%) and decreasing over time.

**Table 1.1 Contribution of Agriculture to GDP and GDP Growth in Ethiopia**

| Items | 2012/13 | 2013/14 | 2014/15 | 2015/16 | 2016/17 | 2017/18 | Average |
|---|---|---|---|---|---|---|---|
| Growth rate of Agricultural value Added | 7.1 | 5.4 | 6.4 | 2.3 | 6.7 | 3.5 | 5.23 |
| Share of Agriculture sector to Total GDP (%) | 42.0 | 40.2 | 38.7 | 37.5 | 36.3 | 34.9 | 38.27 |
| Contribution of Agriculture sector to Total GDP growth (%) | 31.2 | 22.3 | 24.0 | 11.3 | 24.6 | 16.5 | 21.65 |
| Share of rural population to total population (%) | 81.4 | 81 | 80.5 | 80.1 | 79.7 | - | 80.54 |

**Source**: NBE (2018)

### 1.3.2 Use of Agricultural Technologies in Ethiopia

According to (IFPRI, 2011), in Ethiopia, much of the increase in agricultural production in the past decades has been due to increase in the area of cultivation. Recently, however, the arable land is shrinking over time and fallow farming, one strategy for improving soil fertility, becomes impractical (Teklewold, Kassie, & Shiferaw, 2013). To feed the continuously growing population, therefore, adoption of productivity enhancing technologies are found to be quite crucial.

With the objective reducing poverty and food insecurity, the government of Ethiopia has planned to improve productivity through adoption of technologies. Even though the supply of improved seeds and fertilizer that help increase agricultural production and productivity has increased overtime, but still falls short of the target set in order to transform smallholder agriculture (National Planning Commission, 2016).

As shown by table 1.2, between 2012/13-2017/18, only 55.48% of the total area was covered by fertilizer with average growth rate of 1.5% per annum. For instance during 2017/18 agricultural season, from the total crop area of 14.6 million ha, about 8.3 million ha of crop land was covered by about 12.2 million quintal of fertilizer. Since most of the crop land is covered by cereal crops (see figure 1.1), similarly, about 10.4 million quintal of fertilizer was applied to cereal crops of which maize, *teff* and wheat crops consumed 3.4, 3.2 and 2.4 million quintal of fertilizer respectively (CSA, 2018b).

**Table 1.2 Agricultural Technologies Utilized in Ethiopia (Private Peasant Holdings for Meher[1] Season)**

| Types of Technologies | 2012/13 | 2013/14 | 2014/15 | 2016/17 | 2017/18 | Average |
|---|---|---|---|---|---|---|
| Fertilizer | 53.41 | 52.56 | 57.06 | 57.61 | 56.76 | 55.48 |
| *Growth (% Change)* | | -1.59 | 8.57 | 0.48 | -1.48 | 1.50 |
| Improved Seed | 5.97 | 7.33 | 8.55 | 9.64 | 9.75 | 8.25 |
| *Growth (% Change)* | | 22.79 | 16.59 | 6.37 | 1.14 | 11.72 |
| Pesticide | 19.89 | 19.53 | 22.32 | 24.14 | 26.47 | 22.47 |
| *Growth (% Change)* | | -1.78 | 14.28 | 4.08 | 9.65 | 6.56 |
| Irrigation | 1.09 | 1.18 | 1.25 | 1.33 | 1.24 | 1.22 |
| *Growth (% Change)* | | 8.14 | 6.15 | 3.2 | -6.77 | 2.68 |

**Source**: Author's computation based on various agricultural surveys of CSA

Improved seeds are another important factors of production which enhance productivity. According to Mekonnen (2017) and Mcarthur and Mccord (2017), use of improved seed varieties significantly increase agricultural production since improved seeds are better in quality, tolerant to environmental pressures, resistant to pests and diseases .

In Ethiopia, during the period of 2012/13-2017/18, even though its application has shown improvements over time (with average growth rate of 11.25%), still it is found at a very low level where by only 8.25% of the crop area was covered by improved seeds, averagely. In

[1] Main crop production season in Ethiopia which refers to the crop harvesting period between September and February

2017/18, only 593 thousand quintal of improved seeds was applied which covered only 1.4 million ha of crop area. Wheat and maize took the largest share of improved seeds applied in the country which accounted for 316 and 196 thousand quintals respectively.

When extensive pests and weeds damage crops, the use of pesticides is indispensable. As indicated in table 1.2, the total pesticide applied area is appeared to be 22.74% with an average growth rate of 6.56%.

Even though use of irrigation enables farmers to increase the frequency of crop production by alleviating shortage of water caused by poor rains /dry seasons, the use of irrigation in Ethiopia is found to be very low. On average irrigation was practiced in only 1.22% of land. Moreover, its application did not show a significant increment over time. For instance in 2017/18, from 14.6 million ha of total cultivated area, irrigation was practiced in only 181 thousand ha of crop area.

### 1.3.3 Crop Production in Ethiopia

In Ethiopia, cereals are the main food crops both in terms of the area they cultivated and amount of production. As indicated in figure 1.1, cereal crops took up 70.17% of the total crop area under cultivation during 2017/18 agricultural season. Pulses are second major crops produced in Ethiopia next to cereals which covered 10.96% of the total crop area. The most common pulse crops grown in Ethiopia are Faba beans, chick peas and haricot bean. Oilseeds refer to crops which are also classified within grain crops category**,** nonetheless**.**

Stimulant crops which includes chat, coffee and hops constituted about 7% of the crop area where as 5.81 % of the area was covered by oilseeds such as Sesame, *Neug* and linseed. In Ethiopia, oil seeds and stimulant crops are vital crops not only for home consumption but are major sources of foreign exchange earnings. During 2017/18, 29.5% and 9.3% of the country’s export earning was contributed by coffee and chat crops respectively while oilseeds together contributed to 14.9 % of the country’s export earnings (NBE, 2018).

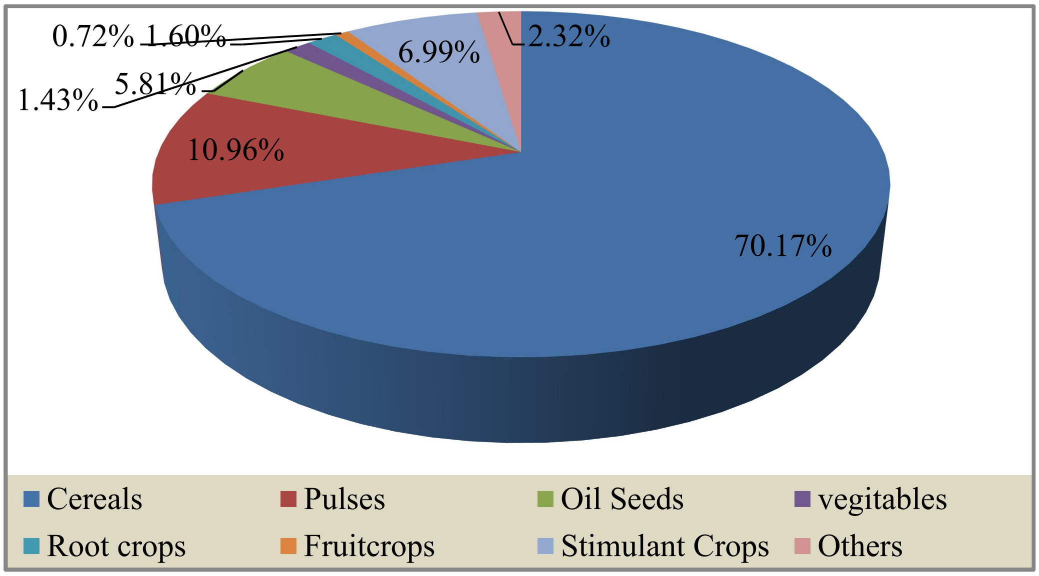


**Figure 1.1 Distribution of Area under major Crops**

**Source:** CSA (2018a)

**Table 1.3 Number of Holder, Area of Cultivation and Production of Cereal Crops in Ethiopia (Private Peasant Holdings for Meher Season)**

| Cereal crops | Number of Holders | % share | Area in Hectares | %share | Production in Quintals | %share |
|---|---|---|---|---|---|---|
| *Teff* | 6,771,977 | 44.99 | 3,023,283 | 29.55 | 52,834,012 | 19.73 |
| Maize | 10,573,934 | 70.25 | 2,128,949 | 20.81 | 83,958,872 | 31.35 |
| Sorghum | 5,368,096 | 35.66 | 1,896,389 | 18.5 | 51,692,525 | 19.30 |
| Wheat | 4,212,518 | 27.99 | 1,696,907 | 16.58 | 46,429,657 | 17.34 |
| Barley | 3,505,609 | 23.29 | 951,993 | 9.30 | 20,529,964 | 7.67 |
| Finger millet | 1,765,407 | 11.73 | 456,057 | 4.46 | 10,308,232 | 3.85 |
| Rice | 161,376 | 1.07 | 53,107 | 0.52 | 1,510,183 | 0.56 |
| Oats/'Aja' | 205,700 | 1.37 | 25,896 | 0.25 | 526,319 | 0.20 |
| ***Total*** | ***15,051,667*** | ***-*** | ***10,232,582*** | ***100.00*** | ***267,789,764*** | ***100.00*** |

**Source:** CSA (2018a)

Within cereals, *teff* is number one crop in Ethiopia which is cultivated in about 30% of the total cereal crop area and produced by more than 6.7 million farmers. In terms of production, however, it took the second rank next to maize. During 2017/18, 52.8 million quintal of *teff* was produced in about 3 million ha of land. Maize is first important cereal crop with regards to volume of production (31.3%) and the second most common crop concerning the area it is planted (20.8%) next to *teff*. Maize grown in 2.13 million ha and 83.96 million quintals of the grain production was drawn from the same crop. Sorghum and wheat constitute the third and the fourth rank both in terms of area coverage and volume of production respectively (see Table 1.3).

Productivity of various cereal crops from 2013/14 to 2017/18 is reported in table 1.4. All cereal crops except rice have shown increment in yield over time. Maize is the most productive crop while *teff* is the lowest in terms of yield measured by quintal/ha.

**Table 1.4 Productivity of Cereal Crops in Ethiopia**

| Cereal Crops | 2013/14 | 2014/15 | 2015/16 | 2017/18 | Average |
|---|---|---|---|---|---|
| *Teff* | 14.65 | 15.75 | 15.6 | 17.48 | 15.87 |
| Maize | 32.54 | 34.29 | 33.87 | 39.44 | 35.04 |
| Sorghum | 22.83 | 23.69 | 23.31 | 27.26 | 24.27 |
| Wheat | 24.45 | 25.43 | 25.35 | 27.36 | 25.65 |
| Barley | 18.72 | 19.65 | 19.66 | 21.57 | 19.90 |
| Finger millet | 18.67 | 20.17 | 20.2 | 22.6 | 20.41 |
| Oats | 17.31 | 18.21 | 18.22 | 20.32 | 18.52 |
| Rice | 27.31 | 28.15 | 27.9 | 28.44 | 27.95 |

**Note: Data for 2016/17 is unavailable**

**Source:** Various Agricultural Surveys of CSA

The average productivity of *teff* was found to be 15.87 for the stated time period. Its productivity has increased by 2.83 quintal/ha over the same period. Similarly, production of maize shown improvements in yield from 32.54 to 39.44 quintal/ha with an average productivity of 35.04 quintal/ha. Other crops such as sorghum, wheat and barley have shown an increment by 4.31 quintal/ha, 2.91 quintal/ha and 2.85 quintal/ha respectively.

## 1.4 Poverty and Distribution of Income in Rural Ethiopia

Like many other developing countries, poverty is a major social and economic problem in Ethiopia. According to National Planning Commission (2017), from the total population 23.5% of them were estimated to live in absolute poverty where the situation is more serious in rural areas than the urban with the headcount index of 25.6% and 14.8%, respectively.

Even though it declined over time, rural poverty in Ethiopia is still high where nearly 1/4$^{th}$ of its rural population lives under poverty line. Table 1.5 presents the trends of rural poverty in Ethiopia from 1995/96 to 2015/16. The results indicate that rural poverty has declined in all its forms, where rural poverty head count, poverty gap and severity were reduced by 46.1%, 44.8% and 41.5%, respectively. The decline in rural poverty may be due to implementation of pro-poor programs in rural areas by the government such as expansion of improved agricultural technologies and farming practices, commercialization of smallholder farming agriculture, rural infrastructural development, productive safety net programs, provision of credit etc (National Planning Commission, 2017).

**Table 1.5 Rural Poverty and Income Inequality in Ethiopia**

| Welfare Indicators | 1995/96 | 1999/00 | 2004/05 | 2010/11 | 2015/16 |
|---|---|---|---|---|---|
| Head Count Index | 47.5% | 45.4% | 39.3% | 30.4% | 25.6% |
| Poverty gap Index | 13.4% | 12.2% | 8.5% | 8.0% | 7.4% |
| Poverty Severity Index | 5.3% | 4.6% | 2.7% | 3.2% | 3.1% |
| Gini Coefficient | 0.27 | 0.26 | 0.26 | 0.27 | 0.28 |

**Source**: National Planning Commission (2017)

The trends in consumption based inequality as measured by the Gini Coefficient over the period of 1995/96-2015/16 are reported in Table 1.5. Even though, rural poverty has been declined across all measures (incidence, depth and severity) as discussed earlier, inequality in rural Ethiopia is appeared to increase slightly over the same period of time. The rural Gini Coefficient inequality was about 0.27 in 1995/96 and rose to 0.28 in 2015/16.

## 1.5 Organization of the Study

This thesis is organized into five chapters. The first chapter presents the introductory part of the study. The second chapter deals on review of both theoretical and empirical literatures related to agricultural technology adoption, poverty and income distribution. Moreover, it identified the research gaps on the area and provided the conceptual framework of the study. The third chapter focuses on objectives of the study followed by the research methodology employed to achieve its objectives. The first section of the third chapter includes the general and specific objectives, research questions, hypothesis and significance of the study. The second section deals with research methodology whereby data sources, method of data collection, sampling techniques and method of data analysis are discussed. While chapter four concerned on presentation of results and discussion on the key findings, the study ended with chapter five by providing conclusion and recommendation, and forwarding suggestions for further research.

# CHAPTER TWO

# LITERATURE REVIEW

## 2.1 Introduction

This chapter provides review of both theoretical and empirical literatures related to the area of the study. In the first section, theoretical reviews of literatures are presented. In this section, topics such as overview of technology adoption, theories and models of technology adoption, concepts of poverty and income inequality and their measurement, and methods of impact evaluation are discussed. The second section reviewed empirical works conducted in various areas of the globe related to adoption of agricultural technology and its determinant, and impact of agricultural technology on poverty and income distribution. The third section of this chapter has tried to identify research gaps from the existing literatures. Finally, the fourth section provided the conceptual framework of the study.

## 2.2 Theoretical Review of Literature

### 2.2.1 Overview of Technology Adoption

The importance of technological progress for economic development is well-known everywhere in the world. It is the engine of society and its economic development. According to (Betz, 2011), "technological progress has become the major historical factor in enabling economic development in the modern world — technology creating wealth". According to Porter 1985, technology can be described as "the integration of people, knowledge, tools, and systems with the objective to improve people's lives". Similarly, Betz (2011), defined technology as " a system of knowledge about how to manipulate nature in a logical scheme to achieve a functional transformation". Technology is the means of innovating new tools or methods serving humans.

According to Premkumar & Roberts (1999), "an innovation is any idea, practice or object that is perceived as new by the adopter". However, innovation of technology by itself is not the ending point. To see the fruits of innovation, it should be put into practice. The basic task, therefore, is speeding up of diffusion of innovation to be adopted by potential adopters. Rogers (2003) defined diffusion as "the process by which an innovation is communicated through certain channels over time among the members of a social system". It is the spread of information about innovations by using interpersonal communication and mass media.

Adoption is considered as "a decision to make full use of an innovation as the best course of action available" (E. M. Rogers, 2003). He further argued adoption depends on five characteristics of innovation; relative advantage, compatibility, complexity, trialability, and observability.

According to Ellis (1993), technological change in the agricultural sector is defined as "the adoption of new method of production by farm households". Agricultural technologies include chemical fertilizers, High Yielding Varieties of seeds, irrigation and soil quality enhancing technologies which farmers use in order to enhance the production and productivity of the land (Abrha, 2015).

### 2.2.2 Origin of Green Revolution

The term Green Revolution can be described as "a series of research, development, and technology transfer initiatives, occurring between 1943 and the late 1970s in Mexico, which increased industrialized agriculture production in many developing nations" (Ameen & Raza, 2017). According to Pinstrup-Andersen and Hazell (1985), Green Revolution is " a term used for rapid increases in wheat and rice yields in developing countries brought about by improved varieties combined with the expanded use of fertilizers and other chemical inputs".

The term Green Revolution was first used by William S. Gaud, USAID director in his speech on 8 March 1968. After remembering the impacts of high yield varieties of wheat and rice on productivity in Pakistan, India, Turkey, and Philippines, he noted that "These and other developments in the field of agriculture contain the makings of a new revolution. It is not a violent Red Revolution like that of the Soviets, nor is it a White Revolution like that of the Shah of Iran. I call it the Green Revolution" (Gaud, 1968).

Norman Borlaug, the 1970 Noble Peace Prize Winner, is considered as the “Father of Green Revolution”. He is known for his research contribution in Mexico who developed disease-resistant high-yield wheat varieties. He is credited for the withdrawal of a billion people from starvation through agricultural research. During the Green Revolution period of Mexico, agricultural output increased by about fourfold from 1940 to 1965 which made the country to be self-sufficient in food requirements by extrication from importing of food (Sonnenfeld, 1992).

In the mid-1960s, scientists developed modern varieties of rice and wheat that were subsequently released to farmers in Latin America and Asia (Evenson & Gollin, 2003). India is among the most successful country in the era of Green Revolution. By realizing the importance of modern wheat varieties, the Indian Agricultural Research Institute (IARI) has requested the help of Norman Borlaug in 1962 and he visited India in March, 1963. Based on his observation Dr. Borlaug sent various varieties of wheat to IARI in November, 1963 (Swaminathan, 2017b). During that period IARI was led by M. S. Swaminathan and he is known as “The Father of Green Revolution in India" for his role in introducing and further developing high-yielding varieties of wheat in India.

Consequently, India becomes a food-sufficient country within a very short period of time. Wheat production has increased from 12 million tons in 1966/67 to 20 and 26 million ton in 1969/70 and 1971/72 respectively (Chakravarti, 1973). According to Swaminathan (2017a), “The yield increases achieved in wheat and then in rice which occurred in just about half decade is far in excess of the yield increases during the preceding 4000 years”.

Though the Green Revolution occurred in the 20th century resulted in advancement in crop production in Latin American and Asian countries, it was not successful in Africa due to daunting political and ecological challenges (Blaustein, 2008) and unsuitability of seed varieties (Evenson & Gollin, 2003).

### 2.2.3 Technology Adoption Theories and Models

With the advancement of technologies over time, the adoption of these technologies by consumers depends of various factors such as technology availability, convenience, security, consumers' need etc. (Lai, 2017). Various theories and models have been developed to describe consumers' acceptance of new technologies.

This section, therefore, provides a comprehensive literature review of technology adoption models and theories. It includes the Diffusion of Innovations Theory, the Theory of Reasonable Action (TRA), the Theory of Planned Behavior (TPB), the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT).

#### *2.2.3.1 Diffusion of Innovation Theory*

The theory of Diffusion of Innovation was developed by Everett Roger's in 1960 and has been widely applied by researches over the years. The theory proposes that spread on new idea depends on four elements (the innovation, communication channels, time and social system). According to this theory diffusion of technology comprises of five steps: knowledge, persuasion, decision, implementation, and confirmation (Rogers, 2003).

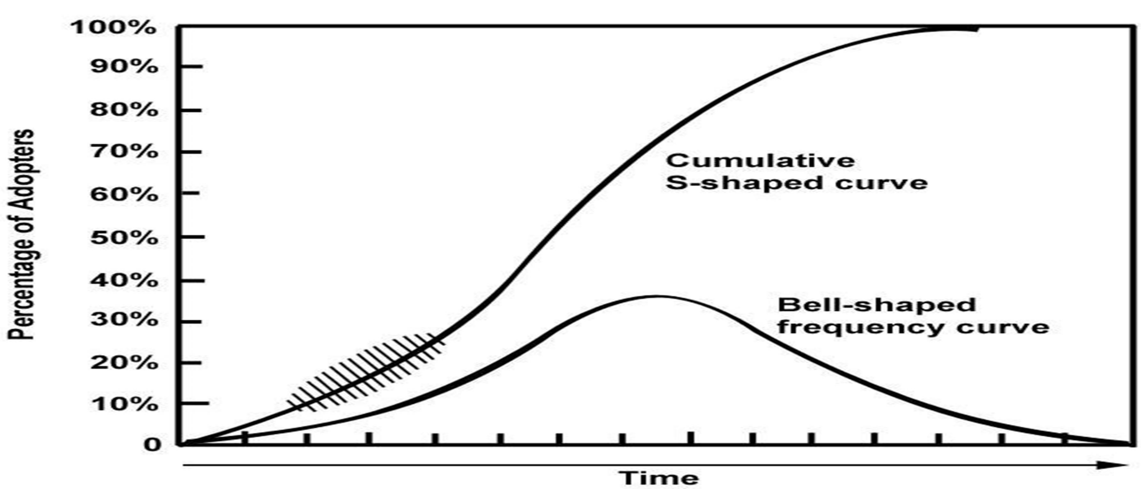


**Figure 2.1 S-shape curve of the diffusion process and the bell-shaped frequency curve.**
**Source:** Rogers (2003)

Adoption of technologies resembles to S-shaped curve when mapped overtime on the cumulative number of adopters and it follows a bell-shaped when it is plotted on the basis of frequency (figure 2.1). At the initial stage of the adoption process, only a few potential adopters adopt the technology and the slope of the curve slowly increases. The adoption will increase at an accelerating rate until it reaches the maximum where nearly half of the potential adopters adopted the technology. Finally, until the remaining potential adopters adopted the technology, the rate of adoption increases at a decreasing rate (Rogers, 2003). According to Betz (2011), “A technology S-curve is a common pattern of progress in a technology’s principal performance parameter over time, with an initial exponential growth, intermediate linear growth, and an eventual asymptotic limit”.

The S-shaped pattern of technology adoption determined by communication channels and other several social characteristics of the potential adopters including, education, age, attitude towards risk, etc. (Rogers, 2003). It is a common phenomenon that large farmers tend to adopt new technology first, followed by small farmers (Ruttan, 1977).

#### *2.2.3.2 Theory of Reasoned Action*

The Theory of Reasonable (TRA) Action was proposed by Fishbein and Ajzen (1975). The theory identified three constructs, namely attitude, subjective norm, and behavioral intention. According to TRA behavioral intention of a person depends on his attitude (beliefs about a particular) and subjective norms (influence of people in one's social environment on his behavioral intentions) as shown in figure 2.2 (Sharma and Mishra, 2014).

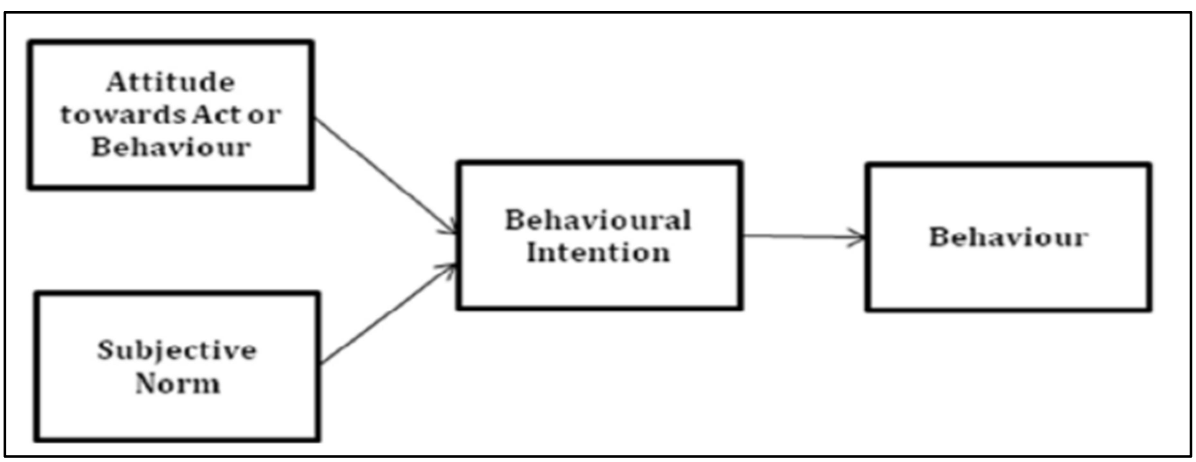


**Figure 2.2 Theory of Reasoned Action.**
**Source:** Fishbein and Ajzen (1975)

### *2.2.3.3 Theory of Planned Behaviour*

Theory of Planned Behavior (TPB) was proposed by Ajzen (1991) which was developed from the TRA. The theory includes one addition construct (Perceived behavioral control) in addition to subjective norms and attitudes which make the TRA. It refers to the perception of people on the ease or difficulty of execution the behavior of subjective norms and attitudes. According to the TPB, Intention is affected by subjective norms, attitudes, and perceived behavioral control. Finally, personal intention and perceived behavioral control affect actual behavior as shown in figure 2.3.

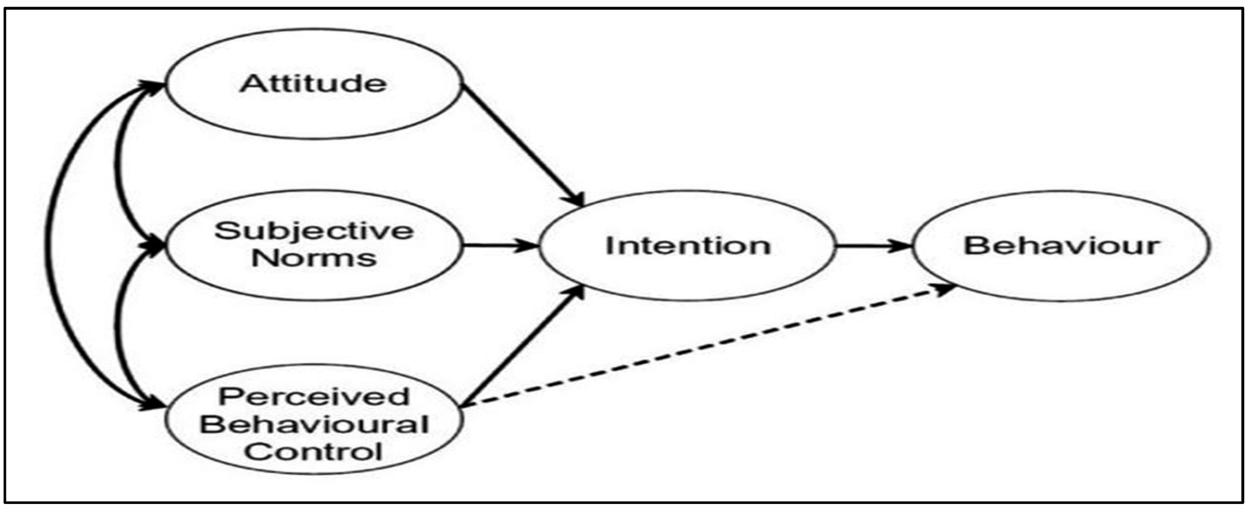


**Figure 2.3 Theory of Planned Behavior.**
**Source:** Ajzen (1991)

### *2.2.3.4 Technology Acceptance Model*

Davis (1989) introduced Technology acceptance model (TAM). The model indicates that behavioral intention to use a system is influenced by perceived ease of use (the extent to which a person believes that using the system will be free of effort) and perceived usefulness (the extent to which a person believes that using the system will enhance his or her job performance). Moreover, perceived ease of use also affects perceived usefulness (see figure 2.4).

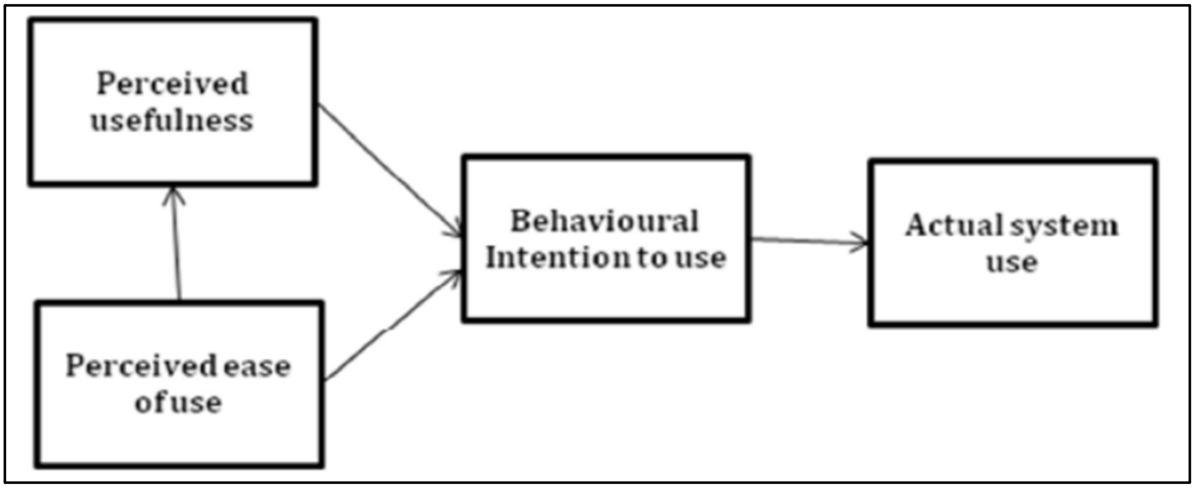


**Figure 2.4 Technology Adoption Model.**
**Source:** Davis (1989)

Though TAM is one of the most widely applied models, it is criticized due to its ignorance of the social influence on technology adoption (Taherdoost, 2018). As a result, TAM was extended to TAM 2 by including additional factors to improve explanatory power, specificity and adaptively of TAM (Maillet et al., 2015).

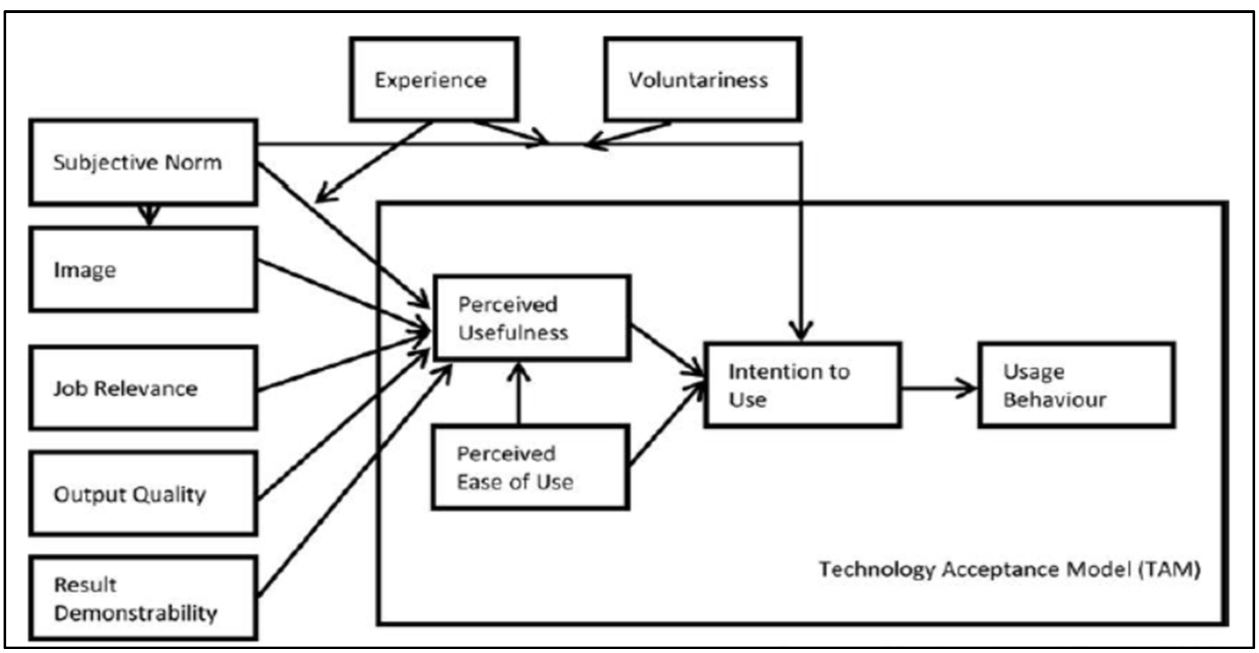


**Figure 2.5 Technology Acceptance Model 2 (TAM 2).**
**Source** : Venkatesh and Davis (2000)

Venkatesh and Davis (2000) proposed TAM 2 by including additional key determinants of perceived usefulness and usage intentions such as social influence processes (voluntariness, subjective norm and image) and cognitive instrumental processes ( output quality, job relevance, result demonstrability, and perceived ease of use). According to TAM 2, that both cognitive instrumental processes and social influence processes were found to be significant determinants of user acceptance. Though TAM 2 increased predictive power, it is criticized since it is more complicated compared to the original TAM (Bagozzi, 2007).

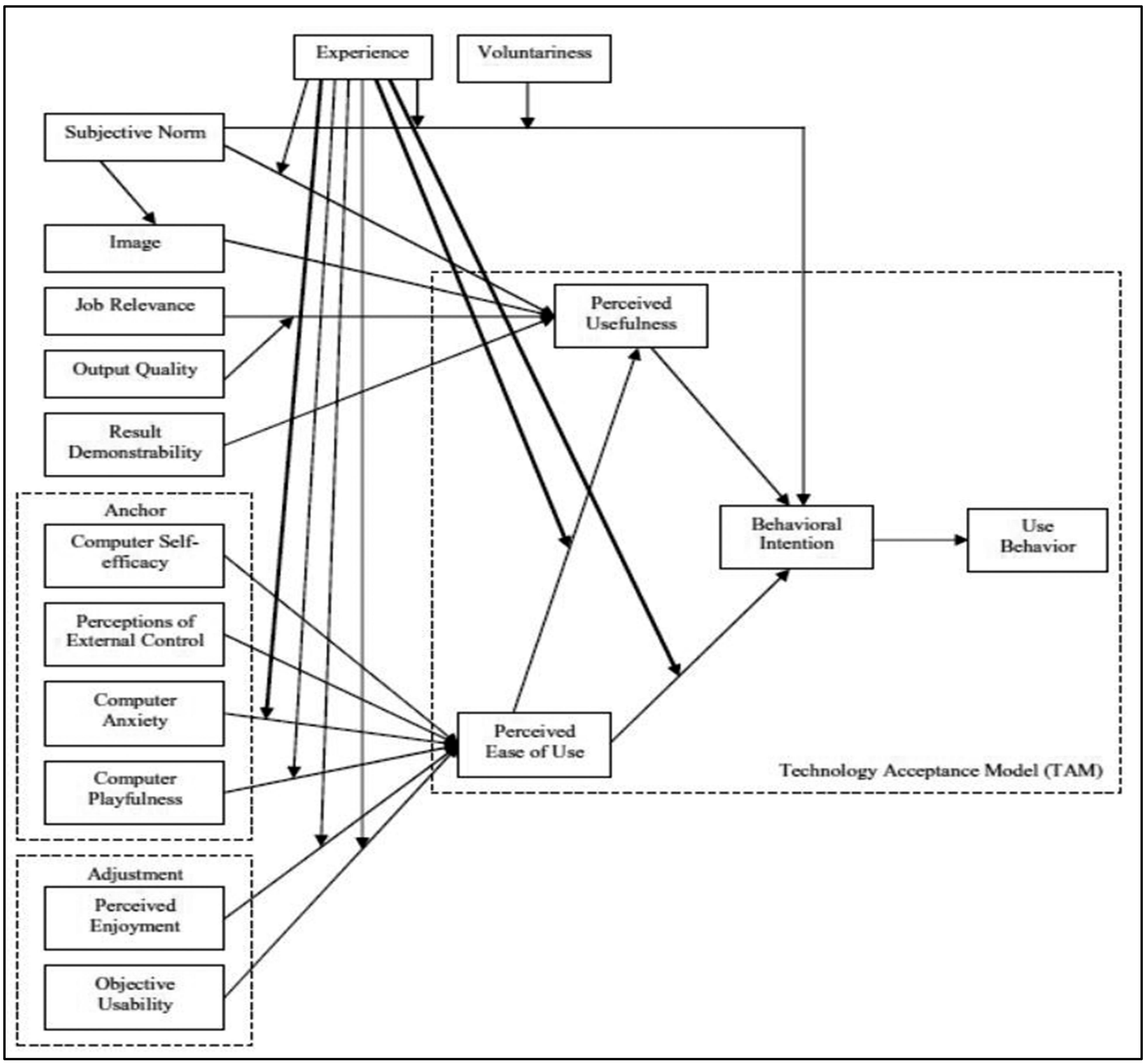


**Figure 2.6 Technology Acceptance Model 3 (TAM 3).**

**Source:** Venkatesh and Balla (2008)

Venkatesh and Bala (2008) further developed TAM 3 by including additional predictors of perceived ease of use and perceived usefulness over TAM 2. TAM 3 includes system characteristics, social influence, individual differences, and facilitating conditions which affects perceived ease of use and perceived usefulness. See the detail in Figure 2.6.

### *2.2.3.5* Unified Theory of Acceptance and Use of Technology

The Unified Theory of Acceptance and Use of Technology (UTAUT) was established by Venkatesh et.al. (2003). UTAUT was developed by reviewing previous models and theories of adoption as shown in figure 2.7. The model tested the significance of various constructs and identified four significant determinants of intention to use information technology: performance expectancy, social influence, effort expectancy and facilitating conditions. However, the remaining three constructs (self-efficacy, attitude, and anxiety) were removed since they were found to be statistically insignificant. Moreover, UTAUT has included four key moderators like age, gender, experience and voluntariness.

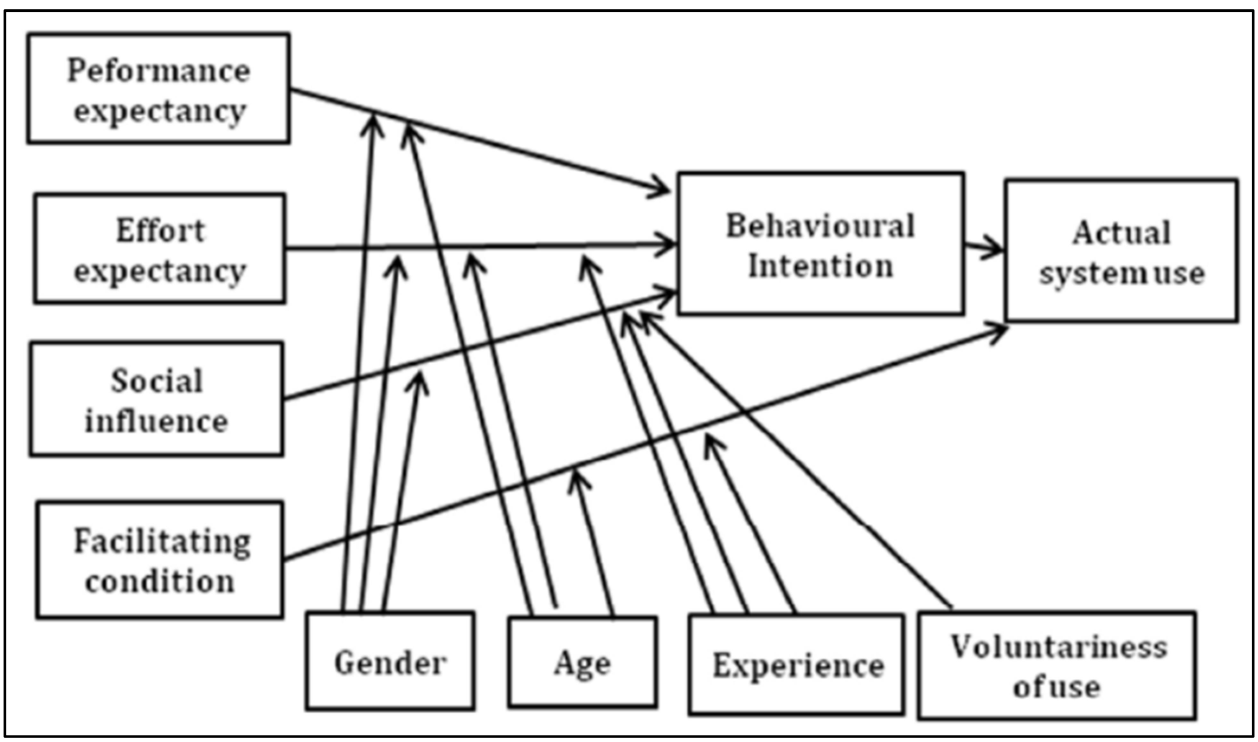


**Figure 2.7 Unified Theory of Acceptance and Use of Technology (UTAUT)**
**Source:** Venkatesh et. al. (2003)

Although UTAUT is found to be superior on the ground of its ability to explain 70% of the variance, it is criticized in terms of its complexity, inability to explain individual behavior and not being parsimonious. As a result, it is rarely applied in empirical studies; it rather has been used for theory-building (Sharma and Mishra, 2014).

### 2.2.4 Concepts of Poverty and Poverty Measurement

There is no consensus on the definition of poverty since it affects many aspects such as physical, moral, and psychological conditions of humans. As a result, it is difficult and there is considerable variation concerning the way in which poverty is perceived and measured. However, these definitions are generally relying on two broad categories. The common applicable definition of poverty is related to the first category in which poverty is linked only with most economic, income or consumption deprivation. Here poverty is understood as having an income below a certain minimal requirement to fulfill basic necessities. In this regard, World Bank (1990) defines poverty as "the inability to attain a minimal standard of living".

In the second framework, some other scholars and organizations defined poverty from a very multidimensional perspective. For these scholars and organizations, poverty is not only about having not enough income to fulfill minimal needs rather it is understood from multidimensional stances. The tough diversion here is that poverty has to be understood and measured through end indicators like health access, education access, living standard improvement, empowerment and sustainability rather than only through income (Alkire & Santos, 2010).

Generally, poverty has a multi-dimensional aspect which is characterized by inadequate food, lack of access to nutrition, health, education, and sanitations. In this regard United Nations (UN) defined poverty as "a condition characterized by severe deprivation of basic human needs, including food, safe drinking water, sanitation facilities, health, shelter, education and information" (UN, 1995).

Moreover, literatures on the area identified two types of poverty; absolute and relative poverty. Absolute poverty is defined as the inability to meet the minimum level of income to satisfy the basic needs of survival such as food, cloth and shelter (Todaro & Smith, 2012). It is measured in absolute terms and needs required for subsistence life are considered to be fixed (Wratten, 1995)

On the other hand, relative poverty refers to the extent to which a household's income falls below the average threshold income of the economy. It is measured with respect to the general distribution of income or consumption in various sections of the population or a country. It is more flexible than absolute poverty since it allows the minimum needs to be revised when living standards of the society changes (Wratten, 1995). However, it has two main disadvantages. First, it is not terribly use full if one wants to monitor poverty over time or space. In this sense, no matter how much income increases, some person will always be judged poor in comparison with others even though their income increases. Second, it does not say anything about the level of deprivation of the various sections of the people.

The above two definitions indicated that absolute poverty means about not having enough income to fulfill biological needs like food, shelter and clothes and which is very objective while relative poverty is the relative economic status of some people in comparison to other members in a given country or between countries.

The first step in the measurement of absolute poverty is the computation of poverty line. Poverty line is a cut-off line that reveals the living standard below which a person is classified as poor (World Bank, 1990). There are two common approaches for determination of poverty line; the Food-Energy-Intake (FEI) and the Cost of Basic Needs (CBN) approaches (Thorbecke, 2003). In FEI approach, the basic idea is to determine the consumption per capita/per adult equivalent which is required to satisfy its calorie requirement. In this regard, poverty line is defined as the amount of income or food consumption expenditure required for a person to meet its food energy requirement. One of the attractiveness of this approach is it automatically yield the non-food components of income or expenditure. This is done using a regression of the cost of a basket of commodities consumed by each household (individuals over the calorie equivalent or the food energy implied from the basket of goods (Greer & Thorbecke, 1986). One difficulty related to setting the food energy requirement is the presence of significant variations among people in physical feature, work habits, and the existence of many food combinations which yield the minimum required level of nutrition.

On the other hand, CBN approach focus on the income or expenditure required to acquire selected basket of goods which meets the basic needs of survival including food, shelter, and clothing. This method has both food and non-food components. The food component of the poverty line is determined by selecting a set of food items mainly consumed by the poor society that satisfy the minimum predetermined level of calorie requirement. The selected basket of food is valued at local prices. Finally, in order to get a total minimum income/expenditure, some estimate of the non-food component is added by taking some portion of the food poverty line.

Given the advantage and disadvantage of FEI and CBN approach, the better and most widely used method of estimating poverty line is the CBN approach since it provides a more representative result and consistent with real expenditure across space, time and socio economic group (National Planning Commission, 2017).

The other important issue while measuring poverty is the choice between consumption expenditure and income as well-being indicator. Many development economists argue that consumption is a better proxy in measuring poverty than income since the former better reflects the standard of living of households. According to Grootaert (1986), in developing countries, consumption expenditure is a preferable measurement of welfare than income due to its superiority in capturing household's consumption capabilities. Similarly, National Planning Commission (2017) argue that consumption expenditure is a better way of poverty measurement over income as it better reflects long run welfare.

### 2.2.5 Income Inequality and Its Measurement

A more equitable distribution of income is a major policy concern of policy makers. In this regard, Hoeller, Joumard, and Koske (2014) argue that economic performance should not take in to account only economic growth, but also consider distribution of income among the society. According to Todaro and Smith (2012), policy makers are worried about the distribution of income because extreme disparity in distribution results in economic inefficiency and leads to social and political instability.

Income inequality refers to "the disproportionate distribution of total national income among households" (Todaro & Smith, 2012). Generally, there are two major types of income distribution measurements; the personal or size distribution of income and the functional or distributive factor share distribution of income. The most commonly used measure of income distribution is, however, the personal or size distribution of income. It basically focuses on individual persons or households with respect to the incomes they receive without considering how they received it. In this type of inequality measurement, attention is placed only for the amount of income each individual/household received in relation of the total income irrespective of the source of income it derived from.

On the other hand**, functional distributions of income** placed emphasis on the sources of income. It measures the share of income received by each factors of production such as labor, capital and land from the total national income. Rather than focusing on individuals/households, it compares the percentage of income that one factor of production, say labor, and receives to the other factors such as capital and land.

Based on the personal or size distribution of income, Todaro and Smith (2012) identified three types of inequality measurements; Kuznets ratio, Lorenz curve and Gini Coefficient.

**Kuznets ratio** is measured by dividing the incomes received by the top 20% of the population to the bottom 40% of the population. Hence, in the derivation of Kuznets ratio, all individuals need to be arranged in ascending order based on their personal incomes.

**Lorenz Curve** depicts the quantitative relationship between the percentage of income recipients and the percentage of the total income they received in a given time period (see figure 2.8). In constructing a Lorenz curve, while the horizontal axis shows cumulative percentages of recipients of income (population), the share of total income received by each percentage of the population are plotted on the vertical axis. The curve is enclosed in a square, and the diagonal line shows the line of perfect equality (the percentage of income received and the percentage of income recipients at each point on the diagonal line are exactly the same). As the Lorenz curves far away from the diagonal line, the degree of income inequality worsens.

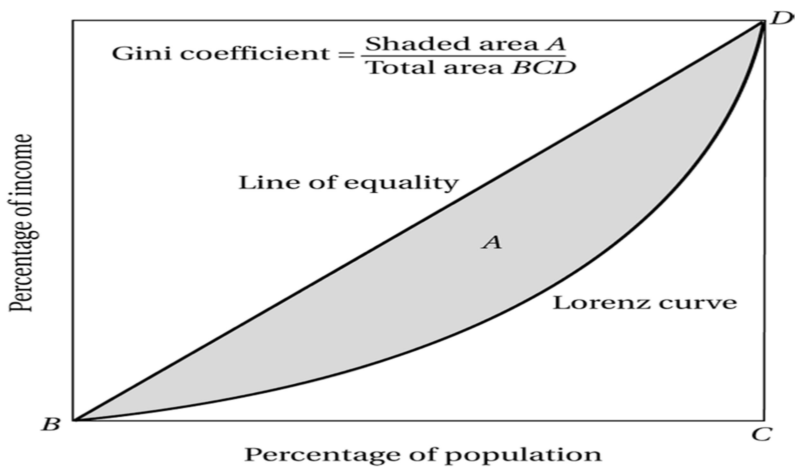


**Figure 2.8 Lorenz Curve and Gini Coefficient.**

**Source: Todaro and Smith (2012)**

**Gini Coefficient** is the most convenient measure of the relative degree of income inequality. According to Shorrocks (1980), Gini coefficient is the most widely applicable measurement of income distribution which satisfies the four desirable properties of inequality measures; Scale independence, population independence, Symmetry and the Pigou-Dalton Transfer principle. As it is indicated in figure 2.2, Gini Coefficient is the ratio of the area between the Lorenz curve and the diagonal line (Shaded area A), and the area of the triangle (total area BCD). Its value ranges from zero to one where Gini coefficient of zero implies perfect equality while one indicates the existence of perfect inequality in the distribution of income.

### 2.2.6 Methods of Impact Evaluation

According to Gertler, Martinez, Premand, Rawlings, and Vermeersch (2011), impact evaluation is the way of checking whether an intervention is responsible for the change in the outcome variable or not. The objective of impact evaluation is quantifying the impacts of programs and projects on the beneficiaries such as individuals, households and the community (Khandker, Koolwal, & Samad, 2010) Similarly, Baker (2000) argue that impact evaluation is aimed to examine whether the implemented program resulted in the needed impact on institutions, households and individuals and whether the impacts are attributed to the intervention.

Impact evaluation helps policy makers to make informed decision about the effectiveness of programs (Gertler et al., 2011). In this regard, Khandker et al. (2010) asserts that in impact evaluation the possible ways in which the intervention affects the beneficiaries should therefore be critically assessed.

Even though various techniques of impact evaluation methods are found, choosing a specific evaluation method needs careful investigation. According to Baker (2000), given various choices, selecting an appropriate technique is not an easy task since the results may be varied based on the methods used. Generally, methods and designs of impact evaluation rely on two broad groups; experimental designs and Quasi -experimental Designs.

**Experimental designs** are also known as randomization. In this type of design, treated and control groups can be compared by allocating interventions randomly (Baker, 2000). According to Blundell and Dias (2000), experimental design yields the correct missing counterfactual that avoids the problem of evaluation related to self-selection. Similarly Gertler et al. (2011) argue that randomized assignment creates comparison between the treated and control groups with low probability of bias which made experimental design a superior valuation method

Even though, experimental designs are often believed to be the most robust method of evaluation, in practice there are several problems. According to Blundell and Dias (2000), these designs are expensive, can't be easily applicable in *ex ante* studies and it assumes the untreated group totally unaffected by the intervention. In practice, however, data usually obtain from observational studies rather than randomized trials (Becker & Ichino, 2002).

Quasi-experimental (nonrandom) methods become relevant types of impact evaluation when random assignments of interventions are found to be difficult. Quasi-experimental designs create comparison group or commonly known as the counterfactual having similar observed characteristics to the treatment group (Baker, 2000; P. J. Rogers, Hawkins, McDonald, Macfarlan, & Milne, 2015). These methods are easier and inexpensive to implement, they can be applied on the existing data and used for ex-post studies (Baker, 2000).

According to Blundell and Dias (2000), the choice of appropriate method for Quasi- experiment design rely on " the type of information available to the researcher, the underlying model and the parameter of interest". Propensity score matching (PSM), instrumental variables (IV), difference in differences (DD) and Heckman selection estimator are the most commonly applied impact evaluation techniques of quasi-experimental design.

**Propensity Score Matching (PSM):** This method of impact evaluation can be applied either with longitudinal or cross-sectional data which require detailed information for both the treated and comparison group (Blundell & Dias, 2000). According to Baker (2000), matched comparison methods are the best among quasi-experimental design methods. "PSM constructs a statistical comparison group that is based on a model of the probability of participating in the treatment, using observed characteristics" (Khandker et al., 2010). PSM compares each observation of the treated group with the control group having similar observed characteristics where the mean outcome difference between the two groups yields the average treatment effect of the intervention (Becker & Ichino, 2002). In PSM, four methods have been mostly used to match treated and untreated groups; Nearest-Neighbor Matching, Kernel Based Matching, Radius Matching and Stratification Matching.

**Instrumental Variables (IV)**: This method uses variables related to the decision of participation but not related to the outcome variable (Blundell & Dias, 2000). It, therefore, gives the needed randomness in assignment of interventions. According to Baker (2000), IV method "identifies the exogenous variation in outcomes attributable to the program, recognizing that its placement is not random but purposive". However, the relevance of IV method relies on the existence of valid instruments, which is usually a challenging task for researchers (Kassie et al., 2011).

**Difference-in-differences (DD)**: is commonly known as "double difference". It "estimates the difference in the outcome during the post intervention period between a treatment group and comparison group relative to the outcomes observed during a pre intervention baseline survey ” (Khandker et al., 2010). In order to employ DD technique, therefore, at least one period preintervention and postintervention observational data should be available.

**Heckman Selection Estimator**: “is a two-step method that uses an explicit model of the selection process to control for the part of the participation decision that is correlated with the error term in the outcome equation” (Blundell & Dias, 2000). Unlike PSM which accounts for selection on observables, in Heckman approach selection is considered on unobservable characteristics.

## 2.3 Empirical Literature Review

Worldwide, various studies were conducted on agricultural technology adoption. This section, therefore, presents the reviews of existing empirical works on agricultural technology adoption and its effects. During reviewing of studies, emphasis was given for the type and source of data used, method of estimation employed and the results obtained. For the sake of convenience, it starts with the review of international studies followed by studies conducted in Ethiopia.

### 2.3.1 International Studies on Agricultural Technology Adoption

In this sub-section, studies carried out in various countries of the world related to agricultural technology are reviewed. For the purpose of convenience, it starts with studies done on economic analysis of technology adoption followed by its determinants, and their impact on poverty and income distribution.

Studies conducted on the economic assessment of agricultural technologies revealed that adoption enhances agricultural productivity which leads to the rise in revenue and profit of farmers from production.

A study by Devi and Ponnarasi (2009) estimated the economic benefit of modern rice production in India by using survey data collected from 100 rice cultivators in Tamil Nadu. The results of the farm management analysis technique found that the benefit-cost ratio in modern rice production was higher than the conventional method of production by 44%. Moreover, the logit model estimated that age, size of farm, farm income, family size (earners) and extension service affects technology adoption positively while literacy level influences negatively.

Akinola and Owombo (2012) analyzed mulching technology adoption in the production of Yam by using survey data collected from 105 households in Osun State, Nigeria. The farm budget approach estimation shows that the benefit-cost ratio for adopters was 4.79 while it was 3.13 for non-adopters. Furthermore, the probit estimates found that hired labor affects adoption positively while the influence of family size was estimated to be negative.

Birthal, Nigam, Narayanan, and Kareem (2012) examined the economic benefit of adoption of improved variety of groundnut in India. The study conducted based on a field survey of 400 farmers in Anantapur district. The paper estimated that the use of improved variety had 23% yield advantage, required 17% less of variable cost and had 30%t less variability in its yield as compared to the ruling variety in the district. Moreover, the result shows that the net-revenue obtained from the adoption of the improved groundnut variety was higher by 36% than other varieties. The probit model estimated that sex, family size, and non-groundnut income influence adoption decision.

Adofu, Shaibu, and Yakubu (2013) studied the economic effect of agricultural technologies adoption on Cassava crop in Nigeria. It was conducted by using survey data gathered from 150 farmers in Kogi state through Multistage sampling technique. The results indicate that 79.33% of the respondents adopt improved cassava variety. The economic analysis of the study shows that the net revenue from agriculture after technology adoption was higher than before adopting agricultural technologies by 2.7 fold.

Myint and Napasintuwong (2016) studied paw san rice adoption in Myanmar. Data were obtained from 370 rice farmers in Ayeyarwaddy and Sagaing regions. The results show the existence of significantly higher revenue due to adoption of pan saw rice cultivation. Moreover, the employed logit model revealed that education, experience, and large-scale farm positively affect adoption of Paw San rice varieties.

A study by Hambirrao (2016) analyzed the economic benefits of technology adoption on sugarcane in India based on survey data collected from 270 sugarcane cultivators in Maharashtra state. Based on descriptive analysis, the results indicate that high technology adopter groups of farmers had earned more per hectare yield and profit than that of medium and low adopter groups. High and medium level technology adoption increases sugarcane yield (tons/hectare) by 3.35 -11.15 and 4.85- 14.30 over low adoption respectively. The economic analysis indicates that the incremental benefit-cost ratio of medium and high-level technology adoption over low-level adoption was estimated from 1.08 - 1.63 and from 1.94 - 2.59 respectively.

Another study by Pal et al. (2016) estimated the benefit of pigeonpea seed adoption in India. Data for the study was obtained from 100 households in Karnataka state. The study found that adoption pigeonpea seed production (improved seed) increased the gross return by 32% and the net return of producers by 44% compared to grain production (traditional seed).
Adoption of agricultural technologies can be influenced by various factors. Researchers have tried to identify the major factors that determine households' decision towards adoption of technology based on a cross-sectional study by employing a variety of estimation techniques. Those studies are reviewed as follows.

Bamire, Fabiyi, and Manyong (2002) studied determinants of fertilizer use intensity in Osun State of Nigeria based Tobit model analysis by using survey data collected from 180 respondents. The paper showed that off-farm and net farm incomes and availability of fertilizer significantly influence farmers' fertilizer adoption and use of decision.

A study by He, Cao, and Li (2007) employed a binary logistic regression model to study factors influencing adoption of irrigation and rainwater harvesting technology in China. Based on survey data from 218 randomly selected households, it revealed that education, labor force, extension, positive attitudes for the technology, and Grain-for-Green project participation influences adoption positively whereas age and water storage tanks distance affects negatively.

Langyintuo and Mungoma (2008) employed double-hurdle model to examine the influence of wealth on improved seeds adoption in Zambia by using survey data gathered from 300 farmers in three districts. It revealed that the influence of various factors on improved maize varieties adoption differs between well-endowed and poorly endowed farmers in terms of productive assets. The study argue that in order to enhance adoption and intensity of use of modern varieties, interventions should be done by considering the wealth status of households.

A study by Adeoti (2009) employed the Heckman two-stage regression model to analyze determinants of treadle pump adoption in Ghana depending on primary data obtained from 108 farmers. It revealed that the number of extension visits per year, dependency ratio and region of residence are the key determinants of treadle pump technology adoption.

A study by Uaiene, Arndt, and Masters (2009) analyzed the determinants of agricultural technology adoption in Mozambique which includes improved seed, fertilizer, pesticide, animal traction and mechanization. By using a panel data for the period of 2002 & 2005 collected from 4104 households, the probit model identified that education, credit access, extension service and member in agricultural associations positively influence adoption of technology.

Simtowe et al. (2011) studied the determinants of improved pigeon pea varieties in Tanzania based on survey data collected from 613 farm households. The probit model estimated that access to pigeonpea seed, size of land holding and livestock ownership determines adoption of improved pigeonpea varieties significantly.

Mariano, Villano, and Fleming (2012) identified determinants of modern rice technologies adoption in the Philippines. They used primary data obtained from 3164 rice producers. The estimated logit model and poisson estimators found that education, ownership of machinery, irrigation, profit-oriented behavior of farmers and activities of capacity-enhancement influence adoption of technologies positively while soil and nutrient deficiencies affects negatively.

A study by Mottaleb, Mohanty, and Nelson (2014) employed multinomial logit in order to analyze factors influencing hybrid rice adoption in Bangladesh based on 2008 agriculture census consists of 384,337 households from 25 districts. The results indicate that irrigation facilities, informal loan, land characteristics, road infrastructure and supply of seed significantly influence the adoption of improved rice varieties.

Rahman and Chima (2014) employed a multivariate probit model and studied the factors influencing decisions to adopt for high yield varieties and fertilizers on multiple crops (yam, rice and cassava). Data for the study came from 400 farmers in Nigeria (Anambra and Ebonyi states). The estimated results show that output price, farming experience, remoteness of extension services, credit accessibility and profit influences adoption.

Ghimire, Huang, and Shrestha (2015) studied determinants of improved rice varieties adoption in Nepal by using survey data from 416 farm households in four districts. The results of the probit model indicates that education, seed access, extension services, farm size, endowment of favorable land type, oxen and yield potential determines decision of adoption.

A study by Chandio and Jiang (2018) examined factors influencing adoption of improved seeds of wheat in Pakistan by using cross-sectional data came from 240 wheat cultivators in Naushahro Feroze and Shaheed Benazirabad districts. The results were estimated by probit model. The study indicate that adoption is influenced positively by education, experience on farming, size of landholding, ownership of tube-well, access to credit and extension contact.

Sánchez-Toledano *et al.* (2018) employed survival analysis model to determine factors affecting improved maize adoption. Farm-level data were collected from 200 farmers in Chiapas state, Mexico. The study found that number of generations, training on best farming practices and risk taking behavior of farmers affect adoption positively while the influence of age and family size of the households were estimated to be negative.

By using logistic regression model, Ashoori *et al.* (2019) studied determinants of Modern Rice adoption in Iran. Data were collected from 400 Smallholders in Guilan Province, northern Iran. The study identified perceived importance and profitability of modern rice varieties, farming experience and holdings of livestock as main factors determining adoption of improved varieties of rice.

Subedi *et al.* (2019) investigated factors influencing improved wheat adoption in Nepal. The study used survey data collected from194 wheat producers from Kailali and Sunsari districts and employed probit model of estimation. Age, number of members in the family, schooling years, subsidy and loan provision were identified as significant determinants of adoption. Moreover, the study revealed that low quality of improved seeds, lack of fertilizers, shortage of labour, lack of irrigation, and agricultural machines are the major problems related to wheat production in the study area.

Ambali, Areal and Georgantzis (2021) analyzed adoption of improved rice by giving special emphasis on risk preference of farmers in Nigeria. Survey data and field experiments were conducted from 328 farmers. The study has employed instrumental variable probit model and the results revealed that risk adverse farmers are less likely to adopt improved rice varieties of seeds compared to risk avoidant farmers. Moreover, variables such as religion, sex, location, extension service and perceptions about attributes of technology affected improved rice adoption decision of farmers

Literatures regarding to the impact of agricultural technology adoption on poverty obtained diverse results. Some studies revealed positive and significant impact of agricultural technology on poverty while others found it insignificant.

Mendola (2007) conclude that adoption of HYVs of rice robustly increase household income and reduce poverty in rural Bangladesh. The result shows that on average income of adopters is almost 30% higher than income of non-adopters. The PSM result indicates that adoption reduced the incidence of poverty by abou14%, on average.

Kijima, Otsuka, and Sserunkuuma (2008) investigated the income and poverty effect of improved rice variety in central and western Uganda based on survey data collected from a total of 1340 households. The study employed OLS to estimate the income effect of adoption while its impact on households' poverty was estimated by using simulation analysis. The estimated results indicate that adoption increases per capita income by 12% and reduce incidence of poverty by 5%. Furthermore, this study found that adoption of improved rice variety improve distribution of income because poorer households adopted on large proportion of their land and use more labor during production.

Wu, Ding, Pandey, and Tao (2010) assessed the effect of technology on well-being of farmers in China using PSM analysis method based on three year (2000, 2002 and 2004) paned data of 473 households. The PSM results indicate that adoption improves households' income (measured in log) ranging from 0.325 to 0.480 in 2000, from 0.270 to 0.356 in 2002, and from 0.139 to 0.317 in 2004. The study estimated that the poverty gap among adopters to be 5.0–8.7%, 4.0–6.1% and 1.0–3.2 % lower than non-adopters in 2000, 2002 and 2004 respectively.

Kassie, Shiferaw, and Muricho (2011) studied the impact of improved groundnut varieties on income and poverty reduction in Uganda by using PSM method. Data for the study came from a survey of 927 households in 7 districts of the country. The study indicated adoption significantly increases household crop income by $130-254 and reduce household's poverty by 7–9%.

Asfaw et al. (2012) assessed the effects of improved pigeonpea adoption on households' poverty in rural Tanzania by using PSM and ESR models. The result indicated that the consumption expenditure of agricultural technology adopters in Tanzania is higher than non-adopters ranges from 18 to 28%. Moreover, they indicated that technological adoption had an impact in reducing incidence of poverty, the poverty gap, and the poverty severity by 12-13%, 8-10% and 4.4-8.1% respectively.

In addition, according to a study by Sofolume, Tijani, and Ogundari (2013), indigenous technology adoption increased cocoa productivity and annual income and reduced incidence of poverty in Nigeria. The PSM estimated results show that adopters were less probably to be poor by about 13.6%.

By using DD and PSM techniques, Nyangena and Juma (2014) studied the simultaneous adoption effect of improved maize varieties and fertilizer on maize productivity in Kenya. The data for the study were retrieved from Tegemeo Institute which is composed of two years panel data that cover almost the entire part of the country. Simultaneous adoption of improved maize seeds and fertilizer robustly improve maize productivity by about 230 kg/ha. Moreover, the study revealed that adoption of agricultural technologies as package is more significant than as an individual element.

Kassie, Jaleta, and Mattei (2014) studied the welfare effect of improved maize varieties in Tanzania based on survey data collected from 680 maize producers which covered 60 villages in 4 districts. Estimation has been done by the help of a generalized PSM, probit, linear and Tobit models. The results found that an increase in the area covered by improved maize seeds by one acre decreased the likelihood of a household to be in chronic food insecurity by 0.7-1.2% and transitory food insecurity by 1.1-1.7%.

A study by Audu and Aye (2014) employed OLS model to investigate the impact of improved maize varieties on households'' welfare in Nigeria. The study used survey data gathered from 125 farm households. The study estimated that improved maize varieties significantly improve households' welfare measured by increase in consumption expenditure. Moreover the logit identify age, education, size of the household and off-farm income as significant factors influencing improved maize adoption.

A study by Bezu, Kassie, Shiferaw, and Ricker-Gilbert (2014) evaluates the effect of improved maize varieties on household welfare in Malawi in by using a three-year survey panel data. The study has employed control function approach and IV. It is found that when the area under improved varieties of maize increase by 1%, it increases own maize consumption by 0.34%, household income by 0.48% and value of asset accumulation by 0.24%. Moreover, the study revealed that poorer household benefited more from adoption.

Afolami, Obayelu, and Vaughan (2015) estimated the welfare impact of improved cassava varieties in southwest Nigeria. The study estimated that improved varieties of cassava increase income by 35.6% and per capita consumption expenditure by 10.4% and reduced incidence of poverty by 5.2%. The estimated logit model found marital status, occupation type, improved cassava cutting accessibility and use of radio as main determinants of improved varieties of cassava adoption.

Awotide, Awoyemi, Omonona, and Diagne (2016) employed local average treatment effect technique based on instrumental variable method to evaluate the effect of improved varieties of rice on rice productivity and welfare of households in Nigeria. 481 rice producers were surveyed. The findings of the study indicate that adoption significantly increases rice productivity by 358.89/kg/ha and improve welfare of households measured by total expenditure of households.

According to a study by Budhathoki and Bhatta (2016) in Nepal, the PSM based findings shows that improved varieties of rice increased annual income of households by \$153–185 and consumption expenditure by \$643–907. Data for the study was obtained from 3350 farmers from all agro ecological regions of Nepal.

Sahu and Das (2016) investigated the poverty reduction impact of agricultural related technologies in India by applying PSM technique. The study used household level data gathered from 270 households. They estimated that adoption of agricultural related technologies reduces household poverty significantly ranging from 12.1-17.4%.

A study by Martey (2018) evaluated the impact of organic fertilizer use on households' welfare in Ghana. The study used a nationally representative data consists of 2188 samples and employed double selection and propensity score matching techniques. The study indicates that adoption of chemical fertilizer significantly increases crop income by \$132 and reduces households' poverty by 8%.

Danso-Abbeam and Baiyegunhi (2019) employed PSM technique in order to examine the welfare effect of fertilizer adoption by cocoa producing farmers in Ghana. Field survey was conducted from 838 cocoa producers residing in four regions. The study estimated that adoption resulted in an increase in farm income and per capita consumption by 11.4-16.8% and 11.9-13.3% respectively. Moreover, it revealed that fertilizer adoption is influenced positively by visit of demonstration farms, access to credit, member in farm-based organizations and farm assets of households.

Using DNA-fingerprinted data, Wossen *et al.* (2019) examined the poverty impact of modern cassava varieties in Nigeria. For the purpose of data collection a total of 2,500 households from 16 states were surveyed. The employed IV regression model estimated that improved cassava adoption resulted in a 4.6% reduction in poverty.

Manda *et al.* (2019) studied the effect of improved cowpea varieties on poverty reduction in Nigeria based on primary data obtained from 1525 households in northeast and northwest regions. Results were estimated by using ESR model. The study indicated that improved cowpea adoption resulted in 17 and 24% increase in per capita income and ownership of asset respectively. Moreover, the counterfactual analysis indicated that adoption reduced income and asset poverty by 5%.

Sinyolo, S. (2020) employed PSM method and Tobit selection model to assess the effect of improved maize adoption on food security by using survey data of 415 maize producers in KwaZulu-Natal province of South Africa. The results found that a hectare increase in area of land covered by improved maize varieties resulted in an increase in per capital food expenditure of 4000 Rand.

Lu et al. (2021) studied the adoption impact of improved rice on food security of households based of survey data obtained from 900 households in Northern Ghana. The estimated results of the PSM model indicate that adoption of improved maize varieties increased subjective food security by 28.8%.

Among studies which found insignificant effect of technology on income and poverty, Omilola (2009) argued that use of modern technology in agriculture may not lead to reduction in poverty. The study based on 400 selected households in Nigeria revealed that even though the income of adopters from agricultural income is higher than non-adopters, non-adopters have better probability to get higher income from other sources such as nonfarm activities. Similarly, a study by Cunguara and Darnhofer (2011) evaluated the income effect of technologies (such as, improved granaries, improved maize varieties, mechanization, and animal traction) in rural Mozambique by using the doubly robust estimator regression and PSM methods and it revealed that adoption did not have a statistically significant effect on income of households.

Studies conducted on the effect of agricultural technology on distribution of income found mixed results. Some studies revealed that adoption of agricultural technology worsen income inequality; while others found that technology adoption reduces income inequality. On the other hand, some other studies argued that adoption of technologies doesn't affect distribution of income.

Based on a review of about 300 studies Freebairn (1995) concluded that adoption of modern agricultural technologies widen distribution of income both on producer-level and intergenerational distribution of benefits.

Rahman (1999) studied the poverty and income distribution effect of agricultural technology in Bangladesh by employing OLS and Gini-decomposition analysis techniques. Data for the study were collected from 406 farm households in three agroecological regions. The study found that exclusive adoption of modern varieties worsens distribution of income by widening the income gap between non-adopters and adopters. But total non-adoption leads to lower income and high incidence of poverty. It further revealed that the lowest poverty incidence and lowest inequality is found in the medium technology adopter villages than the high and low adopter villages. The study, therefore, recommend balanced adoption of improved technology for the betterment of the welfare of the society.

According to Sahoo (2014), new technology adoption worsens distribution of income by increasing the income of the large and medium farmers more than proportionately with the enlargement of farm size due to their greater access to the modern farm inputs. The study found that both the Lorenz curve and Gini Coefficient indicated the existence of greater income inequality in technologically developed villages than technologically less developed villages of Odisha, India.

Similarly, a study by Huang et al. (2015) conclude that adoption of modern varieties of peanut improves income received from peanut and total income of households, however, worsen income inequality in China. The study was carried out by using a survey data gathered from 712 households including 19 provinces, and employed PSM estimation technique and inequality was measured by Gini Coefficients.

In contrary, some other studies revealed that adoption of agricultural technology benefited small farmers to a greater extent than large farmers and hence reduces income inequality.

Warr and Coxhead (1992) examined the effect of agricultural technology progress on income distribution in Philippines based on quintile distribution of income. According to this study, the poorest households not only gain absolutely disposable income from the technical change but they also gain proportionately the most. These results indicate that technical change in Philippine agriculture lowers the degree of income inequality since the poorest groups benefited more proportionately.

Ut, Hossain, and Janaiah (2000) examined the income distribution effect of modem farm technology in Vietnam. The study collected data from a total of 376 farm households drawn using a multistage random sampling method. Based on the estimated Lorenz curve and Gini coefficient, the study observed that the distribution of income among the households is appeared to be better for modern varieties adopter households than non-adopters which indicate that adoption of agricultural technologies reduces income inequality.

A study by Matuschke, Mishra, and Qaim (2007) in India revealed that adoption of hybrid wheat is not biased for larger farms; rather smallholder farmers are more benefited. This finding is also supported by the study of Becerril and Abdulai (2010) in Mexico. The PSM model estimated that adoption of improved varieties of maize benefited small farmers to a greater extent than large farmers.

A study by Kilima et al. (2013) investigated the impact of improved technologies on income inequality by using data collected from 240 farmers from on-farm research projects in Tanzania. The study estimated that income inequality have been reduced after the intervention (adoption of improved technologies). The Gini coefficients appeared to be 0.54 before the intervention and reduced to 0.51 after adoption of technologies whereas the Theil-T statistics were 0.61 before and declined to 0.52 after the adoption of technologies.

On the other hand, Otsuka, Cordova, and David (1992) studied on the impact of green revolution on income distribution in Philipines based on selected households survey located in two top rice growing villages using stratified random sampling. The results indicate that adoption of modern rice varieties have not been significantly affects distribution of income at the study area because the inequality impacted from rice income was mitigated due to increase in income from non-rice production through resource reallocation and land reform activities. Similarly Hossain (1992) observed that the application of seed-fertilizer-irrigation technology did not intensify income inequality in Bangladesh.

Lin (1999) studied the effect of hybrid rice adoption on distribution of income in China based on data collected from 500 households by using General Equilibrium Model. The net effect of hybrid rice's on income inequality was estimated to be negligible due to the offsetting effect in production-mix adjustments; the income of adopter increased from rice while for non-adopters their income increased from non-rice income sources. A more similar result is found by Ding, Meriluoto, Reed, Tao, and Wu (2011) which indicated that even though improved upland rice adopters received nearly 15% higher income than non-adopters, its impact on income inequality was negligible; the Gini coefficients of technology adopters and non-adopters were nearly the same. It was due to the existence of nearly equivalent adoption of improved technology by higher income and lower income households.

### 2.3.2 Agricultural Technology Adoption Studies in Ethiopia

Even though few studies are found on agriculture technologies In Ethiopia, the existing works have focused on adoption decision of farmers and their impact on poverty. For the purpose of convenience, those studies in Ethiopia are reviewed and presented chronologically.

A study by  Alene, Poonyth, and Hassan (2000) using Tobit model has identified determinants of improved maize varieties adoption in Ethiopia. Data for the study collected from 110 farmers from West Shoa Zone. Accordingly, education, age, household labor, extension services, farm size, farm income, improved maize availability and off-farm income were found as significant determinants of adoption and intensity of improved maize application.

Croppenstedt, Demeke, and Meschi (2003) studied determinants of adoption of fertilizer in Ethiopia based on a survey covered 6147 cereal producing households from four regions. By applying double-hurdle model, they found that access of fertilizer, credit availability, family size, education and value-to-cost ratio are the major factors that affect households' decision for fertilizer adoption.

According to Dadi, Burton, and Ozanne (2004), economic incentives such as prices are appear to be the most important determinants for the speed of adopting new technologies followed by oxen ownership and infrastructural factors. However, the influence of other factors such as agricultural inputs and households characteristics is found to be very low. The study was conducted based on accelerated lifetime model by using survey data of 200 households from East and West zones, Ethiopia.

Feleke and Zegeye (2006) used logit model to determine factors affecting adoption of improved maize varieties in southern Ethiopia.  The data for the study collected from 222 maize producing farm households residing in three selected zones. While education, extension service, access to credit, labor force and land size influences adoption positively, the influence of distance to the market is found to be negative and significant.

Fufa and Hassan (2006) conducted a study on factors affecting adoption and intensity of fertilizer application on maize crop in Ethiopia by employing Probit and Tobit models. It was conducted based on survey data obtained from 100 maize producing households in Oromiya national regional state.  The result indicated that the use and intensity of fertilizer adoption is influenced by farmers' age, rainfall expectation and perception of fertilizers price.

Asfaw, Shiferaw, Simtowe, and Haile (2011) examined the determinants of agricultural technology adoption and their impact on farmers' integration into output market in Ethiopia based on cross-section sample of 700 farmers. The Double-Hurdle model results show that awareness about improved chickpea varieties, active labor force availability and wealth of households influences adoption of technology. Moreover, the PSM model show that adoption impacted on farmers' integration into output market.

Beshir, Emana, Kassa, and Haji (2012) studied factors influencing adoption of chemical fertilizer by using double hurdle approach. Data gathered from 252 selected farmers in North Eastern Ethiopia. The study found that gender, age, size of farm land, education, ownership of livestock, off-farm income, distance from market/input supply, extension service and access to credit affects the adoption of inorganic fertilizer.

A study by Hailu, Abrha, and Weldegiorgis (2014) investigated determinants adoption and its effect on farm income by using probit and OLS models respectively in Northern Ethiopia. Fertilizer adoption is influenced by sex, irrigation, off-farm income, market and plot distance while age, credit availability, irrigation and market distance influences HYVs adoption. Additionally, OLS results showed that adoption of chemical fertilizer and HYVS increased income of households by ETB 6672 and obtained 4717 respectively.

Bingxin and Alejandro (2014) examined determinants of fertilizer adoption and intensity based on four major cereal crops (barley, maize, *teff*, and wheat) by using double hurdle model. The study was conducted by using four years survey data employed by CSA which covered all regions of Ethiopia. Extension services, risk aversion behavior, skill and knowledge in production of cereals, wealth and fragmentation of land were found to be influential factors.

A study by Eba and Bashargo (2014) investigated determinants of adoption and intensity of fertilizer use in Ethiopia based on survey data collected from 350 farm households in Guto Gida district. The results of the Probit and Tobit models estimated that factors such as family size, education, information, extension, farm income, off- farm activities credit, distance to market, livestock, landholding size and farming experience influences fertilizer adoption and its intensity of use in the study areas.

Zeng et al. (2015) studied the poverty reduction effect of improved maize adoption in Ethiopia by using PSM. It obtained data from 2496 households residing in four maize producing regions. The study found that improved maize adoption decreased incidence, depth and severity of poverty. However, poor households were less benefited due to small size of landholding.

Abate, Rashid, Borzaga, and Getnet (2016) employed PSM technique to evaluate the impact of rural finance on adoption of technology based on 817 household survey data. It revealed that if the households have access to finance, the probability of fertilizer and improved seeds adoption will increase by 11% and 32%.

A study by Verkaart, Munyua, Mausch, and Michler (2017) done on the welfare impacts of improved chickpea based on three years panel data from 606 randomly selected households by using double-hurdle model. The study reported that adoption of improved chickpea robustly boosts household income and decrease rural poverty.

Mekonnen (2017) employed endogenous treatment effect model to analyze the effect of technology on productivity and households' welfare. Data was obtained from 1500 households in four regions. The findings of the study shows that HYVs and fertilizer improves crop yield and increase consumption expenditure (real per capita) significantly.

A study by Husen, Loos, and Siddig (2017) used probit model to evaluate the impact of social capital on agricultural technology among Ethiopian farmers using socio-economic data of 398 farming households around Hawassa town. The estimated probit model revealed that being members of *Jarsumma* (informal conflict resolution) increased the probability of adopting agricultural technologies such as fertilizers and HYVs by 17.8%. However, *Iddir* members were 12.8% less likely to adopt productivity enhancing technologies.

A study by Kebede and Ketema (2017) examine determinants of fertilizer use intensity on potato production by using primary data obtained from 171 potato producers in Eastern Ethiopia. The estimated results of the Tobit model showed that access to irrigation, extension contact, and livestock holding influences intensity of fertilizer adoption significantly. Similarly, Ketema and

Kebede (2017) investigated factors influencing intensity of fertilizer adoption by employing Tobit model. Data was gathered from 383 maize producers in Eastern Ethiopia. The results revealed that adoption of DAP and Urea fertilizers is determined by family size, location (districts), and membership in cooperatives.

Ahmed, Geleta, Tazeze, and Andualem (2017) evaluated the productivity and welfare impact of improved maize varieties in East Hararghe Zone, Ethiopia. PSM technique combined with ESR was employed to estimate the welfare impact while the effect on maize productivity was evaluated by sample selection corrected stochastic frontier technique. The findings indicate that adoption increases consumption expenditure by 14.4-19.2% and improves maize productivity measured by technical efficiency by 4.42%.

A study by Jaleta, Kassie, Marenya, Yirga, and Erenstein (2018) assessed the effect of improved maize on food insecurity in Ethiopia based on ESR model. The data for the study covered all parts of Ethiopia with sample size of 2327 maize producers. The results indicate that adoption reduces the probability of being food insecure by 2.5%. Similarly, the food consumption expenditure of non-adopters was found to be lower by $119 per year.

A study by Abebe and Debebe (2019) identified factors influencing fertilizer adoption based on survey data came from 155 households in Northwestern Ethiopia. The results of the logit model show that fertilizer adoption affected by education, sex, health status, slope and fertility of land and extension service.

Biru, Zeller and Loos (2020) evaluated the poverty and vulnerability impact of agricultural technologies in Ethiopia by using a three year panel data collected from 390 households. The study employed an ordered probit and multinomial ESR models. Both the ATT and random effect results indicate that adoption of improved technologies reduce the probability of poverty or vulnerability. Moreover, it proved that simultaneous adoption of complementary agricultural technologies has substantial benefit rather that adopting as a single technology.

Feyisa (2020) reviewed 12 articles conducted on the determinants of agricultural technology adoption in Ethiopia between 2010 and 2018 by using random effect model. The study concludes that due to heterogeneity in the study areas, the practical applicability at national level is limited. However, the study identified the most common factors affecting adoption of agricultural technologies such as age of head of the household, level of education, size of farm, holding of livestock, extension service and credit access.

Wordofa et al. (2021) studied the income effect of the adoption of improved agricultural technologies in Eastern Ethiopia by survey data collected from 248 rural households. The results of the PSM estimation technique indicate that adoption of improved technologies increased the income of adopters by ETB 23, 031.

Massresha et al. (2021) investigated factors affecting agricultural technology adoption in Ethiopia by using primary data collected from 796 farm households in North Shoa zone. The results of the estimated logit model revealed that adoption of improved seed, irrigation and fertilizer was influenced by age, years of schooling, family size, livestock, and access to extension service.

Zegeye (2021) examined the impacts of adoption of multiple agricultural technologies (organic fertilizer, inorganic fertilizer and Herbicide) on poverty in Amhara region of Ethiopis. The study was employed based on Ethiopian socio economic survey that included 656 households. The results of the Multinomial Logit model revealed that education, family size, livestock, credit, extension visit, off-farm participation, distance and remittance influence adoption of agricultural technologies. On the other hand, the ESR models indicate that adoption of multiple technologies significantly increase consumption expenditure and reduces poverty.

A study by Habtewold (2021) investigated the Impact of row planting and fertilizer on multidimensional poverty in Ethiopia. The study used Ethiopian Socioeconomic Survey data of 2 752 farm households. The results estimated by ESR and PSM models indicate that adoption of these climate smart technologies reduced multidimensional poverty by increasing consumption/income mainly though production gain.

Kassa, Giziew and Ayalew (2021) employed double-hurdle model to identify determinants of farmers' adoption of improved faba bean in Ethiopia based on survey data collected from 168 farm households in Basona Werana district. The estimated results revealed that while a farmer's adoption decision is determined by family size, extension contact and awareness of farmers' about the existing improved cultivars, adoption intensity is influenced by market accessibility and livestock holding.

### 2.3.3 Summary of Literature Review

Table 2.1 presented the summary of literatures related to adoption of agricultural technology. Each study was summarized based on the type of data/sample used, estimation methods/techniques applied and the major findings of the study.

**Table 2.1 Summary of Selected studies focus on agricultural Technology Adoption**

| Author/s | Data/Sample | Methods/ Techniques | Findings |
|---|---|---|---|
| **Economics Analysis of Technology Adoption** | | | |
| Devi and Ponnarasi (2009) | 100 rice cultivators in Tamil Nadu, ***India*** | Descriptive analysis | The benefit-cost ratio was higher in system of rice intensification (2.25) than in conventional (1.56) method. |
| Akinola and Owombo (2012) | 105 Yam producers in Osun State, ***Nigeria*** | Farm budgetary techniques | The benefit-cost ratios were 4.79 for adopters of mulching technology 3.13 and 3.13 for non-adopters. |
| Birthal et al. (2012) | 400 farmers from Anantapur district, ***India*** | Descriptive analysis | Adoption of the improved groundnut variety increased net-revenue by 36%. |
| Adofu et al. (2013) | 150 farmers in Kogi state, ***Nigeria*** | Descriptive analysis | The net agricultural revenue after technology adoption has increased by 2.7 folds compared to the value before adoption. |
| Myint and | 370 farmers from 2 | Cost-return | Adoption of paw san rice cultivation increase |

| | | | |
|---|---|---|---|
| Napasintuwong (2016) | regions in ***Myanmar*** | analysis | revenue of farmers significantly. |
| (Hambirrao, 2016) | 270 sugarcane cultivators in Maharashtra, ***India*** | Descriptive analysis | The incremental benefit-cost ratio of medium and high level technology adopters was estimated from 1.08 - 1.63 and from 1.94 - 2.59 respectively. |
| Pal et al. (2016) | 100 farmers in Gulbarga district of Karnataka, ***India*** | Descriptive statistics | Adoption of improved seed boosts total revenue by 32% and net return by 44%. |
| **Determinants of Agricultural Technology Adoption** | | | |
| Alene et al. (2000) | 110 farmers from West Shoa Zone, ***Ethiopia*** | Tobit Model | Age, education, labor force, farm size, farm and off-farm income, extension services and availability of input affects adoption improved maize varieties. |
| Bamire et al. (2002) | 180 respondents in Osun State, ***Nigeria*** | Tobit Model | Off-farm income, net farm incomes, and availability of fertilizer influences fertilizer adoption and use decision. |
| Croppenstedt et al. (2003) | 6147 cereal producers from four regions in ***Ethiopia*** | Double-hurdle Model | Access of fertilizer, availability of credit, household size, formal education and value-to-cost ratio influences households' decision for fertilizer adoption. |
| Dadi et al. (2004) | 200 households from East and West Shewa, ***Ethiopia*** | Accelerated lifetime model | Economic incentives, oxen ownership and infrastructural factors such as proximity to markets substantially influence adoption of technology. |
| Feleke and Zegeye (2006) | 222 households from three selected zones in southern ***Ethiopia*** | Logit Model | Extension service, credit, education, labor force, land and distance to the market affects adoption of improved maize varieties. |
| Fufa and Hassan (2006) | 100 farmers in Dadar district, ***Ethiopia.*** | Probit and Tobit models | The result indicated that the use and intensity of fertilizer adoption is influenced by farmers' age, rainfall expectation and perception of fertilizers price. |
| He et al. (2007) | 218 households from four villages, ***China*** | Logit Model | Age, education, active labor, extension contact, participation in project, and distance from water |

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| | | | storage tank affects rainwater harvesting and supplementary irrigation technology. |
| Langyintuo and Mungoma (2008) | 300 households in three districts of ***Zambia***. | Double-hurdle model | Factors affecting adoption of improved maize varieties depends on the wealth status of households. |
| Adeoti (2009) | 108 farmers from Volta and Ashanti region, ***Ghana*** | Heckman two-stage model | Extension service, dependency ratio and location affects adoption treadle pump. Moreover, treadle pump adoption increases per capita income by 28.1%. |
| Uaiene et al. (2009) | 2 years panel from 4104 households in ***Mozambique*** | Probit model | Education, extension advisory, access to credit and being member of agricultural associations affects adoption of new agricultural technologies positively. |
| Simtowe et al., (2011) | 613 households in Northern Zone, ***Tanzania***. | Probit model | Adoption of improved pigeonpea seed determined by seed accessibility, size of land and livestock ownership. |
| Asfaw et al. (2011) | 700 farmers from 3 districts in shewa zone, ***Ethiopia*** | Double-Hurdle model, PSM | Awareness about improved varieties, wealth of households and labor force availability determines adoption of improved chickpea. Moreover, adoption impacted on farmers' integration into output market. |
| Beshir et al. (2012) | 252 farmer from north east ***Ethiopia*** | Double hurdle approach | Gender, age, size of farm land, education, ownership of livestock, off-farm income, extension service and access to credit affects the adoption of inorganic fertilizer. |
| Mariano et al. (2012) | 3164 samples from 30 provinces in ***Philippines*** | Logit and Poisson estimators | Education, machinery, irrigation, capacity-development activities, profit-oriented behavior and soil type influence adoption of improved technology. |
| Asfaw et al. (2012) | 613 households from 4 districts in ***Tanzania***. | PSM and ESR | Improved pigeonpea adoption enhanced consumption expenditure and reduced incidence of poverty, poverty gap, and poverty severity. |
| (Mottaleb et | 384,337 households | Multinomial | Loan, irrigation, land characteristics, availability of |

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| al., 2014) | from 25 districts in ***Bangladesh***. | logit | roads and seed supply significantly influence adoption of hybrid and modern rice varieties. |
| Rahman and Chima (2014) | 400 farmers in Anambra and Ebonyi states, ***Nigeria*** | Multivariate probit model | Output price, farming experience, remoteness of extension services, access to credit, profit are the main determinants of adopting modern technologies. |
| Hailu et al. (2014) | 270 smallholder farmers from Tigray region, ***Ethiopia.*** | Probit and OLS Models | Technology adoption is determined by irrigation, credit access, market and plot proximity, off-farm participation and livestock. Adoption significantly enhances income of farm households. |
| Bingxin and Alejandro (2014) | Four years CSA survey data from all regions of ***Ethiopia*** | Double hurdle model | Adoption and intensity of fertilizer use influenced by extension services, farmers' knowledge, risk aversion behavior, household's wealth and land fragmentation. |
| Eba and Bashargo (2014) | 350 farm households in Guto Gida district, ***Ethiopia*** | Probit and Tobit models | Family size, education, information, extension, farm income, off- farm activities, credit, distance to market, livestock, landholding size and farming experience influences fertilizer adoption and its intensity of use |
| Ghimire et al. (2015) | 416 households in four districts, ***Nepal*** | probit model | Education, farm size, type of land, seed access, extension services, oxen, yield potential and acceptability affected improved rice adoption. |
| Abate et al. (2016) | 817 household from 21 districts, ***Ethiopia*** | PSM | Access to rural finance enhanced both adoption and extent of fertilizer and improved seed use. |
| Kebede and Ketema (2017) | 171 household in Eastern ***Ethiopia*** | Tobit model | Access to irrigation, extension contact, and livestock holding influences intensity of fertilizer adoption. |
| Ketema and Kebede (2017) | 383 households in Eastern ***Ethiopia*** | Tobit model | Intensity of fertilizer use influenced by variation in districts, family size, and membership in cooperatives. |
| Husen et al. (2017) | 398 Households around Hawassa town, ***Ethiopia*** | Probit model | While being a member of *Jarsumma* (informal conflict resolution) increased adoption, *Iddir* members were less likely to adopt productivity |

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|---|---|---|---|
| | | | enhancing technologies. |
| Chandio and Jiang (2018) | 240 wheat cultivators in Sindh province, ***Pakistan*** | Probit model | Education, experience, size of landholding, ownership of tube-well, access to credit and extension contact influenced adoption. |
| Sánchez-Toledano *et al.* (2018) | 200 farmers in Chiapas state, ***Mexico*** | survival analysis model | Adoption of modern maize varieties is influenced training, risk taking behavior of farmers, age and family size of the households. |
| Ashoori *et al.* (2019) | 400 Smallholders in Guilan Province, ***Iran*** | Logit Model | Profitability perception of modern rice varieties, experience and holdings of livestock affected adoption of improved varieties of rice. |
| Subedi *et al.* (2019) | 194 wheat producers in Kailali and Sunsari districts, ***Nepal*** | Probit model | Adoption is influenced by age, number of members in the family, schooling years, subsidy and loan provision. |
| Abebe and Debebe (2019) | 155 households in Northwestern ***Ethiopia*** | logit model | Fertilizer adoption affected by education, sex, health status, slope and fertility of land and extension service. |
| Feyisa (2020) | 12 articles conducted in ***Ethiopia*** between 2010 and 2018. | Random effect model | Age, level of education, size of farm, holding of livestock, extension service and credit access. Affect adoption of agricultural technologies. |
| Massresha et al. (2021) | 796 farm households in North Shoa zone, ***Ethiopia*** | Logit model | Adoption of improved seed, irrigation and fertilizer was influenced by age, years of schooling, family size, livestock, and access to extension service. |
| Ambali, Areal and Georgantzis (2021) | 2752 households in ***Nigeria*** | Probit model | Religion, sex, location, extension service and perceptions about attributes of technology affected improved rice adoption decision of farmers. |
| Kassa, Giziew and Ayalew | 168 farm households in Basona Werana district, ***Ethiopia***. | Double-hurdle model | The estimated results revealed that while a farmer's adoption decision is determined by family size, extension contact and awareness |

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| (2021) | | | of farmers' about the existing improved cultivars, adoption intensity is influenced by market accessibility and livestock holding. |
| **Impact of Technology on Poverty** | | | |
| Mendola (2007) | 3800 households from 2 clusters in ***Bangladesh*** | PSM | Adoption of high yield varieties of rice increased income of adopters by 30% and reduced poverty incidence by about 14%. |
| Kijima et al. (2008) | 1340 households from central and western ***Uganda*** | OLS | Improved rice adoption increases per capita income, reduces incidence of poverty and improve distribution of income. |
| Becerril and Abdulai (2010) | 325 farmers from Oaxaca and Chiapas regions of ***Mexico*** | PSM | Adoption of improved maize varieties reduces poverty by about 19–31%. The effect of adoption was found to be higher for small farmers than large farmers. |
| Wu et al. (2010) | 473 households from Yunnan Province, ***China*** | PSM | Improved upland rice varieties significantly improved welfare of farm households measured by increase in income and reduction in the incidence of poverty. |
| Kassie et al. (2011) | 927 households from 7 districts in ***Uganda*** | PSM | Application of improved varieties of groundnut rise crop income by $130-254 and decrease incidence of poverty by 7–9%. |
| Sofolume et al. (2013) | 300 cocoa farmers from Osun state in ***Nigeria*** | PSM | Adoption of Siam Weed Soap Solution increased the yield of cocoa, improved annual income and reduced poverty rates. |
| Nyangena and Juma (2014) | Two years panel data in ***Kenya*** | DD and PSM | Maize productivity increased by about 230 kg/ha due to simultaneous adoption of improved varieties of maize and fertilizers. |
| Kassie et al. (2014) | 680 maize producers from 4 districts, ***Tanzania*** | PSM, Probit, OLS and Tobit | A rise in the land covered by improved varieties of maize resulted in significant reduction in food insecurity. |

| | | | |
|---|---|---|---|
| Audu and Aye (2014) | 125 households from farm Benue State, ***Nigeria*** | OLS | Adoption of improved maize varieties significantly improve households' welfare measured by increase in consumption expenditure |
| Bezu et al. (2014) | Three-year panel data from ***Malawi*** | control function and IV | Use of improved maize varieties increase own maize consumption, household income and asset accumulation |
| Afolami et al. (2015) | 312 cassava producers in Southwestern ***Nigeria*** | Descriptive analysis, Logit model | Improved cassava varieties improved income and reduced incidence of poverty. |
| Zeng et al. (2015) | 2496 households from four regions, ***Ethiopia***. | PSM | Improved maize varieties have significantly reduced incidence, depth and severity of poverty at the study area. |
| Awotide, Awoyemi, Omonona, and Diagne (2016) | 481 rice producers in ***Nigeria*** | local average treatment effect and IV | Improved varieties of rice adoption resulted in yield improvement by 358.89/kg/ha and increase consumption expenditure of households. |
| Budhathoki and Bhatta (2016) | 3350 farmers from all agroecological regions of ***Nepal***. | PSM | Use of modern rice varieties improved income and consumption expenditure of households by \$153–185 and \$643–907 respectively. |
| Sahu and Das (2016) | 296 households from Odisha state, ***India*** | PSM | Adoption of agricultural technology significantly improves per capita consumption expenditure and reduces poverty. |
| Verkaart et al. (2017) | Three years panel data from 606 households, **Ethiopia** | Double hurdle and fixed effect model | Adoption of improved chickpea substantially increases income of households and reduce poverty. |
| Mekonnen (2017) | 1500 households drawn from four regions, ***Ethiopia*** | ESR | Adoption of high yield varieties of seeds and fertilizer significantly increases crop productivity and improve welfare of households (consumption expenditure). |
| Ahmed et al. | 355 households from | PSM | Improved maize adoption increases maize |

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|---|---|---|---|
| (2017) | East Hararghe Zone of **Ethiopia** | combined with ESR | productivity and households' consumption expenditure. |
| Jaleta et al. (2018) | 2327 maize producers from entire ***Ethiopia*** | ESR | Due to improved maize adoption food insecurity is reduced by 2.5% and increase consumption expenditure by $119 |
| Martey (2018) | 2188 households from all regions of ***Ghana*** | Double selection and PSM | Chemical fertilizer significantly increases crop income and reduces households' poverty. |
| Danso-Abbeam and Baiyegunhi (2019) | 838 cocoa producers from four regions, ***Ghana*** | PSM | Fertilizer adoption resulted in an increase in farm income by 11.4-16.8% and per capita consumption by 11.9-13.3%. |
| Wossen *et al.* (2019) | 2,500 households from 16 states, ***Nigeria*** | IV regression model | Adoption of improved cassava adoption resulted in a reduction in poverty. |
| Manda *et al.* (2019) | 1525 households in two regions, **Nigeria** | ESR model | Improved cowpea adoption reduced income and asset poverty by 5%. |
| Biru, Zeller and Loos (2020) | Three year panel data collected from 390 households, ***Ethiopia*** | Ordered probit and ESR | Adoption of improved technologies reduces the probability of a household being poor. |
| Sinyolo, S. (2020) | 415 maize producers in KwaZulu-Natal province of ***South Africa*** | PSM and tobit | The results found that a hectare increase in area of land covered by improved maize varieties resulted in an increase in per capital food expenditure of 4000 Rand. |
| Wordofa et al. (2021) | 248 rural households from Eastern ***Ethiopia*** | PSM | Adoption of improved technologies increased the income of adopters by ETB 23, 031. |
| Zegeye (2021) | 656 households in ***Ethiopia*** | ESR | Adoption of multiple technologies significantly increase consumption expenditure and reduces poverty. |
| Habtewold (2021) | 2752 households in ***Ethiopia*** | ESR and PSM | Adoption of these climate smart technologies reduced multidimensional poverty by |

| | | | |
|---|---|---|---|
| | | | increasing consumption/income mainly though production gain |
| Ambali, Areal and Georgantzis (2021) | 2752 households in ***Nigeria*** | Probit model | Religion, sex, location, extension service and perceptions about attributes of technology affected improved rice adoption decision of farmers. |
| Lu et al. (2021) | 900 households in Northern ***Ghana***. | PSM | Results of the model indicate that adoption of improved maize varieties increased subjective food security by 28.8%.. |
| **Impact of Technology on Income Distribution** | | | |
| Warr and Coxhead (1992) | Time series /Secondary data from ***Philippines*** | Quintile distribution of income | Technical change in agriculture reduces income inequality by benefiting poorest groups more proportionately. |
| Otsuka et al. (1992) | 378 households from ***Philippines*** | Gini coefficients | Adoption of modern rice varieties have not been significantly affects distribution of income. |
| Hossain (1992) | Time series /Secondary data from ***Bangladesh*** | Wage determination model | Although adoption of new technology such as seed, fertilizer and irrigation reduced rural poverty, it did not worsen distribution of income. |
| Lin (1999) | 500 households from Hunan Province, ***China*** | General Equlibrium Model | The net effect of hybrid rice adoption on income inequality is found to be negligible due to the offsetting effect in production-mix adjustments. |
| Matuschke et al. (2007) | 284 wheat farmers in Maharashtra state, ***India*** | Probit Model OLS | Adoption of improved wheat varieties has benefited smallholder farmers to a greater extent than larger-scale farmers. |
| Ding et al. (2011) | 473 households Southern Yunnan Province, ***China*** | OLS, PSM and Gini coefficients | Though adoption of improved upland rice technologies increase income of adopters by 15%, its impact on income distribution is found to be negligible |
| Kilima et al. (2013) | 240 farmers from ***Tanzania*** | Gini coefficient | Improved technologies increased farm income and the benefits were equitably distributed. |
| Sahoo (2014) | 108 households from | Lorenz | Technology adoption worsens income distribution |

| | | | |
|---|---|---|---|
| | Odisha state, ***India*** | curve and Gini coefficient | by increasing the income of large and medium farmers than small farmers. |
| Huang et al. (2015) | 712 households from 19 provinces, ***China*** | PSM, Gini Coefficient | Adoption of modern peanut varieties enhances households' income significantly, but increases inequality by Gini coefficient of 0.004-0.006. |

## 2.4 Research Gaps

Though some worldwide studies were conducted on the economic benefits of agricultural technologies (Akinola & Owombo, 2012; Devi & Ponnarasi, 2009; Myint & Napasintuwong, 2016; Pal et al., 2016), no studies were undertaken in Maize and *Teff* crops. Moreover, this paper estimated productivity differences between adopters and non-adopters of agricultural technologies by using Blinder-Oaxaca decomposition technique which was hardly applied in such kind of studies.

Various studies were carried out on the determinants of agricultural technology adoption both nationally and internationally. However, the results of these studies are varied subject to the specific demographic and socio-economic condition of their study area. Hence, due to farmers' heterogeneity behavior and the dynamic nature of adoption decision, it is found to be quite imperative to undertake location and time specific study on the area. In this regard, no study is found to be conducted related to adoption of agricultural technology in Awi Zone, the study area of this research.

Studies conducted on the impact of technology adoption on poverty reduction show inconsistent results; some of them found a significant poverty reduction impact (Afolami et al., 2015; Budhathoki & Bhatta, 2016; Kassie et al., 2011; Mendola, 2007; Sahu & Das, 2016; Sofolume et al., 2013) while others found insignificant result (Cunguara & Darnhofer, 2011; Omilola, 2009). In addition, in Ethiopia, though studies were conducted on the area, some of them used income as a proxy for welfare measurement (B. K. Hailu et al., 2014; Verkaart et al., 2017; Zeng et al., 2015b) while others did not adequately measure poverty since they considered only the changes in consumption expenditure without estimating the impact on various poverty indices (Ahmad &

Heng, 2012; Jaleta et al., 2018; Mekonnen, 2017). Moreover, various existing studies have examined the impact of single agricultural technology on households' welfare rather than dealing with complementary technologies as a package.

As it is observed from the literatures, the impact of agricultural technology adoption on income distribution is far from clear. Some studies revealed that adoption of agricultural technology worsen income inequality (Freebairn, 1995; Huang et al., 2015; Sahoo, 2014); while others found that technology adoption reduces income inequality (Becerril & Abdulai, 2010; Kilima et al., 2013; Matuschke et al., 2007; Ut et al., 2000). On the other hand, some studies argued that adoption of technologies doesn't affect distribution of income (Ding et al., 2011; Hossain, 1992; Lin, 1999; Otsuka et al., 1992). Moreover, no study has been conducted related to the impact of agricultural technology adoption on income distribution in Ethiopia.

Therefore, the above research gaps implies the need of further studies on the area. Hence this study has tried to fill these research gaps by focusing on the two main agricultural productivity enhancing technologies; Chemical fertilizer and Improved Seeds in Awi zone, Ethiopia. The study area, Awi zone, is selected due to the absence of studies on the area.

## 2.5 Conceptual Framework of the Study

Based on the reviewed literatures and objectives settled for this study, the conceptual framework of this study is developed as depicted by figure 2.9. Adoption of agricultural technologies such as fertilizer and improved seeds was expected to be influenced by various demographic, socio-economic and institutional factors. Adoption of agricultural technologies further influence the welfare of households (poverty and income distribution) through direct and indirect effects (Becerril & Abdulai, 2010; Bhalla, 1976; De Janvry & Sadoulet, 2002; Kassie et al., 2011). Direct effects are primarily through productivity increment of adopters while indirect effects include lowering of food prices and employment creation for the poor.

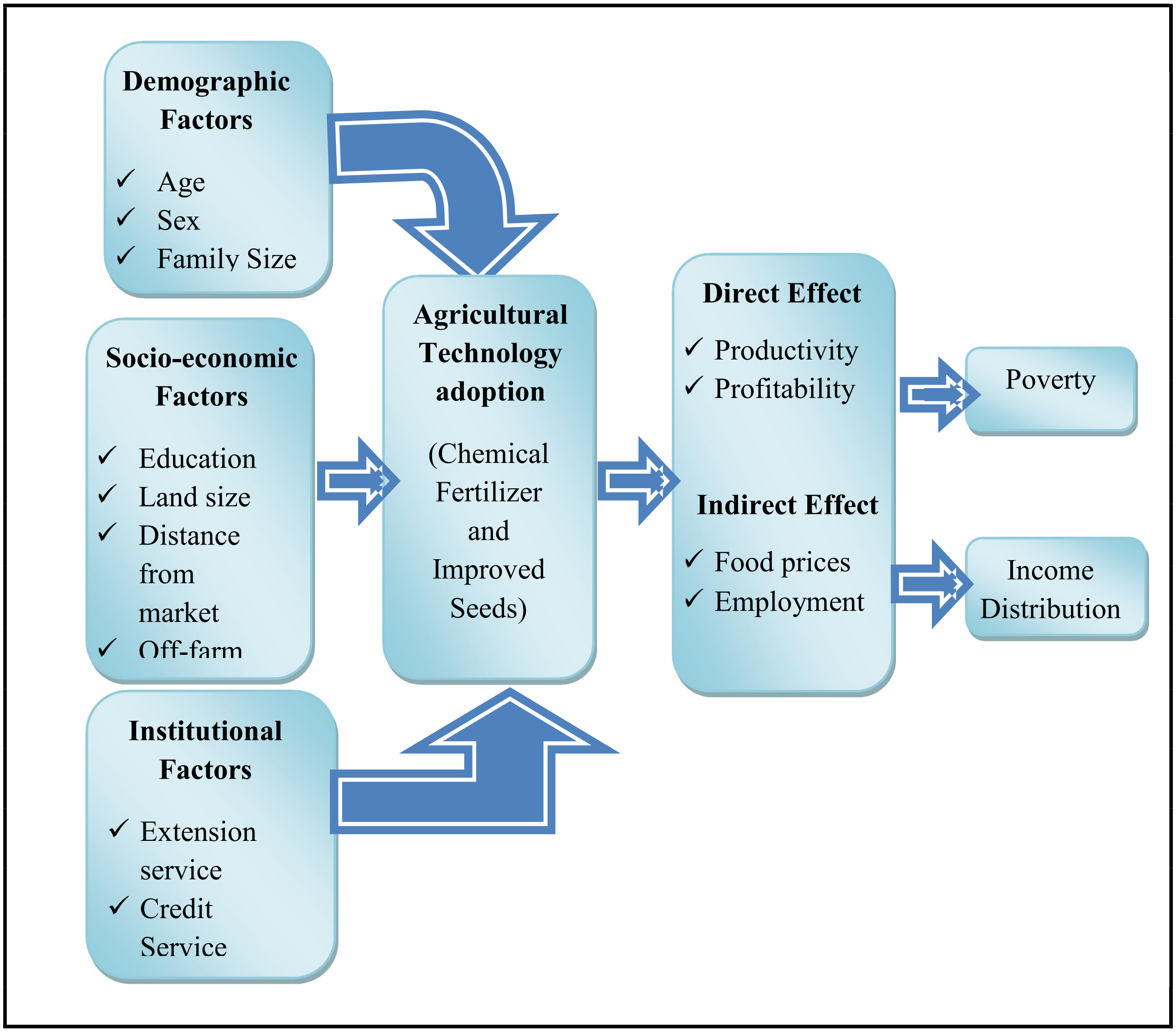



**Figure 2.9 Conceptual Framework of the Study.**

**Source:** Own depiction, 2018

# CHAPTER THREE

# OBJECTIVES AND RESEARCH METHODOLOGY

## 3.1 Introduction

Once the research gaps are identified the next step is formulation of objectives followed by methodology. Objectives and the subsequent research questions/hypothesis originates from the research problems/gaps identified from the reviewed literature (Denicolo & Lucinda, 2012). Setting a clear objective and a clear path to reach that objective determines the successfulness of any research. Having definite objectives helps the researcher to have a clear direction and protects from any diversion. This chapter, therefore, presents the objectives of the study along with its subsequent such as research questions, hypothesis and significance of the study in the first section while the second section of this chapter deals on research methodology.

## 3.2 Objectives of the Study

### 3.2.1 General Objective

The general objective of this study is to analyze the economic benefits of agricultural technology adoption and its impact on poverty reduction and distribution of income among households at Awi Administrative Zone, Ethiopia.

### 3.2.2 Specific Objectives

- To investigate the economic benefit of agricultural technology adoption.
- To identify determinants of agricultural technology adoption.
- To analyze the impact of technology adoption on poverty reduction.
- To examine the impact of technology adoption on distribution of income.

### 3.2.3 Research Questions

- Is there any difference in net-return on agricultural production between technology adopters and non-adopters?
- What factors influence technology adoption decision of farm households?
- Does agricultural technology adoption reduce poverty?
- Is distribution of income affected by adoption of agricultural technology?

### 3.2.4 Hypotheses of the study

Based on the objectives and research questions, the following four hypotheses were formulated.

***Hypothesis 1***

H0[2]$_1$: *There is no difference in net-benefit on agricultural production between technology adopters and non-adopters.*

H1[3]$_1$: *The net-benefit on agricultural production for technology adopters is different from non-adopters.*

***Hypothesis 2***

$H0_2$: *Demographic, socioeconomic and institutional variables do not affect agricultural technology adoption*

$H1_2$: *Demographic, socioeconomic and institutional variables influence adoption of agricultural technology.*

***Hypothesis 3***

$H0_3$: *Adoption of agricultural technology does not affect poverty*

$H1_3$: *Adoption of agricultural technology influence poverty.*

[2] $H_0$: indicates Null Hypothesis

[3] $H_1$: indicates Alternative Hypothesis

***Hypothesis 4***

$H0_4$: *Agricultural technology adoption does not have an impact on income distribution.*

$H1_4$: *Agricultural technology adoption affects income distribution among farm households*

### 3.2.5 Significance of the study

In general, conducting studies on Ethiopian agriculture have paramount importance since the sector is the backbone of the Ethiopian economy and the main source of livelihood for the bulk of the rural population.

Hence, identifying those factors which influence adoption of technologies and estimation of their impact on profitability, poverty and income distribution is important in order to enhance adoption of agricultural technologies in such a way that can improve the welfare of the rural population. More specifically, this study is expected to provide an input for policy makers, government organizations and other stakeholders who are working on the improvement of the welfare of rural households in the study area and other zones and states in Ethiopia having similar characteristics. Furthermore, the study is expected to contribute for the existing literature and it can be served as a stepping stone for further research in the area.

## 3.3 Research Methodology

According to Kothari (2004), research methodology deals with several procedures followed by a researcher in doing a certain study along with the reasons behind their relevance. This section, therefore, discus the research methods adopted by this study so as to attain its objectives. It starts by describing the location and nature of the study area followed by research design, data sources, sampling techniques and data analysis methods.

### 3.3.1 Description of the Study Area

Awi zone is one of 11 Zones in Amhara National Region State of Ethiopia. The zone is bordered on the east by West Gojjam zone, on the north by North Gondar zone and on the west by

Benishangul -Gumuz Region. The Zone is divided into 12 administrative districts with nine rural districts (Ankesh, Guagusa-Shikudad, Ayehu-Guagusa, Banja, Zigem, Guangua, Jawi, Dangla and Fagita-lekoma) and three town administrations (Chagni, Enjibara and Dangla). Location map of the study area is depicted by figure 3.1.

**Table 3.1 Major crops produced in Awi Zone, Ethiopia**

| Crops | Number of holders | Area in hectares | Production in quintal | Yield (quintal/ha) |
|---|---|---|---|---|
| *Teff* | 158028 | 74042.14 | 1162152.59 | 15.7 |
| Maize | 270242 | 71123.56 | 2702698.65 | 38 |
| Finger millet | 113270 | 56951.92 | 1530843.72 | 26.88 |
| Potatoes | 68552.00 | 3088.48 | 564955.04 | 182.92 |

**Source:** CSA, 2016

Awi zone is situated with an altitude ranging from 1,800 to 3,100m above sea level. Based on CSA (2015), this zone has a total population of 1,165,625 people, of whom 16% are urban inhabitants. The zone covers an area of 9,148.43 square km with a population density of 127.44. As indicated in table 3.1, the major crops produced in Awi zone are *teff*, maize, finger millet, and potatoes (CSA, 2016a).

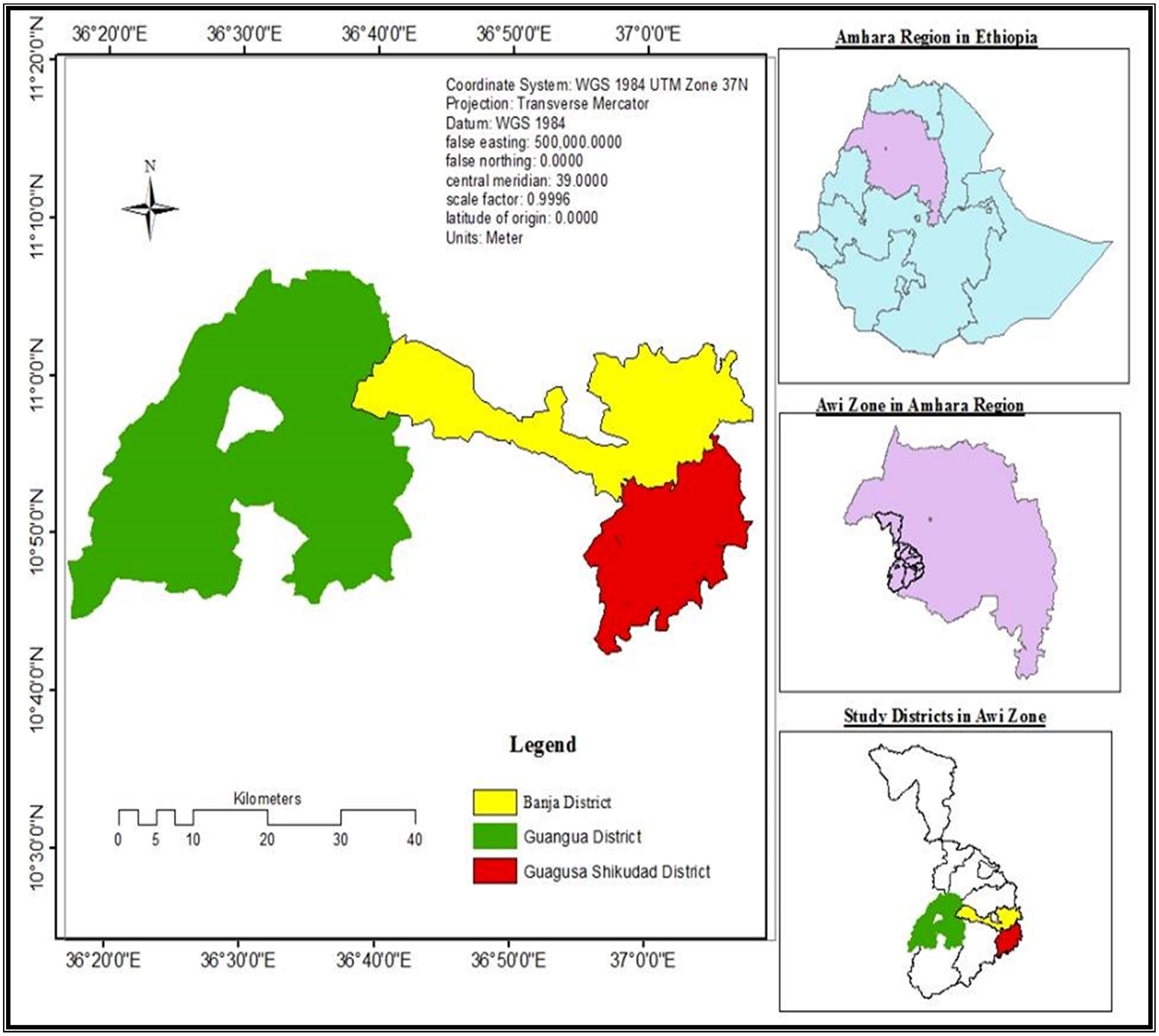



**Figure 3.1 Location Map of Awi Zone**

### 3.3.2 Research Design

Selecting appropriate research design is foundation stone any research. However, the choice of suitable research design depends of the researcher's determination of the approach he/she intends to attain its objectives (Saunders, Lewis, & Thornhill, 2009; Sekaran & Bougie, 2003). This study, therefore, has employed cross-sectional research design so as to achieve the stated objective of the study. In cross-sectional research design, either sample may be selected or the entire population may be studied and research questions will be answered based on data collected from each individuals included in the study (Olsen & St.George, 2004). This research design comprises of using various groups of respondents who differ in the variable of interest but share other characteristics, such as socioeconomic status, educational background, and ethnicity. Moreover, cross-sectional research design enables researchers to compare various variables at the same time.

### 3.3.3 Sources of Data and Procedure of Data Collection

This study has been conducted mainly based on primary data (survey data) collected from sample respondents by using questionnaire and interview. In this study, therefore, structured questionnaire has been prepared to collect necessary data related to household's characteristics, the practices of technology adoption, cost and benefits in agricultural production, income and expenditure related information of farm households (see Appendix 9). This instrument allows the researcher to gather large data on households' socioeconomic behavior.

Interview is an important instrument which allows participants to discussion that can lead to increased insights and dig detail facts on the area. In this study, therefore, heads and experts of agricultural offices were interviewed by preparing in-depth interview questions (see Appendix 10).

With the purpose of getting additional information on the area, secondary data was also gathered from Awi zone agricultural department annual reports and various agricultural sample surveys of CSA, Ethiopia.

In order to collect survey data from rural households, the process was started from selection of data enumerators. In each kebele, two data enumerators who have better knowledge on agricultural activities and are serving as agricultural development agent (extension workers) were selected. Moreover, they were trained and briefed about the purpose of the research, detail contents of the data gathering tool and on how they could approach respondents. Furthermore, before the main survey, pilot survey was conducted in order to confirm the reliability of questions included in the questionnaire. Finally, the required data was collected from the selected sample households through data enumerators.

On the other hand, 3 heads (one from each district) and 6 experts (two from each district) from three district agriculture offices were interviewed. Hence, the identification of relevant experts was done and then with the necessary permission, the researcher has contacted and interviewed each of them separately.

### 3.3.4 Sample Size Determination and Sampling Techniques

In conducting a research, the unit of the study may be a person, groups, community, organizations, country, object, or any other entity. Enumeration of all peoples or items (population) is called census (Kothari, 2004). However, in practice it is hardly possible to study all individuals/items since it is time taking and costly. It, therefore, necessitates the selection of some items (samples) from the population. Consequently, determination of representative sample size and its selection becomes the fundamental task of the researcher.

According to Israel (2003), usually three criteria are desirable to decide the suitable size of the sample; Level of precision (e), Confidence level (Z) and Degree of variability (p). A proportion of 0.5 is usually considered to determine a more reasonable sample size since it indicates the maximum variability in a population. Hence, the researchers have taken the conservative value as proxy for P, (P= 0.50). The total population or the sampling frame from which the required number of sample were drawn is the total number of rural households found at Awi Administrative Zone. According to CSA (2015), the rural population of the Awi zone was 978, 931. To come up with the number of households at 2015, the population to household ratio of the same area during 2007 was used which was 4.79. Hence, the total number of rural households (N) in Awi Zone is estimated to be 204370 (=978931/4.79).

Consequently, following Yamane (1967) simplified sample size determination formula, the appropriate sample size based on the abscissa of the normal curve (Z) of 1.96 and 5% level of precision (e) is estimated as;

$$\mathbf{n} = \frac{\mathbf{N}}{\mathbf{1+N(e^2)}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{[1]}$$

$$= \frac{\mathbf{204370}}{\mathbf{1+204370(0.05^2)}} \cong \mathbf{400}$$

Samples have been selected by using Multistage sampling procedure (see figure 3.2). Firstly, three out of nine districts have been randomly selected. At the second stage six kebeles (two kebeles from each district) have been randomly chosen. Finally, samples from the six kebeles were determined based on their population proportion. Each sample was selected from each kebele by using simple rando, sampling technique. In doing so, initially, the list of all rural households was obtained from each kebele administration office. Then each household was marked with a specific number. Finally, the required samples (400) were selected from eackh kebele by using lottery method. Kebele is the lowest governmental division in Ethiopia which consists of at least five hundred households, or the equivalent of 3,500 to 4,000 persons. The detail is presented in table 3.2.

**Table 3.2 Sample Size Determination**

| **Selected Districts** | **Selected Kebeles** | **Total Households (A)** | **Proportion of each kebele households (B = (A/7891)*100)** | **Samples selected from each kebele (C=B*400)** |
|---|---|---|---|---|
| Banja | Sankit Lideta | 804 | 10.2% | 41 |
| | Basa-anguana | 842 | 10.7% | 43 |
| Guangua | Semien Degera | 2330 | 29.5% | 118 |
| | Lunse Degera | 1703 | 21.5% | 86 |
| Guagusa -Shikudad | Gusha | 1259 | 16.0% | 64 |
| | Agza | 953 | 12.1% | 48 |
| ***Total*** | | ***7891*** | ***100 %*** | ***400*** |

**Source:** Awi Zone Office of Environmental Protection, Land Administration and Use Authority, 2018

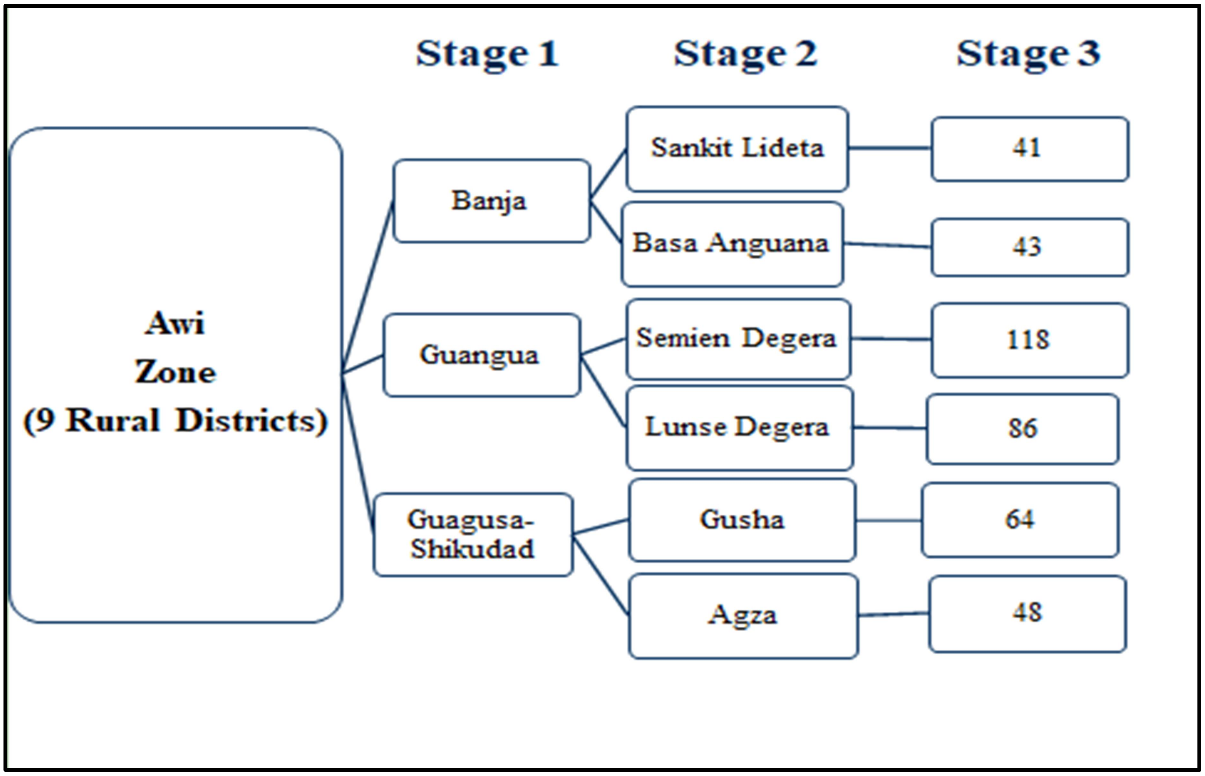



**Figure 3.2 Multistage Sampling Procedures**

### 3.3.5 Reliability Test

Testing the reliability of data is an essential tool to check the consistence of variables. Reliability is defined as the extents to which a set of variables are consistent in what it is extended to measure (Hair et al., 2010). Hence, in this study, the internal consistency analysis has been conducted by using Cronbach's alpha. According to Johnson and Christensen (2010), an alpha score of higher than 0.7 is generally considered to be acceptable.

In this study, the Cronbach's alpha value for all the variables and their combination were found to be greater than 0.7, which indicates a good measure of reliability (see appendix 1).

### 3.3.6 Method of Data Analysis

After the collection of relevant data from respondents and documents, data was analyzed using both descriptive analysis and econometrics models by the help of STATA software.

#### 3.3.6.1 *Descriptive Analysis*

Descriptive data analysis has been used to assess the demographic and socio-economic characteristics of respondents and to analyze the costs and benefits associated with agricultural technology adoption by comparing with non-adopters. Hence, in this type of data analysis frequency, percentage and mean values based on responses revealed from respondents was used. Particularly, t-test and chi-square tests were employed to test for difference in demographic, socio-economic and institutional variables between adopters and non-adopters. Moreover, tables and graphs were prepared and used during data analysis.

#### *3.3.6.2 Total Farm Budgetary Analysis Technique*

Studies conducted on the economic analysis of agricultural technology adoption employed total farm budgetary analysis technique (Adofu et al., 2013; Akinola & Owombo, 2012; Birthal et al., 2012; Pal et al., 2016). Similarly, in this study, a total farm budgetary analysis technique was employed in order to estimate the economic benefits of agricultural technologies for *teff* and maize crops, the major cereal crops in Ethiopia. In this technique, the total return, costs and profits from crop production for non-adopters and adopters were quantitatively computed.

Total profit is computed as the difference between total revenue and total production cost. It can be expressed mathematically as;

$$Total\ Profit = Total\ Revenue - Total\ Production\ Cost \text{ ........... [2]}$$

Where: $Total\ Revenue = Price * Qunatity$

$$Total\ Production\ Cost = Labor\ Cost + Animal\ Cost + Fertilizer\ Cost + Seed\ Cost + Pesticide\ Cost$$

Finally t-test was conducted to check whether there exists a significant difference on their cost, revenue, and profit between adopters and non-adopters of agricultural technologies.

*3.3.6.3 Blinder-Oaxaca (B-O) Decomposition*

The Blinder-Oaxaca (B-O) decomposition was developed by Blinder (1973) and Oaxaca (1973), and it becomes popular for the decomposition of wage earning gaps and the estimation of discrimination in gender earning differentials. However, this technique can also be used in other disciplines in order to examine the differences in the outcome variable based on different groups (Jann, 2008). Meughoyi (2018) has employed B-O decomposition to assess difference in agricultural productivity due to adoption of agricultural technology.

Similarly, in this study, B–O decomposition method has been carried out to estimate productivity differences between adopters and non-adopters of fertilizer and improved seeds.

Given are two groups, adopters (*A)* and non-adopters (NA); an outcome variable, agricultural productivity ($\ln Y$); and a set of independent variables (XB).

The first step of the B–O decomposition is to estimate agricultural productivity regressions for adopters and non-adopters of agricultural technologies separately.

$$\ln(Y_A) = X_{Ai}\beta_A + \mu_{Ai} \quad \text{[3]}$$

$$\ln(Y_{NA}) = X_{NAi}\beta_{NA} + \mu_{NAi} \quad \text{[4]}$$

Where *A* and *NA* represents adopters and non-adopters respectively; *lnY* indicates agricultural productivity which is the outcome variable; *X* is a set of independent variables; $\beta_A$ and $\beta_{NA}$ contains the slope parameters and the intercept; and $\mu_A$ and $\mu_{NA}$ are the error terms.

In this paper, authors employed the classic twofold B-O decomposition by using the Stata command of ‘oaxaca’ (see Jann (2008) for the detail). Hence, in the second step, the mean productivity difference between the two groups can then be written as;

$$E(\ln(Y_A)) - E(\ln(Y_{NA}) = [E(\mathrm{X_A}) - E(\mathrm{X_{NA}})]\beta^* + [E(\mathrm{X_A})(\beta_A - \beta^*) + E(X_{NA})(\beta^* - \beta_{NA})] \ldots\text{[5]}$$

Where, $E(\ln(Y_A)) - E(\ln(Y_{NA})$, is the mean productivity difference. The first right side component, $[E(\mathrm{X_A}) - E(\mathrm{X_{NA}})]\beta^*$, represents the endowment effect or the explained component. This portion of productivity gap is explained by the differences in the observable characteristics. The second component, $[E(\mathrm{X_A})(\beta_A - \beta^*) + E(X_{NA})(\beta^* - \beta_{NA})]$, belongs to the structural effect or unexplained part. This amounts to the differential not explained by the differences in observed characteristics (often attributed to discrimination, but may also result from the influence of unobserved variables). $\beta^*$ is a nondiscriminatory coefficient vector from the pooled model which is used to determine the contribution of the differences in the predictors.

In order to determine the productivity equation, most studies applied the Cobb-Douglas production function (Enu & Attah-Obeng, 2013; G. Hailu, Weersinka, & Bart, 2016; Urgessa, 2015). The Cobb- Douglas production function in which output (Y) is related to the inputs of labor (L) and capital (K) can be represented as follows;

$$Y = f(K, L) = AK^{\alpha}L^{\beta} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [6]$$

Where Y= the output level; K = input of capital; L = input of labor; A = total factor productivity; $\alpha$ and $\beta$ are the output elasticity's of capital and labor respectively.

Equation 6 can be estimated as a linear relationship by its log-transformation form which gives us,

$$ln\,Y = A + \alpha lnK + \beta lnL \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [7]$$

In this study, with several independent variables, the Cobb-Douglas production function was formulated as follows for maize and *teff* crops respectively.

$$lnY_M = \beta_0 + \beta_1 lnANIMAL + \beta_2 lnLABOR + \beta_3 AGE + \beta_4 SEX + \beta_5 EDUC + \beta_6 EXT + \beta_7 DIST + \mu \ldots [8]$$

$$lnY_T = \beta_0 + \beta_1 lnANIMAL + \beta_2 lnLABOR + \beta_3 AGE + \beta_4 SEX + \beta_5 EDUC + \beta_6 EXT + \beta_7 DIST + \mu \ldots [9]$$

**Dependent Variables**

**Output of Maize ($Y_M$)**: represents the amount of maize in quintal/ha produced by a given household during the agricultural season of 2017/18.

**Output of *Teff* ($Y_T$)**: represents the amount of maize in quintal/ha produced by a given household during the agricultural season of 2017/18.

**Explanatory Variables**

**Use of animal (ANIMAL):** It is measured by the number oxen/horse hours/ha used during the production of either maize/*teff*. In the study area, farm households are using either Oxen or horses for tillage. Animals are important sources of agricultural production. The use of more animal hours/ha implies the increase in tillage frequency which leads to increment in agricultural productivity (Abro, Jaleta, & Teklewold, 2018). Hence the expected sign is positive

**Use of labor force (LABOR):** represents the use of labor force in hours used for the production of maize/*teff*. Labor is one of the main factors of production in the agricultural sector. Use of more labor hour enhances agricultural yield by increasing the performance of farming activities such as tillage frequency and weeding. Therefore, it is hypothesized that the higher the number of labor hours engaged in agricultural activities, the greater the output from agriculture will be.

**Age of the household head (AGE):** It is a continuous variable measured in number of years. The effect of age on agricultural productivity is far from clear. As age increases, their experience on handling agricultural practices may be improved and can resulted in increment in productivity (Abrha, 2015). On the other hand, as age increases farmers becomes more reluctant in practicing new ways of farming which can result in productivity enhancement (B. K. Hailu et al., 2014). Hence, the expected sign is indeterminate.

**Sex of Household Head (SEX):** is a dummy variable represented by, female = 0, male = 1. It is expected that female headed households use less technologies and other sources of production than their counter part of male headed households. Hence, it is hypothesized that male headed households produce more than females.

**Educational level of the household head (EDUC):** is a categorical variable which takes a value of 0 = illiterate, 1= primary education, 2= secondary education and above. Educated households are expected to have better exposure to information that enhances agricultural production and practice easily new ways of farming. Thus, the expected sign is positive.

**Access to extension service (EXT)** is a binary variable which takes 1 if the household has got extension service from agents and 0 otherwise. Extension service may increases agricultural productivity by enhancing farmers' awareness and skills to efficiently use of agricultural resources.

**Distance to the main market (DIST):** This is a continuous variable measured in kilo meters between farmers home and their nearest market. The longer is the distance of the market, the lesser is the probability of buying and applying better agricultural inputs. As a result, the expected sign is negative.

Hence, based on equation 8&9, agricultural productivity regressions for adopters and non-adopters of agricultural technologies were carried out separately for the first step of the Blinder–Oaxaca decomposition.

#### *3.3.6.4 The Logit and Tobit Models*

In this study the logit model was employed in order to identify the determinants of technology adoption and to compute the propensity scores which is used for impact analysis. The dependent variable in the case of adoption decision of farm households is binary in nature since a household either adopt technology or not. When the dependent variable becomes binary in nature, researchers commonly employed either logit or probit models due to their superiority over the usual OLS method. According to (Gujarati, 2004), among other limitations, the assumption of linear relationship between probabilities and explanatory variables made the application of OLS method unrealistic.

Both logit and probit models yield very similar results; their difference is that the logistic distribution has slightly heavier tails (Verbeek, 2004). Though it is not convincing to select probit or logit model over the other, in this study logit model is employed for its mathematical simplicity (Gujarati, 2004).

The logit model could be represented as;

$$P_i = E(Y = 1 \mid xi) = \frac{1}{1+e^{-(\alpha+\Sigma\beta_i X_i)}} \text{.................................................} [10]$$

Where $X_i$ = vector of independent variables which affects agricultural technology adoption of rural households and $P_i$ = is the probability of adopting agricultural technology.

The Odds ratio can be written as;

$$\left(\frac{\mathrm{Pi}}{1-\mathrm{Pi}}\right) = \mathrm{e}^{(\alpha+\Sigma\beta_i X_i)} \text{ ......................................................................} [11]$$

Now equation [11] is said to be the *odds ratio*. It is the ratio of the probability of adopters' to non-adopters'.

Logs of odds ratio for K explanatory variables can be computed by taking the natural logarithm of equation [11]

$$L_i = ln\left(\frac{Pi}{1-Pi}\right) = \alpha + \sum_{i=1}^{k} \beta_i X_i + \mu_i \text{ ...................................................} [12]$$

Based on the above method, the following two equations have been estimated for each dependent variable. The first is concentrated on only fertilizer adoption while the second regression model is related to simultaneous adoption of fertilizers and improved seeds. Even though it was planned to develop a separate regression for adoption of only improved seeds, in the study area no farm household is found who adopted improved seeds without fertilizer. Based on the results of previous empirical studies, in this study various demographic, socio-economic and institutional variables are considered and the models are identified as;

$$\text{FERT} = \alpha + \beta_1\text{AGE} + \beta_2\text{SEX} + \beta_3\text{EDUC} + \beta_4\text{FAM} + \beta_5\text{EXT} + \beta_6\text{ CRED} + \beta_7\text{DIST} + \beta_8\text{LAND} + \beta_9\text{OFFINC} + \varepsilon_i \quad \ldots\ldots [13]$$

$$\text{FERTIS} = \alpha + \beta_1\text{AGE} + \beta_2\text{SEX} + \beta_3\text{EDUC} + \beta_4\text{FAM} + \beta_5\text{EXT} + \beta_6\text{ CRED} + \beta_7\text{DIST} + \beta_8\text{LAND} + \beta_9\text{OFFINC} + \varepsilon_i \quad \ldots\ldots [14]$$

**FERT** represents fertilizer which took 1 if a household adopts fertilizer in at least one of the cultivated crops during 2017/18 agricultural season (adopter) or 0, otherwise (non-adopter).

**FERIS** indicates for simultaneous adoption of fertilizer and improved seeds which took 1 if the household adopts both fertilizer and improved seeds simultaneously (adopter) or 0, otherwise 0 (non-adopter).

Moreover, in this study, Tobit model has been employed in order to identify major factors influencing use of fertilizer intensity. The application of Tobit analysis is preferred in such cases because it employs both data at the limit as well as those above the limit (Smith & Brame, 2003). In this study there are two groups of farm households, adopters and non-adopters of fertilizers. Hence, the application of the usual Ordinary Least Squares (OLS) yields inconsistent result (Gujarati, 2004). Therefore, Tobit Model is preferable than OLS since it allows for the inclusion of non-adopters of fertilizer in the regression. Moreover, Tobit model is believed to be superior to other alternative methods such as the Heckman two step estimation procedures since it involves the method of maximum likelihood (ML). According to Gujarati (2004), the estimates of the parameters of the Heckman procedure are not as efficient as the ML estimates.

Following Verbeek (2004), the tobit model can be expressed as

$$\boldsymbol{y_i}^* = \boldsymbol{x'_i\beta} + \boldsymbol{\varepsilon_i}, \qquad i = 1, 2, \; . \; . \; . \; , \; \text{N.} \qquad \ldots\ldots [15]$$

$$y_i = \begin{cases} y_i^* & \text{if } y_i^* > 0 \\ 0 & \text{if } y_i^* \leq 0 \end{cases}$$

Where, $y_i^*$ is the latent variable (unobservable), $y_i$ is the observed dependent variable (intensity of fertilizer use), $x'_i$ indicates a vector of independent variables affecting intensity of fertilizer use and $\varepsilon_i$ the error term.

Tobit model is usually estimated through maximum likelihood method. Hence, he loglikelihood function can be written as;

$$\log L(\beta, \sigma^2) = \sum_{i \in I_0} \log P(y_i = 0) + \sum_{i \in I_1} [\log f(y_i | y_i > 0) + \log P(y_i > 0)]$$

$$= \sum_{i \in I_0} \log P(y_i = 0) + \sum_{i \in I_1} \log f(y_i) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{[16]}$$

Where $f(.)$ denotes for a density function and $I_0$ and $I_1$ are defined as the sets of those indices corresponding to the zero and the positive observations.

The above equation can be expressed as follows for the normal distribution function;

$$\log L(\beta, \sigma^2) = \sum_{i \in I_0} \log \left[1 - \Phi\left(\frac{x'_i \beta}{\sigma}\right)\right] + \sum_{i \in I_1} \log \left[\frac{1}{\sqrt{2\pi\sigma^2}} exp\left\{-\frac{1}{2} \frac{(y_i - x'_i \beta)^2}{\sigma^2}\right\}\right] \ldots\ldots\ldots\ldots \text{[17]}$$

The change in the intensity of fertilizer for a change in the explanatory variables for the entire sample can be estimated as;

$$\frac{\partial E(y_i)}{\partial x_{ik}} = \beta_k \Phi\left(\frac{x'_i \beta}{\sigma}\right) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{[18]}$$

The above expression indicates that the marginal effect of a change in explanatory variables upon the intensity of fertilizer use is given by the model's coefficient multiplied by the probability fertilizer adoption.

Moreover, the change in fertilizer use intensity with respect to a change in independent variable for those having positive outcome (fertilizer adopters) can be computed as;

$$\frac{\partial E(y_i | y_i > 0)}{\partial x_{ik}} = \beta_i \left[1 - z\frac{f(z)}{F(z)} - \left(\frac{f(z)}{F(z)}\right)^2\right] \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{[19]}$$

where $z = \frac{x'_i\beta}{\sigma}$

$f$(.) represents the density function of the standard normal distribution and F (.) indicates cumulative distribution function.

Finally, by including the same explanatory variables used in the case of the logit model, the tobit model was identified as follows;

$$\mathrm{FERTINT} = \alpha + \beta_1\mathrm{AGE} + \beta_2\mathrm{SEX} + \beta_3\mathrm{EDUC} + \beta_4\mathrm{FAM} + \beta_5\mathrm{EXT} + \beta_6\ \mathrm{CRED} + \beta_7\mathrm{DIST} + \beta_8\mathrm{LAND} + \beta_9\mathrm{OFFINC} + \varepsilon_i \quad \ldots\ldots [20]$$

**FERTINT** represents the intensity of fertilizer applied in kg/ha for a household during 2017/18 agriculture season.

*Definition of Explanatory Variables*

Based on the results of previous empirical studies, in this study various demographic, socio-economic and institutional variables were considered. The measurement of each variable and their expected influence on the dependent variables are described below.

**Age of Household Head (AGE)** is measured in years. As age of the farmers increase, they may gather more personal capital and, therefore, their probability of adopting and intensity of fertilizer use may be improved (Bamire et al., 2002). On the other hand, with age, farm households would become unwilling and more conservative for adoption of modern technologies (Fufa & Hassan, 2006; B. K. Hailu et al., 2014). Therefore, the expected sign is indeterminate.

**Sex of the Household Head (SEX)** is binary in nature which takes 1 if the head of the household is male and 0 for female. Male farmers are expected to have better probabilities of technology adoption since they are exposed to new information and tend to be risk takers. Hence the expected sign is positive.

**Education level of the Household Head (EDUC)** is a categorical variable which takes a value of 0 = illiterate, 1= primary education, 2=secondary education and above. More educated farmers may have better information about agricultural technologies which enhance the adoption of technologies (Adeoti, 2009; Kassie et al., 2011). As a result, the expected sign of education on technology adoption is positive.

**Family Size (FAM)** is measured by the number of family in the household. Studies argued that farmers with larger family sizes are more likely to adopt chemical fertilizer in the sense that large households have a more secure labor for a labor- intensive technology (Alene et al., 2000). Therefore, the sign of the coefficient is expected to be positive.

**Access to extension service (EXT)** is binary nature which takes 1 if the farmer has got extension service from agents and 0 otherwise. Extension services for instance advice and training on the utilization of agricultural technologies will enhance farmers' capacity to adopt technologies (Mariano et al., 2012; Uaiene et al., 2009). Hence, the effect of extension service is expected to be positive.

**Access of credit (CRED)** it is a binary variable which take 1 if the farmer gets credit accessibility 0, otherwise. The probability of adopting and use of more intensity of chemical fertilizer would be better for farmers who have access to sources of finance since credit availability reduces the challenge of capital shortages. Therefore, the expected sign of credit accessibility is positive.

**Distance to the main market (DIST):** It is the distance between household's residence area and the nearest market measured in km. The greater the distance, the higher the acquisition cost and the lower the information which reduces the probability of the farmer to adopt technologies. Consequently, its expected coefficient is negative.

**Size of Landholding (LAND)** represents household's landholding size measured in hectare. However, the impact of land size on technology adoption is inconclusive. Some argued that households with big farm size adopted more improved technologies since they are less vulnerable to failure from trying new technologies relative to households having small land size (Mariano et al., 2012) and due to the economies of scale. On the other hand, small land size holders may adopt more technologies so as to enhance productivity in order to feed their family. As a result, the impact of land size on technology adoption is indeterminate.

**Table 3.3 Summary of Explanatory Variables for the Logit and Tobit Models**

| Variables | Description | Type & measurement of variables | Expected sign |
|---|---|---|---|
| AGE | Age of the household head | Continuous variable measured in years | +/- |
| SEX | Sex of the household head | 0 = female and 1= male | + |
| EDUC | Educational level of the household head | 0 = illiterate<br>1= primary education<br>2= secondary and above | + |
| FAM | The total family size in the household | Continuous variable measured in the number of family in the household. | + |
| EXT | Access to extension service | 0= no access to extension service<br>1= has access to extension service | + |
| CRED | Access to credit | 0 = no access to credit<br>1 = has access to credit | + |
| DIST | Distance to the main market | Continuous variable measured in km | - |
| LAND | The size of arable land available for the household | Continuous variable measured in hectare | +/- |
| OFFINC | The total annual of off-farm income for the household | Continuous variable measured in ETB. | + |

**Off-Farm Income (OFFINC):** Off-farm income and non-farm income are used interchangeably in several studies. According to Babatunde (2013), the difference between the two is that off-farm income is much broader than non-farm income and it is made up of agricultural wage income plus non-farm income. Hence, in this study off-farm income represents the amount of income measured in Ethiopian Birr (ETB) obtained by farm households from agricultural employment on other people's farm and non-farm income (such as wage from non-farm employment, income from trade and services, interest earnings, and remittances). As off-farm income increases, the probability to adopt and the use of fertilizer intensity increases since the household will get additional source of capital for the purchase of chemical fertilizer. Hence, the expected sigh is positive.

Table 3.3 summarizes the description and measurement independent variables included in the logit and tobit models along with their expected influence on the dependent variables.

*3.3.6.5 Propensity Score Matching*

Among others, one of the central objectives of the study is to estimate the effect of fertilizer and improved seed adoption on households' poverty and income distribution. However, a direct comparison of non-adopters and adopters on the outcome variables is misleading because the difference may not exclusively obtained from adoption but also from other characteristics of farmers. It means that since technology adoption is not random rather it depends on various factors, self-selection problem may be occurred. Hence, identifying appropriate technique for the estimation of the true effect of technology adoption on poverty and distribution of income become an important task of the researcher.

According to Blundell and Dias (2000), the choice of appropriate method depends on (1) the type of information available to the researcher (2) the underlying model and (3) the parameter of interest. As discussed earlier in chapter 2, the most frequently used quasi-experimental design methods are propensity score matching (PSM), difference in differences (DD), Heckman two-step selection approach and instrumental variables (IV). However, Heckman two-step selection procedure and IV address the selection of unobservable by imposing distributional and functional form assumptions, such as linearity on the outcome equation and extrapolating over regions of no common support, where no similar adopter and non-adopter observations exist (Kassie et al.,

2011) whereas DD method can be applied only when there exists repeated cross-sectional data (Blundell & Dias, 2000)

In this study, therefore, PSM technique is found to be more appropriate. It is useful to resolve the challenge of self-selection that might be resulted from observed difference in the characteristics of treated and control groups (Budhathoki & Bhatta, 2016; Simtowe et al., 2011). PSM compares each observation of the treated group with the control group having similar observed characteristics. In other words, it matches adopters to non-adopters on the basis of their propensity score.

PSM approach is a two-step procedure; the estimation of propensity scores followed by matching of adopters to non-adopters. In this study, logit model has been employed to calculate the probability (or propensity scores) of technology adoption for each observation as explained above.

According to Rosenbaum and Rubin (1983), propensity score is defined as the conditional probability of receiving a treatment given pretreatment characteristics and it can be expressed as:

$$P(X) = \Pr(\mathrm{T} = 1|\mathrm{X}) = \mathrm{E}(\mathrm{T}|\mathrm{X}); \qquad \mathrm{p}(\mathrm{X}) = \mathrm{F}\{\mathrm{h}(X_i)\} \text{ ……………… [21]}$$

Where T is the indicator of treatment (adoption), X is a vector of observed characteristics and $\mathrm{F}\{.\}$ can be a normal or logistic cumulative distribution.

Once the propensity scores are estimated, the average treatment effect of the treated (ATT) was computed. The ATT is the mean outcome difference between adopters and non-adopters with similar propensity scores. It can be specified mathematically as;

$$ATT = E\{Y_{iA} - Y_{iN}|T = 1\},$$
$$ATT = E[E\{Y_{iA} - Y_{iN}|T = 1, p(X)\}],$$
$$ATT = E[E\{Y_{iA}|T = 1, p(X)\} - E\{(Y_{iN}|T = 0, p(X)\}] \text{ ………………… [22]}$$

Where $Y_{iA}$ and $Y_{iN}$ represents the mean outcome value of adopters and non-adopters respectively. $E\{Y_{iA}|T=1,p(X)\}$ represents the mean outcome of adopters (observable) while $E\{(Y_{iN}|T=0,p(X)\}$ indicates the mean outcome of the adopters had it not be adopted (counterfactual situation).

Adopters and non-adopters can be compared with various matching estimators. In this study, the two commonly used matching estimators; the nearest neighbor matching (NNM) and kernel-based matching (KBM) have been used (Becerril & Abdulai, 2010; Budhathoki & Bhatta, 2016; Kassie et al., 2011; Mendola, 2007). In NNM each individual from the treated group is matched with the control group having the closest propensity score whereas in KBM, all individuals from the treated group are matched with a weighted average of all control group (Becker & Ichino, 2002).

Finally, tests of matching quality have been carried out in order to check the validity of matching process. According to Rosenbaum and Rubin (1983), the lower the pseudo $R^2$, insignificant of the likelihood ratio and the higher the reduction in the mean standardized bias after matching indicates the quality of the matching procedure.

Even though income or consumption is traditionally used as a measurement of households' welfare, consumption is viewed as the preferred welfare indicator since it better reflects households' ability to meet basic needs (standard of living). Moreover, especially in developing countries, income report of households is likely to be understated compared to their consumption expenditure report (National Planning Commission, 2017). Hence, in this study poverty has been measured based on households' level of consumption.

Setting the line of poverty is the first step in the measurement of poverty. In this study, CBN approach has been employed in order to estimate poverty line. As it is discussed in chapter two, estimation of poverty line by using CBN method provides a more representative result and consistent with real expenditure across space, time and socio economic group. Accordingly, food poverty line was computed by selecting a set of food items commonly consumed by the poor that meets a minimum caloric requirement recommended by World Health Organization of 2200 kcal/day/person (National Planning Commission, 2017).

In this study, therefore, 19 food items were selected as basic food items consumed by the poor and the average annual consumption in kg per adult equivalent for each item is estimated. Then, the annual average calories consumed by an adult is computed by multiplying the average annual consumption per adult and calorie value of each food items obtained from (EHNRI, 1998). The average quantity per adult of each food item scales up/down by a constant value so as to provide total of 8030000 kcal/adult/annum (=365 days*2,200 kcal/adult/day). Finally, the food poverty line is estimated by summing each food items after scaling up/down valued at local price. Poverty line is the sum of food and non-food poverty lines. Hence, in order to account the non-food poverty line and to arrive at the absolute total poverty line, the food poverty line is divided by the food share of the poorest 25 % of the sample households (National Planning Commission, 2017).

Poverty reports in developing countries including Ethiopia use the three poverty indices of Foster- Greer- Thorbecke (FGT) measures of poverty; the head count ratio, the poverty gap and the severity of poverty. FGT is one of the most desirable measures of poverty which is used in most literatures and widely accepted by development economists (Todaro & Smith, 2012). The FGT formula is given as;

$$P_{\alpha} = \frac{1}{N}\sum_{i=1}^{H}\left(\frac{Y_p - Y_i}{Y_p}\right)^{\alpha} \quad \text{...............} [23]$$

Where N is the sample size, Yi is consumption expenditure per adult equivalent for the $i^{th}$ poor household, Yp is the poverty line, H is the total number of poor households and α is the poverty aversion parameter where it measures head count index (if α = 0), poverty gap index (if α = 1) and poverty severity index (if α = 2).

**Head Count Index**: If α = 0 then, FGT measures the share of sample households whose expenditure falls below the poverty line. It is commonly called incidence of poverty. In such type of poverty measurement no concern is given for the depth of the shortfall.

**Poverty Gap Index:** If α = 1 then, FGT measures the aggregate poverty deficit of the poor relative to the poverty, i.e., the depth of poverty. It captures the mean aggregate consumption shortfall relative to the poverty line across the sample. It is, therefore, a much more powerful measure than the head count ratio because it takes into account the distribution of poor below the poverty line.

**Poverty Severity Index:** if $\alpha = 2$ then, FGT measures the severity of poverty. It is sensitive to the inequality among the poor households. It takes in to account not only the distance separating the poor from poverty line, but also inequality among the poor.

Therefore, based on the above methods, the impact of technology adoption on poverty has been analyzed in two different cases independently for; fertilizer adoption, and simultaneous adoption of both fertilizer and improved seeds.

In order to estimate the impact of technology adoption on income inequality, this paper employed the method used by Ding, Meriluoto, Reed, Tao, and Wu (2011) and Huang, Zeng, and Zhou (2015). Accordingly, distribution of farmers' income with and without technology adoptions is compared which the difference in the respective distributions indicates the effect of technology adoption on income inequality.

But it is not easy to get the income of agriculture technology adopters before they have adopted the technology. Hence, simulation method has been employed. To calculate farmers' incomes without technology adoption, it is started by estimating the effect of technology adoption on the income of adopters. The impacts of technology adoption on households' income which is the Average Treatment for the Treated (ATT) was computed based on PSM method discussed above.

Then the estimated ATT of total household income was subtracted from the observable income of technology adopters to get an estimate of what their income would be without technology adoption. For non-adopting farmers, the observable income is used.

Finally, in order to examine the impact of technology adoption on income inequality, Lorenz curves and Gini coefficients have been constructed for the two scenarios independently. One based on the observable household income distributions and the other based on the counterfactual income distribution which the differences between them represents the impacts of technology adoption on income inequality.

Lorenz curve is an instrument to analyze personal income statistics. In constructing a Lorenz curve, while the cumulative percentages income recipients are plotted on the horizontal axis, the vertical axis shows the share of total income received by each percentage of population. The entire figure is enclosed in a square and a diagonal line is drawn from the lower left corner (the origin) of the square to the upper right corner. The more the Lorenz curve line is away from the diagonal (perfect equality), the greater the degree of inequality represented (Todaro & Smith, 2012).

The Gini coefficient is one of the most widely used measures of inequality which satisfies the four desirable properties of inequality measures; Scale independence: if all incomes were doubled, the measure would not change; (b) Population independence: If the population were to change, the measure of inequality should not change; (c) Symmetry: If you and I swap incomes, there should be no change in the measure of inequality; (d) Pigou-Dalton Transfer principle: the transfer of income from rich to poor reduces measured inequality (Shorrocks, 1980).

The value of Gini coefficient varies from zero (perfect equality) to one (perfect inequality). Therefore the higher the value of the Gini indicates the existence of high inequality of income distribution while the lower the Gini shows better income distribution among the household.

In this study, Gini coefficients based on households' total annual income was estimated by using the formula of Lerman and Yitzhaki (1985). It can be written as;

$$G = \frac{2}{n\mu} \mathrm{cov}(i, y_i) \qquad [24]$$

G = Gini Coefficient

i = the rank of household i when the population is ordered by increasing income.

$y_i$ = income of household i.

μ = the average value of household income

n = the number of households

Hence, like the case of impact analysis on poverty, the impact of each type of adoption (fertilizer adoption, and simultaneous adoption of both fertilizer and improved seeds) on income distribution was examined independently.

Moreover, in order to measure the contribution of each sources of income (income from crop production, income from livestock and off-farm income) to the total income inequality, this study employed decomposition of the Gini coefficient as formulated by Pyatt, Chen, and Fei (1980). The decomposition is as follows;

$$G = \sum_{K=1}^{K} W_K C_K = \sum_{K=1}^{K} W_K R_K G_K \quad \text{[25]}$$

Where;

$W_K$ is the share of income from source K

$C_K = R_K G_K$ is the concentration ratio of income source K

$R_K$ is the rank correlation ratio for income source K

$G_K$ is the Gini coefficient for income source K

*3.3.6.6 The Dose Response Function*

In order to estimate the impact of intensity of fertilizer adoption, this study employed the dose response function. The dose response function is a useful estimation technique when the treatment variable takes a continuum of values (Bia and Mattei, 2008). Hirano and Imbens (2004) have extended PSM method to evaluate the impact of a continuous treatment on the outcome variables by using generalized propensity Score (GPS) technique.

The GPS technique comprises of three steps. In the first step the conditional distribution of the treatment given the covariates is estimated as;

$$g(T_i)|X_i \sim N\{h(\gamma, X_i), \sigma^2\} \quad \text{[26]}$$

Where $g(T_i)$ is a suitable transformation of the treatment variable, $h(\gamma, X_i)$ is a function of covariates with linear and higher-order terms, which depends on a vector of parameters, $\gamma$.

Then the estimated GPS will be computed as;

$$\hat{R}_i = \frac{1}{\sqrt{2\pi\hat{\sigma}^2}} exp\left[-\frac{1}{\sqrt{2\hat{\sigma}^2}}\{g(T_i) - h(\hat{\gamma}, X_i)\}\right] \text{ .......................................... [27]}$$

Where $\hat{\sigma}^2$and $\hat{\gamma}$ are the estimated parameters in equation [26].

In the second step, the conditional expectation of the outcome given the treatment and GPS is estimated. By using polynomial approximations of order not higher than three, the model is specified as;

$$\varphi\{E(Y_i|T_i, R_i)\} = \psi(T_i, R_i;\ \alpha)$$
$$= \alpha_0 + \alpha_1.T_i + \alpha_2.{T_i}^2 + \alpha_3.{T_i}^3 + \alpha_4.R_i + \alpha_5.{R_i}^2 + \alpha_6.{R_i}^3 + \alpha_7.T_i.R_i \text{ .................... [28]}$$

The third step is the estimating the dose–response function by using the following formula;

$$E\{\widehat{Y(t)}\} = \frac{1}{N}\sum_{i=1}^{N}\hat{\beta}\{t, \hat{r}(t, X_i)\} = \frac{1}{N}\sum_{i=1}^{N}\varphi^{-1}\left[\hat{\psi}\{t, \hat{r}(t, X_i);\ \hat{\alpha}\}\right] \text{ ............................. [29]}$$

Finally, the estimation of the does response function has been conducted by using STATA syntax developed by Bia and Mattei (2008).

# CHAPTER FOUR
# RESULTS AND DISCUSSION

## 4.1 Introduction

The growth of the agriculture sector primarily related to the adoption of productivity enhancing technologies due to less possibility of getting new area of land for cultivation. Many studies revealed that technological adoption in agriculture such as introduction of improved seeds and fertilizers enhance productivity of land and bring about rapid increase in production, ensuring food security and reducing poverty.

This chapter presents and discusses both the descriptive and econometric results of the study. Firstly, it deals with descriptive analysis which tried to compare adopters and non-adopters of agricultural technology based on selected variables of interest by using t-test and chi-square tests. Secondly, the economic benefit of fertilizer and improved seeds adoption was analyzed and discussed based on a total farm budgetary analysis technique and the Blinder-Oaxaca decomposition method. Thirdly, determinants of agricultural technology adoption were investigated by using logit and tobit models and the results are interpreted accordingly. Finally, the impact of adoption on households' poverty and distribution of income is evaluated and discussed.

In this study, two main agricultural technologies namely chemical fertilizer and improved seeds were considered. Hence analysis were employed for the two scenarios independently; adoption of fertilizer and simultaneous adoption of fertilizer and improved seeds. However, a separate analysis for adoption of improved seeds were not undertaken since no farm household was found who adopted improved varieties of seeds without fertilizer in the study area. It means that all adopters of improved seeds were adopted fertilizer simultaneously.

## 4.2 Demographic Characteristics of Sample Respondents

From the total 400 sample households, 91.75% of them were male headed farmers while 8.25% of the sample respondents were female headed (Table 4.1). It indicates that most of rural households in the study area are headed by males. The results are similar with other studies such as Ahmed, Geleta, Tazeze, and Andualem (2017) and Asfaw et al. (2011) who found the ratio of male headed households to be 89.9% in Eastern Ethiopia and 92.96% in Central Ethiopia respectively.

**Table 4.1 Sample Households by Sex**

| Sex of Households | Obs. | Percent |
|---|---|---|
| Male | 367 | 91.75 |
| Female | 33 | 8.25 |
| ***Total*** | ***400*** | ***100*** |

**Source:** Field Survey, 2018

As shown in table 4.2, the average age of sample household heads were found to be 45.97 years with minimum and maximum age of 22 and 89 years. In addition, in the study area, the average family size of farm households was found to be 6.26 which is greater than the average size of the zone, 4.89 (CSA, 2016b).

**Table 4.2 Age and Family Size of Respondents**

| | Obs. | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Age | 400 | 45.97 | 11.88 | 22 | 89 |
| Family Size | 400 | 6.26 | 1.92 | 1 | 13 |

**Source:** Field Survey, 2018

Table 4.3 presents educational level of household heads in the study area. From the total sample households 62.25% of them were found to be illiterate who are unable to read and write. This rate is higher than the findings of Abrha (2015) and Feleke and Zegeye (2006) who found illiteracy rate of 52.75% in Northern region of Ethiopia and 51.35% in Southern Ethiopia, respectively. In the study area, on the other hand, 31.75% and 6.00% of the households attended primary and secondary level of education, respectively.

**Table 4.3 Household Heads' Level of Education**

| Level of Education | Obs. | Percent |
|---|---|---|
| Illiterate | 249 | 62.25 |
| Primary | 127 | 31.75 |
| Secondary | 24 | 6.00 |
| ***Total*** | ***400*** | ***100*** |

**Source:** Field Survey, 2018

## 4.3 Adoption of Fertilizer and Improved Varieties of Seeds in the Study Area

As indicated in table 4.4, 71.75% of farm households applied chemical fertilizer in at least one of their crops during the agricultural season of 2017/18. On the other hand, 52.75% of farmers adopted both chemical fertilizer and improved seeds simultaneously. The adoption rate of this study is similar to the results of recent studies in Ethiopia while it is much higher than earlier studies. For instance, Beshir, Emana, Kassa, and Haji (2012) and B. K. Hailu, Abrha, and Weldegiorgis (2014) have found the adoption rate of fertilizers at 17.8% and 26.67% respectively where as more recent studies such as Husen, Loos, and Siddig (2017) and Mekonnen (2017) revealed that 56.8% and 63% of households were adopters of fertilizer. The existence of better adoption rate in this study is, therefore, an indicator of improvement in adoption of agricultural technologies over time.

**Table 4.4 Technology Adoption Status of Sample Households**

| **Description** | **Fertilizer** | | **Both Fertilizer and Improved seeds** | | **Total Sample HH** |
|---|---|---|---|---|---|
| | Adopters | Non-adopters | Adopters | Non-adopters | |
| Frequency | 287 | 113 | 211 | 189 | 400 |
| Percentage | 71.75 | 28.25 | 52.75 | 47.25 | 100 |

**Source:** Field Survey, 2018

As it is reveled from the response of sample households and interview of agricultural experts the most common types of chemical fertilizers applied by farm households in the study area are DAP and Urea. Regarding to improved seeds, farmers in Awi zone use improved seeds of Maize, wheat and potato. However, few farmers adopted improved seeds of *teff* and finger millet. Though about half of the farm households adopted at least one variety of improved seeds, the proportion of arable land covered by improved seeds is found to be very low. According to CSA (2016), from the total amount of land for cereal production in Awi zone, only 16.1% of it was covered by improved seeds.

**Table 4.5 Adoption of Agricultural Technology by District**

| **Districts** | **Fertilizer** | | | | **Both Fertilizer and Improved seeds** | | | | **Total Sample HH** | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Adopters | | Non-adopters | | Adopters | | Non-adopters | | | |
| | Obs. | percent | Obs. | percent | Obs. | percent | Obs. | percent | Obs. | percent |
| Banja | 52 | 61.9 | 32 | 38.1 | 24 | 28.57 | 60 | 71.43 | 84 | 21 |
| Guangua | 152 | 74.51 | 52 | 25.49 | 112 | 54.9 | 92 | 45.1 | 204 | 51 |
| Guagusa S. | 83 | 74.11 | 29 | 25.89 | 75 | 66.96 | 37 | 33.04 | 112 | 28 |
| chi2(2) | 5.0905 (0.078)* | | | | 29.1604 (0.000)*** | | | | | |

**Source**: Field Survey, 2018

Note: *** and * indicates 1% and 10% level of significance

Regarding to district disaggregation, adoption of fertilizer in Guangua and Guagusa Shikudad was found to be similar with adoption rate of 74.51% and 74.11% respectively. However, in Banja district, only 61.9% of farmers adopted fertilizer which is smaller than the two districts. On the other hand, 66.96% of farm households in Guagusa Shikudad district adopted fertilizer and improved seeds simultaneously followed by Guangua (54.9%) and Banja (28.57%) districts. The results of the chi-square tests indicate the existence of statistically significant difference on adoption of agricultural technologies among districts.

The average chemical fertilizer applied by farm household was found to be 120.49 kg/ha for the entire sample and 167.93 kg/ha for adopters (Table 4.6). The results are somewhat greater than other similar studies in Ethiopia. For Example Abate et al. (2016) reported 133.3 kg/ha and Abrha (2015) estimated the average application of fertilizer for adopters to be 153.56 kg/ha. This may reflect the improvement of fertilizer application by farmers' overtime.

**Table 4.6 Quantity of Fertilizer Used by District**

| Districts | Adopters | | | | | Whole Sample | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Obs. | Mean | Std. Dev | Min | Max | Obs. | Mean | Std. Dev | Min | Max |
| Banja | 52 | 124.68 | 91.04 | 2.28 | 360 | 84 | 77.18 | 93.82 | 0 | 360 |
| Guangua | 152 | 179.96 | 85.27 | 30 | 500 | 204 | 134.08 | 107.65 | 0 | 500 |
| Guagusa S. | 83 | 173.00 | 72.66 | 16 | 400 | 112 | 128.20 | 98.46 | 0 | 400 |
| ***Total*** | ***287*** | ***167.93*** | ***85.18*** | ***2.28*** | ***500*** | ***400*** | ***120.49*** | ***104.55*** | ***0*** | ***500*** |

**Source:** Field Survey, 2018

The intensity of fertilizer use in Guangua and Guagusa Shikudad districts were nearly the same. It was estimated to be 134.08 and 128.2 kg/ha for the entire households and 179.96 and 173 kg/ha for adopters only respectively. However, similar to the rate of adoption, intensity of fertilizer use in Banja district is found to be very low; 77.18 and 124.68 kg/ha for the entire sample and fertilizer adopters respectively.

**Table 4.7 Fertilizer Adopters with their Intensity of Fertilizer Application**

| Description | Intensity of fertilizer application | | |
|---|---|---|---|
| | **Less than 200kg** | **Equal or greater than 200kg** | **Total** |
| Frequency | 154 | 133 | 287 |
| Percent | 53.66 | 46.34 | 100 |

**Source:** Field Survey, 2018

The issue of agricultural technology is not only whether to adopt or not but also on the intensity of its application. In Ethiopia, on average, the recommended application of chemical fertilizer (DAP and Urea) is 200 kg per hectare (Abate et al., 2016; Abrha, 2015). In the study area, out of the total fertilizer adopters, 46.34% of them applied fertilizer as per the recommended rate while more than half of them (53.66%) applied below the recommended rate (table 4.7). This result is similar with the findings of Abrha (2015) who found that 59.63% of the respondents adopted fertilizer below the recommended rate of 200 kg/ha.

The minimum amount of fertilizer use (2.28 kg/ha) shown in table 4.6 is also an indicator of application of fertilizer below the required ratio. The results support the argument that intensity of fertilizer use in Africa is much lower than other developing countries (Druilhe & Barreiro-hurlé, 2012; Morris, Kelly, Kopicki, & Byerlee, 2007)

Adopters of fertilizer and improved seeds were further asked to reply on the number of years that they practiced these technologies during cultivation of their crops. As indicated in table 4.8, on average, farmers have used fertilizer for 12.44 years with a maximum and minimum of 30 and 4 years, respectively. On the other hand, in the study area, the mean years of improved seeds adoption by farm households were 9.69 with 2 and 26 years of minimum and maximum years of adoption. The results indicate that use of fertilizer and improved seed in Ethiopia is not a recent phenomenon. However, farmers have started adoption of fertilizer relatively earlier than improved seeds.

**Table 4.8 Years of Experience on Application of Fertilizer and Improved Seeds**

| Agricultural Technologies | Obs. | Mean | Std. Dev. | Minimum | Maximum |
|---|---|---|---|---|---|
| Fertilizer | 287 | 12.44 | 5.87 | 4 | 30 |
| Fertilizer and Improved Seeds | 211 | 9.69 | 4.88 | 2 | 26 |

**Source:** Computed from field Survey, 2018

In contrary, non-adopters were asked to mention the reasons behind their absence of fertilizer and improved seeds adoption. As a result, expensiveness of improved seeds and inadequacy of supplies were the major reasons mentioned by non-adopters of fertilizer and improved seeds. Few farmers believed that the soil type of their land is inconsistent with the existing fertilizers and improved seeds. Moreover, some of farmers used manure instead of chemical fertilizers for production of crops.

## 4.4 Demographic, Socio-Economic and Institutional Factors and Adoption of Technology

This section describes the characteristics of sample farm households by their adoption status. Hence, comparison is made between adopters and non-adopters based on various demographic, socio-economic and institutional factors independently. To check whether there exists a statistically significance difference between adopters and non-adopters or not, the usual t-test and chi-square test were employed for continuous and categorical variables respectively.

The study found that while majority of male headed farmers (76.66%) adopted fertilizer, the adoption rate of female headed households was less than half (39.39%). Similarly, the simultaneous adoption rate of fertilizer and improved seeds by male headed households (54.77%) was found to be better than females (30.30%). The results further indicate the existence of statistically significant (1%) difference in adoption of technology between male and female headed households where males adopt more than females. This may be due to the fact that male farmers are more exposed to new information and tend to be risk takers than their counterparts.

**Table 4.9 Sample Households by Sex and Technology Adoption**

| Description | Fertilizer | | | | Both Fertilizer and Improved Seeds | | | |
|---|---|---|---|---|---|---|---|---|
| | Adopters | | Non-adopters | | Adopters | | Non-adopters | |
| | Obs. | percent | Obs. | percent | Obs. | percent | Obs. | percent |
| Male | 271 | 73.84 | 96 | 26.16 | 201 | 54.77 | 166 | 45.23 |
| Female | 16 | 48.48 | 17 | 51.52 | 10 | 30.30 | 23 | 69.70 |
| chi2(1) | 9.6046*** | | | | 7.2711*** | | | |

**Source:** Field Survey, 2018

Note: *** indicates 1% level of significance

As shown in table 4.10, the mean age of fertilizer adopters was 50.04 years whereas for non-adopters it was estimated to be 44.36 years. On the other hand, the average age of both fertilizer and improved seeds adopters and non-adopters was 47.47 and 44.62 years respectively. The results of the t-test show that average age of adopters was found to be lower than non-adopters at

1% and 5% level of significance, implying that as age increases the likelihood of adopting agricultural technologies will decline. This may be due to the fact that as age increases, farm households would become too reluctant and conservative in adopting agricultural technologies (B. K. Hailu et al., 2014) while younger household heads may be more flexible and hence likely to adopt new technologies.

**Table 4.10 Sample Households by Age, Family Size and Technology Adoption**

| Description | | Fertilizer | | Both Fertilizer and Improved seeds | |
|---|---|---|---|---|---|
| | | Adopters | Non-adopters | Adopters | Non-adopters |
| Age | Mean | 44.36237 | 50.04425 | 44.62085 | 47.4709 |
| | t-test | 4.4027*** | | 2.4087** | |
| Family Size | Mean | 6.609756 | 5.362832 | 6.729858 | 5.730159 |
| | t-test | -6.0908*** | | -5.3629*** | |

**Source**: Field Survey, 2018

**Note**: *** and ** indicates 1% and 5% level of significance

Moreover, the results in table 4.10 indicate that family size of agricultural technology adopters is greater than non-adopters with 1% level of significance. The result is not surprising since adoption of fertilizer and improved seeds are labor intensive technologies. Adopters of technologies used more labor for farming activities such as cultivation, planting and weeding than non-adopters (Adofu et al., 2013; Asfaw et al., 2011; Birthal et al., 2012).

Education is believed to improve technology adoption by promoting awareness on the importance and effective utilization of agricultural technologies. As it is indicated in table 4.11, 65.06% of illiterates, 82.68% of those who attended primary education and 83.33% of those who attended secondary education adopted fertilizer. Regarding to simultaneous adoption of fertilizer and improved seeds, the share of adopters was found to be 45.78%, 63.78% and 66.78% for households whose education levels were illiterate, primary education and secondary education respectively.

**Table 4.11 Education Level of Respondents by Adoption Status of Fertilizer and Improved seeds**

| Level of Education | Fertilizer | | | | Both Fertilizer and Improved Seeds | | | |
|---|---|---|---|---|---|---|---|---|
| | Adopters | | Non-adopters | | Adopters | | Non-adopters | |
| | Obs. | percent | Obs. | percent | Obs. | percent | Obs. | percent |
| Illiterate | 162 | 65.06 | 87 | 34.94 | 114 | 45.78 | 135 | 54.22 |
| Primary | 105 | 82.68 | 22 | 17.32 | 81 | 63.78 | 46 | 36.22 |
| Secondary | 20 | 83.33 | 4 | 16.67 | 16 | 66.67 | 8 | 33.33 |
| chi2(2) | 14.5677 *** | | | | 12.9125 *** | | | |

**Source**: Field Survey, 2018

**Note**: *** indicates 1% level of significance

The results show the existence of statistically significant (1%) difference in technology adoption depending on their education level implying that education enhances adoption of fertilizer and improved seeds. This may be due to the fact that education promotes awareness about the possible advantages of agriculture technologies that can enhance its adoption (Adeoti, 2009; Kassie et al., 2011).

In Ethiopia, land is the most important factor of production since more than 80% of the population lives in rural area where the agriculture sector is the main source of livelihood. In the study area, from the total sample households, 367(91.75%) of them possess their own land while the rest of them, 33(8.25%) of rural households hadn't. Those who hadn't possessed their own land were further asked to identify their means of earnings and they replied that work on rented land and participation on off-farm activities were their major sources of livelihood.

The average landholding size in the study area was 1.14 hectare which is smaller than the zonal average, 1.31 hectare (CSA, 2016b). Regarding to spatial distribution of land, the average landholding size of households living in Guangua district (1.21 ha) was the largest followed by Guagusa Shikudad district (1.14 ha.). The average land size is smallest in Banja District which was found to be only 0.99 ha. Though land is a key factor to sustain the livelihood of rural households, the landholding size of all districts is found to be low and below the zonal average.

**Table 4.12 Average Land size in Hectare by Technology Adoption and District**

| Districts | Fertilizer | | Both Fertilizer and Improved seeds | | Total Sample HH |
|---|---|---|---|---|---|
| | Adopters | Non-adopters | Adopters | Non-adopters | |
| Total | 1.197233 | 1.00292 | 1.194289 | 1.084344 | 1.14234 |
| Banja | 1.032135 | 0.9126562 | 1.03375 | 0.9677667 | 0.986619 |
| Guangua | 1.244243 | 1.09375 | 1.239955 | 1.164402 | 1.205882 |
| Guagusa S. | 1.214578 | 0.9396552 | 1.177467 | 1.074324 | 1.143393 |
| t-test | 2.92*** | | 1.8235* | | |

**Source**: Field Survey, 2018

**Note**: *** and * indicates 1% and 10% level of significance

As indicated in table 4.12, the average landholding size of fertilizer adopters and simultaneous adopters of fertilizer and improved seeds was greater than non-adopters with 1% and 10% level of significance. Households with relatively large farm size adopt agricultural technologies better than small size land holders since they are less vulnerability to failure in implementing new technologies ((Mariano et al., 2012).

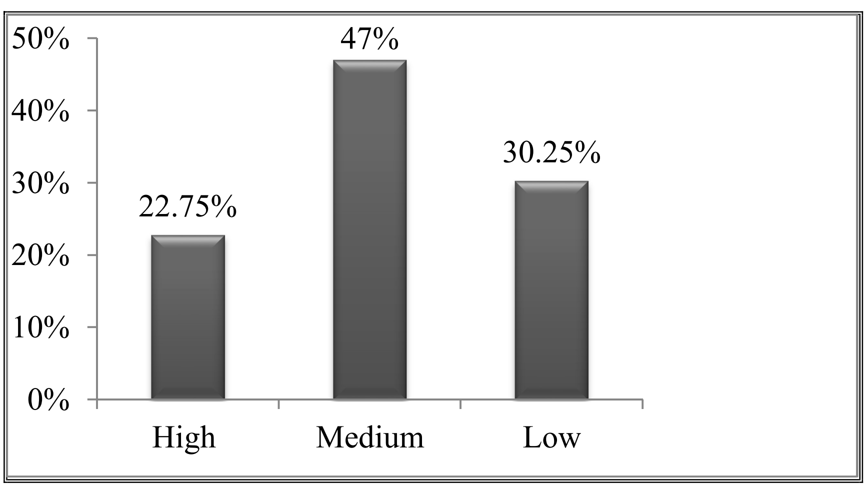



**Figure 4.1 Level of Land Fertility.**

**Source:** Field Survey, 2018

It is well known that welfare of the society is not only determined by the size of their land but also its fertility. Hence, farm households were requested to rate the average fertility level of their land. Accordingly, 47% and 22.75% of them rate the fertility of their land as medium fertile and high fertile while 30.25% those possessed infertile land, averagely (figure 4.1).

The availability of farm animals determines the farming ability of farm operators since they are the primary choices to cultivate land and pull heavy loads in most developing countries including Ethiopia. In the study area, farmers use oxen and horses for tillage. From the total households, 53.75% of them use oxen and 30.25% of farmers depend on horses in order to undertake their farming activities (table 4.13). The rest 16% of the sample households use both oxen and horses. According to the results obtained from interview of agricultural experts, farmers do not use tractor due to unavailability of tractor through rent, the poor economic status of farmers and small size of landholding per household.

**Table 4.13 Use of Animals in Farming Activities**

| Variables | Categories | Frequency | Percent |
|---|---|---|---|
| Animals used for farm tillage | Oxen | 215 | 53.75% |
| | Horses | 121 | 30.25% |
| | Both | 64 | 16.00% |
| | ***Total*** | ***400*** | ***100%*** |
| Are your animals enough for the farming activities? | Yes | 266 | 66.5 % |
| | No | 132 | 33.5% |
| | ***Total*** | ***400*** | ***100%*** |

**Source:** Field Survey, 2018

Though more than half of the households (66.5 %) possess enough number of animals for their farming activities, 33.5% of them were in lack of the required numbers. Furthermore, respondents who faced shortage of animals were asked to point out the mitigation mechanisms that they applied and they replied that coupling their animals with others, exchanging animals for labor and hiring of additional animals were the main solutions taken by farmers to solve shortage of animals, respectively based on their frequency of application.

It is believed that the distance between household's residence area and their nearest market influences adoption of agricultural technology negatively by increasing acquisition cost and reduce the probability of getting information about their availability and importance. As shown from table 4.14, the average distance between the residential home of the households and the nearest main market was estimated to be 6.4 km. The average distance to the market center in this study was found to be higher than a study by Feleke and Zegeye (2006) who found average distance of only 3.9 km in southern Ethiopia. But it is lower than the findings of Asfaw et al. (2011) which estimated the average distance of 12.8 km for adopters of improved variety of chickpea and 9.3 km for non-adopters in Central Ethiopia.

**Table 4.14 Distances from the Nearest Market Center by Technology Adoption**

| Description | | Fertilizer | | Both Fertilizer and Improved seeds | | Total Sample |
|---|---|---|---|---|---|---|
| | | Adopters | Non-adopters | Adopters | Non-adopters | |
| Distance from the main Market (in km) | Mean | 6.369861 | 6.385398 | 6.37346 | 6.375132 | 6.3742 |
| | t-stat | 0.0063 | | 0.0531 | | |

**Source:** Field Survey, 2018

In this study, however, there is no statistically significant difference in technology adoption based on distance from market (table 4.14).

Participation in off-farm activities is believed to be one of the major means of income diversification in developing countries since agriculture is a risky occupation. As indicated in table 4.15, 58 % of the households participate in off-farm activities while 42 % of them were non-participants. The participation rate in this study is found to be much lower than the result of Abrha (2015) but higher than a study by Abate et al. (2016) who found 88% and 39.5% respectively.

**Table 4.15 Participation in Off-farm Activities by Adoption of Technology**

| Off-Farm Participation | Fertilizer | | Both Fertilizer and Improved seeds | | Total Sample |
|---|---|---|---|---|---|
| | Adopters | Non-adopters | Adopters | Non-adopters | |
| Participants | 67.36% | 32.76% | 44.83% | 55.17% | 58% |
| Non-participants | 77.98% | 22.02% | 63.69% | 36.31% | 42% |
| chi2(1) | 5.5397** | | 13.9101*** | | |

**Source:** Field Survey, 2018

**Note:** *** and ** indicates 1% and 5% level of significance

The results further indicate that participants in off-farm activities adopted fertilizers and improved seeds less proportionately than non-participants. In this regard, Gebregziabher *et al.* *(*2014), revealed that off-farm activities may divert time & labor from agricultural activities and reducing investments in agricultural technologies.

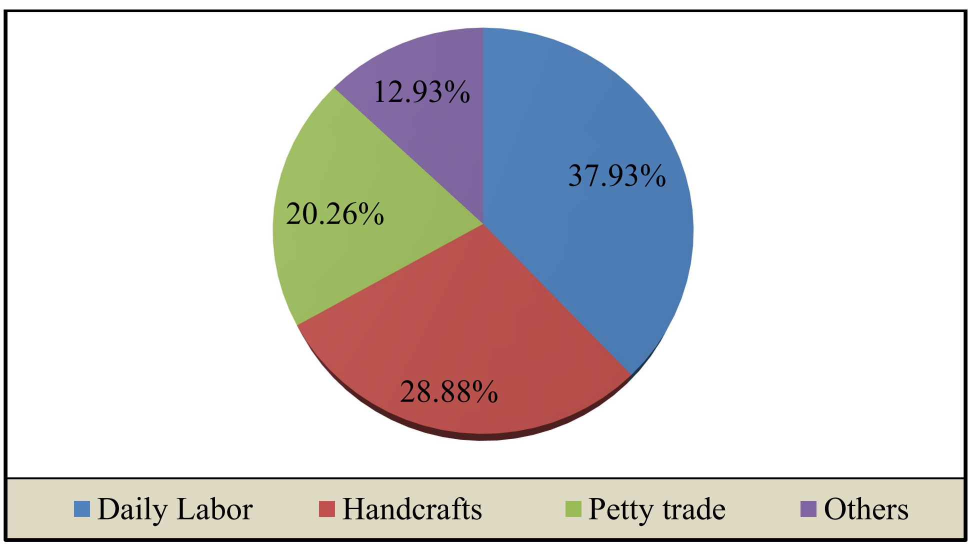



**Figure 4.2 Major Type of Off-farm Activities.**

**Source:** Field Survey, 2018

Participants on off-farm activities were asked to describe the main activities which they were engaged in. Accordingly, as indicated in figure 4.2, daily labor work, handcrafts and petty trade were identified by farm households as the major off-farm activities in the study area.

**Table 4.16 Participation on Off-farm Activities by Seasons**

| Description | Frequency | Percentage |
|---|---|---|
| Seasonal | 130 | 56.03 |
| *Meher season* | *41* | *17.67* |
| *Belg season* | *89* | *38.36* |
| *Throughout the year* | 102 | 43.97 |
| ***Total*** | ***232*** | ***100*** |

**Source**: Field Survey, 2018

Furthermore, participants on off-farm activities were requested to answer how often they were engaged in off-farm activities. As shown in table 4.16, more than half of the participants (56.03%) select favorable seasons for off-farm activities in order to avoid diversion of time and labor during the peak period of on-farm activities. Moreover, the type of off-farm activity also determine the favorable season for participation. On the contrary, 43.97 % of them participated throughout the year.

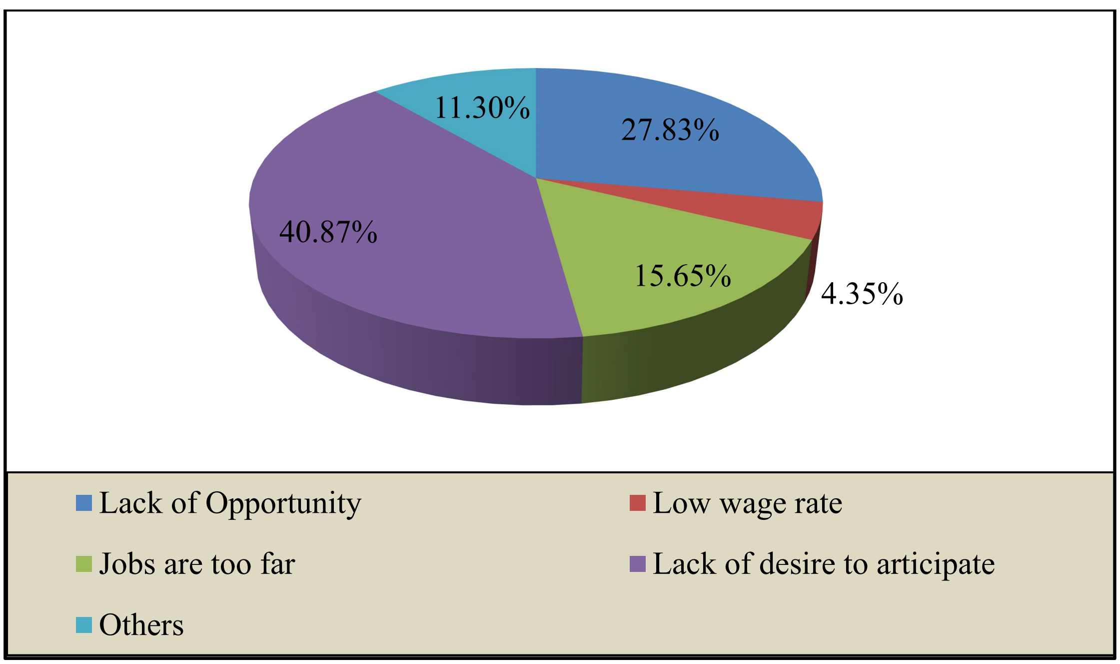



**Figure 4.3 Major reasons for the absence of participation in off-farm activities.**

**Source:** Field Survey, 2018

On the other hand, non-participants were replied that lack of desire to participate in off-farm activities, lack of off-farm job opportunities and faraway of off-farm jobs as the main reasons behind their absence of participation.

Extension service is the main channel through which information about new and improved technologies is transmitted to rural farmers particularly in developing countries like Ethiopia where rural literacy rate is low. According to Mekonnen (2017), information dissemination enhances farmers awareness about modern agricultural technologies and better farm practices. Out of the total farm households, 62.75% of them received extension service by development agents (extension workers) in their respective kebele (table 4.17).

In Ethiopia, agricultural extension services have been provided and financed by the government (Spielman, Byerlee, Alemu, & Kelemework, 2010). Development agents provide both advisory service and training at agricultural demonstration sites (MoFED, 2003). According to the information gathered from interview of agricultural office experts, in each kebele there are three development agents (plant science, animal science and natural resource) with specific activities carried out by each agent as per their areas of specialization. Particularly, plant science experts provides support to farmers related to the application of improved seeds, fertilizers, tilling, snowing and harvesting, according to the response of respondents.

**Table 4.17 Accessibility of Extension Service and Technology Adoption**

| Extension Service | Fertilizer | | | | Both Fertilizer and Improved seeds | | | | Total Sample HH | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Adopters | | Non-adopters | | Adopters | | Non-adopters | | | |
| | Freq. | percent | Freq. | percent | Freq. | percent | Freq. | percent | Freq. | Percent |
| Accessible | 200 | 79.68 | 51 | 20.32 | 155 | 61.75 | 96 | 38.25 | 251 | 62.75 |
| Non-Accessible | 87 | 58.39 | 62 | 41.61 | 56 | 37.58 | 93 | 62.42 | 149 | 37.25 |
| chi2(2) | 20.9119*** | | | | 21.9127*** | | | | | |

**Source:** Field Survey, 2018

**Note:** *** indicates 1% level of significance

Extension workers are expected to provide necessary information regarding to the importance, their application and sources of agricultural technologies and hence enhances adoption. As indicated in table 4.17, the share of adopters who received extension service was found to be greater than non-adopters in both technologies at 1% level of significance. Access to extension service may increases technology adoption by enhancing farmers' awareness and skills to efficiently use of new technologies (Husen et al., 2017).

Moreover, farmers were asked to reply whether the provided extension service is enough or not and 76.29% of them replied as it was sufficient (table 4.18). It implied that most of the rural households satisfied by the service provided by extension workers. On average, those who received extension service were visited by extension agents 8.5 times in a year. However, this frequency is much lower than a study by Abrha (2015) who found the average numbers of contacts to be 23 per year.

**Table 4.18 Sufficiency of Extension Service in the Study Area**

| Sufficiency of Extension service | Frequency | Percent |
|---|---|---|
| Yes | 177 | 76.29 |
| No | 55 | 23.71 |
| ***Total*** | ***232*** | ***100*** |

**Source:** Field Survey, 2018

Availability of credit tackles the financial shortages of farmers for the purchase of modern agricultural inputs. According to MoFED (2003), though farmers want to use modern agricultural technologies to increase their income, dearth of finance is the big challenge for millions of farmers in Ethiopia.

In this study, 55% of the households had access to credit for the purchase of chemical Fertilizer and improved seeds either in cash or in kind while the rest 45 % of them hadn't (table 4.19). The rate of credit accessibility in the study area is not far from the results of similar studies conducted in Ethiopia. For instance, a study by Abrha (2015) found that 59.75% of the farmers had access to credit in Northern Ethiopia. According to Ahmed et al. (2017), only 37.2% of the farmers were facing credit constraints in Eastern Ethiopia.

**Table 4.19 Credit Accessibility by Adoption of Technology**

| **Credit Access** | **Fertilizer** | | | | **Both Fertilizer and Improved seeds** | | | | **Total Sample HH** | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Adopters | | Non-adopters | | Adopters | | Non-adopters | | | |
| | Obs. | percent | Obs. | percent | Obs. | percent | Obs. | percent | Obs. | Percent |
| Accessible | 187 | 85 | 33 | 15 | 156 | 70.91 | 64 | 29.095 | 220 | 55 |
| Non-Accessible | 100 | 55.56 | 80 | 44.44 | 55 | 30.56 | 125 | 69.44 | 180 | 45 |
| chi2(2) | 42.3449 *** | | | | 21.9127 *** | | | | | |

**Source:** Field Survey, 2018
**Note:** *** indicates 1% level of significance

Table 4.19 indicates that the probability of adopting technologies for households who have access of credit was better than non-adopters in both technologies. Accessibility of credit reduces the problem of capital shortages for the purchase improved technologies at the right time (Abate et al., 2016; Mekonnen, 2017). According to Abrha (2015), in the absence of credit, adoption of chemical fertilizer will be reduced since smallholder farmers face constraint of cash.

In Ethiopia, provision of credit access is a government program for the purpose of encouraging smallholder farmers to adopt modern agricultural technologies (Mekonnen, 2017). Consequently, it supports the establishment and expansion of agricultural cooperatives. From those households who received credit, agricultural cooperatives (40.45%) were the main source of credit. In Ethiopia, the importance of agricultural cooperatives is highly recognized. They basically facilitate services provided by other financial institutions and filling the shortage of credit availability (MoFED, 2003). Amhara Credit and Saving Institution (ACSI), and friends and relatives comprise of 28.18 and 21.82% of the credit sources in the study area, respectively. The rest 9.55 % of farm households got credit from local money lenders.

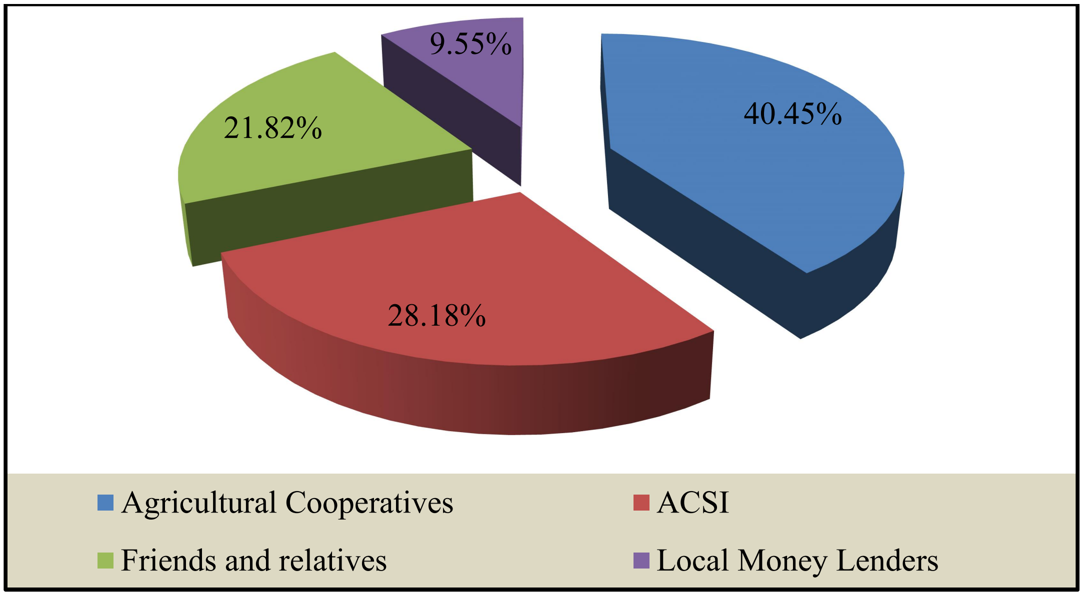



**Figure 4.4 Sources of Credit.**

**Source:** Field Survey, 2018

Furthermore, farm households were asked to mention the reasons behind their absence of getting credit during the agricultural season of 2017/18. Accordingly, as indicated in figure 4.5, high rates of interest and fear of repaying the loan were identified as the main reasons for non-accessibility of credit by the households.

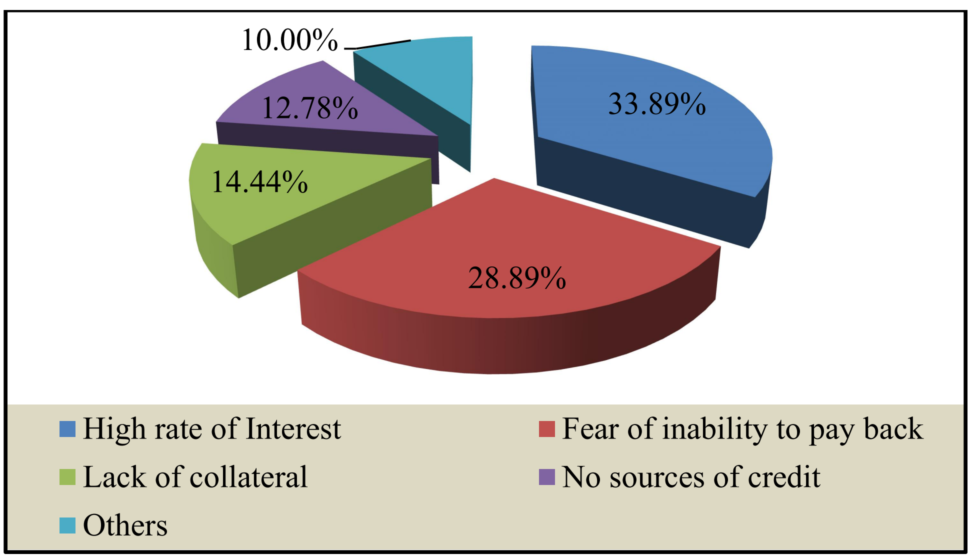



**Figure 4.5 Reasons for non-accessibility of Credit.**

**Source**: Field Survey, 2018

Moreover, lack of collateral and inability to get source of credit are among the reasons mentioned by farmers. Finally, some of the respondents identified other reasons such as group lending system and requirement of minimum saving in financial institutions as bottlenecks for getting credit timely.

Irrigation increases the level of agricultural production by increasing the frequency of crop production and alleviates water shortage caused by drought. However, in Ethiopia, irrigation practice is found to be very low. In 2016/17, irrigation was practiced by only 10.64% of farm households and only 1.33% arable land was covered by irrigation (CSA, 2016b).

**Table 4.20 Practice of Irrigation in the Study Area**

| Irrigation | Frequency | Percent |
|---|---|---|
| Users | 101 | 25.25% |
| non-users | 299 | 74.75% |
| ***Total*** | ***400*** | ***100*** |

**Source:** Field Survey, 2018

In the study area, out of the total respondents, only 25.25% of the households were irrigation users while most of the farmers were not users of irrigation. Considering the proportion of irrigated land to the total arable land available for farmers provides better understanding of the situation of irrigation in the study area.

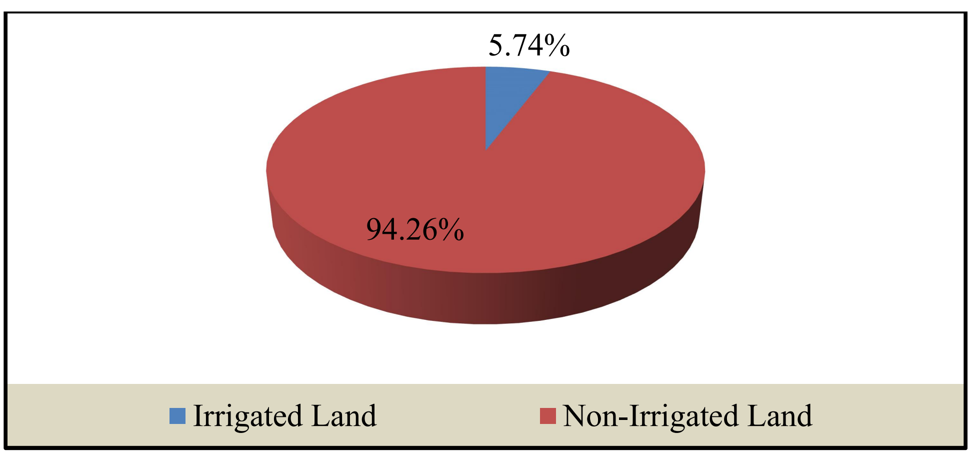



**Figure 4.6 Share of irrigated land to the total arable land**

**Source:** Field Survey, 2018

However, the study estimated that only 5.74% of the total landholding was irrigated during 2017/18 agriculture season (figure 4.6). Though the importance of irrigation for increasing agricultural production and productivity is well recognized, its practice is found to be at very low level.

Furthermore, as indicated in table 4.21, most irrigation users (83.17%) were practiced traditional way of irrigation such as diverting stream/ river, use of tanks and ponds. The rest 16.83% of them practiced modern irrigation through of drip irrigation and sprinkler mechanism.

**Table 4.21 Types of Irrigation**

| Categories | Frequency | Percent |
|---|---|---|
| Modern | 17 | 16.83% |
| Traditional | 84 | 83.17% |
| ***Total*** | ***101*** | ***100*** |

**Source:** Field Survey, 2018

## 4.5 Economic Analysis of Agricultural Technology Adoption

Studies argue on the importance of technology adoption such as fertilizer and improved seeds on productivity improvement which further leads to boost profitability of farmers (Devi & Ponnarasi, 2009; Myint & Napasintuwong, 2016; Pal et al., 2016). This section, therefore, deals with the economic benefits of fertilizer and improved seeds by focusing on the two most stable crops produced and consumed in Ethiopia, *teff* and maize.

*Teff* (*Eragrostis tef)* is the most stable food and highly valued crop for Ethiopian and Eritrean population (Haileselassie, Stomph, & Hoffland, 2011). It is mainly used for the preparation of *Injera*, Ethiopia's (and Eritrea's) popular dish (IFPRI, 2018). Its adaptability to various environmental conditions and lower vulnerability to disease make the crop more attractive and less risky (Haileselassie et al., 2011; G. Hailu et al., 2016). In terms of cultivation, *teff* is number one crop in Ethiopia which is cultivated in 23.85% of the total grain crop area and the second in terms of production that took 17.26% of the country's grain production (CSA, 2018a). Regarding to consumption, *teff* is the most consumed stable crop which makes up about 12 % of the food expenditure of Ethiopian population (IFPRI, 2018).

Maize is one of the most important crop in the world next to rice and wheat both in terms of production and consumption (Kornher, 2018; Shrestha, 2018). Worldwide, nearly 180 million hectare of land was covered by maize and about 1 billion tons of maize was produced. It is produced in more than 170 countries and used as a stable food for about 1.2 billion people. Maize is Africa's most important cereal crops which feeds more than 300 million people. In Africa, nearly 24% of the farmland is covered by maize crop and about 95% of its production uses as food (IPBO, 2017). In the Eastern and Southern parts of Africa, maize production contributes up to 20% of farm households income and more than 15% of their expenditure goes to maize crop alone (Depetris-Chauvin, Porto, & Mulangu, 2017).

In Ethiopia, maize is first important cereal crop with regards to volume of production and the second most common crop concerning the area it is planted next to *teff*. For instance in 2017/18 main agricultural season, maize grown in 2.13 million ha and 83.96 million quintals of the grain production was drawn from the same crop (CSA, 2018a).

In this section, therefore, the economic impact of fertilizer and improved seed adoption on maize and *teff* productivity is examined. Budgetary analysis technique was employed for maize and *teff* crops independently in order to estimate the difference in costs and returns between adopters and non-adopters. Moreover, Blinder–Oaxaca decomposition technique was carried out to determine productivity differences between adopters and non-adopters

### 4.5.1 Production of Maize and *Teff* Crops in the Study Area

Table 4.22 presents the share of maize producing farmers along with the area of land under maize cultivation. In the study area, 84.25% of the farmers were participated in maize production. In terms of area coverage, it occupied 25.75% of the total size of arable land available for farmers. The results are very similar to the zonal average estimates of (CSA, 2016a) which found that maize production practiced by 89.9% of the households and covered 24.38% of the area under grain production.

**Table 4.22 Number of Holders and Area of Land Covered by Maize Crop**

| | **Maize Producers** | **Total sample** |
|---|---|---|
| Number of Holders | 337 | 400 |
| Percent | 84.25 | 100 |
| Area of land in Hectares | 117.62 | 456.94 |
| Percent | 25.74 | 100 |

**Source:** Field Survey, 2018

On the other hand, this study found that 51.5% of the farmers cultivated *teff* within 21.03% of their land (Table 4.23). Similarly, these results are consistent with the results of (CSA, 2016a); in Awi zone 25.38% land was under *teff* cultivation which participated 52.5% of households during the agricultural season of 2015/16.

**Table 4.23 Number of holders and area of land covered by *Teff* Crop**

| | ***Teff* Producers** | **Total sample** |
|---|---|---|
| Number of Holders | 206 | 400 |
| Percent | 51.5 | 100 |
| Area of land in Hectares | 96.09 | 456.94 |
| Percent | 21.03 % | 100 |

**Source:** Field Survey, 2018

To conclude, as shown in table 4.22 and 4.23, maize and *teff* crops are the main stable crops in the study area which altogether cultivated in nearly half of the total arable land available for households.

Concerning to adoption of agricultural technology, about half of maize producers (46.59 %) adopted both fertilizer and improved seeds during their cultivation (table 4.24). Moreover, 20.77% of them used fertilizer without improved seeds. However, the rest 32.64 % of maize producing households neither adopted fertilizer nor improved seeds.

On the other hand, out of the total *teff* producers, 69.42% of *teff* producing farmers applied only chemical fertilizer while 26.7% of them did not adopt any of the technologies. On the contrary, only 3.88% of them adopted both fertilizer and improved seeds simultaneously. The result shows that adoption of improved varieties of *teff* in the study area is found to be very low. As a result, the economic analysis of technology adoption on *teff* crop is restricted to fertilizer adoption only.

**Table 4.24 Technology Adoption Status of Sample Farmers by Selected Crops**

| Crops | Non-adopters | | Adopters of Fertilizer | | Adopters of Both Fertilizer and Improve Seeds | | Total producers | |
|---|---|---|---|---|---|---|---|---|
| | Obs. | Percent | Obs. | Percent | Obs. | Percent | Obs. | Percent |
| Maize | 110 | 32.64 | 70 | 20.77 | 157 | 46.59 | 337 | 100 |
| *Teff* | 55 | 26.70 | 143 | 69.42 | 8 | 3.88 | 206 | 100 |

**Source:** Field Survey, 2018

### 4.5.2 Economic Benefits of Fertilizer and Improved seeds Adoption: The Budgetary Analysis Technique

In this section the economic impact of fertilizer and improved seeds adoption in maize and *teff* crops is discussed. To come up with the results, the budgetary analysis technique is applied as discussed earlier in chapter three. To this end, costs, revenue and profit per hectare of adopters and non-adopters of agricultural technologies are compared. In case of maize crop, comparison was done between three categories; (1) non-adopters of any of the two technologies, (2) fertilizer adopters only, and (3) simultaneous adopters of both fertilizer and improved seeds. In the case of *teff* crop, however, adopters of fertilizer were compared with non-adopters. The third category, which consists of simultaneous adopters of fertilizer and improved varieties of *teff* are deliberately ignored since they are very negligible (see table 4.24).

**Table 4.25 Budgetary Analysis of Maize Production (Only Fertilizer Adoption)**

| Description | Non-adopters | Adopters | Difference | t-stat |
|---|---|---|---|---|
| Labor Cost | 2170 | 2556 | 386 | 9.51*** |
| Animal Cost | 1893 | 1951 | 58 | 1.39 |
| Fertilizer Cost | 0 | 3069 | 3069 | 43.35*** |
| Seed Cost | 201 | 196 | -5 | 1.12 |
| Pesticide Cost | 21 | 40 | 19 | 1.59 |
| Total Production cost | 4285 | 7812 | 3527 | 41.44*** |
| Output/ha | 24.5 | 36.9 | 12.4 | 17.73*** |
| Total Revenue | 17174 | 25820 | 8646 | 17.73*** |
| ***Total Profit*** | ***12889*** | ***18008*** | ***5119*** | ***10.43**** |

**Note:** *** indicates 1% level of significance

**Source:** Field Survey, 2018

Table 4.25 indicates the budgetary analysis results of maize crop which compared adopters and non-adopters of fertilizer. The total production cost of fertilizer adopters was higher than non-adopters by ETB 3527 at 1% level of significance. It implies that adoption of fertilizer increases cost of cultivation by 82.31%. For non-adopters labor cost took the largest share which accounts about half (50.64%) of the total cost of maize production. On the contrary, for adopters of fertilizer, cost of fertilizer contributed the largest share followed by labor cost which constitutes 39.15 and 32.72% of the total production cost respectively. Labor cost for fertilizer adopters was found to be higher than non-adopters by ETB of 386 (17.78%) at 1% level of significance. However, there is no statistically significant difference in other costs of cultivation such as animal cost, seed cost and pesticide cost. As shown by figure 4.7, the major difference in cost of production between non-adopters and adopters of fertilizer is resulted from fertilizer cost followed by labor cost which accounts for 87.01 and 10.94% respectively.

It is found that adoption of fertilizer significantly increases maize productivity. As shown in table 3, the productivity of maize for non-adopters was found to be 24.5 quintal per ha while it was 36.9 quintal per ha yielding an improvement by 12.4 quintal per ha (50.61%). However, this result is lower than the zonal average of 52 (Awi Zone Agricultural Department Office, 2018). Due to improvement in productivity, total revenue and total profit obtained from adoption of fertilizer has increased by 50.34% and 39.72% respectively. Due to the increase in total production cost, however, the increase in profit is lower than the increase in revenue.

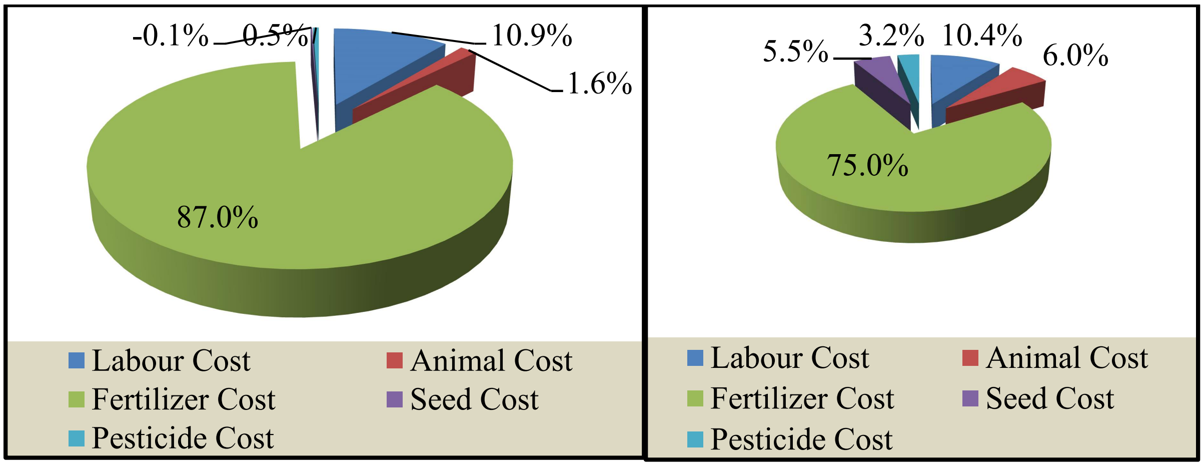
**Table 4.26 Budgetary Analysis of Maize Production (Simultaneous Adoption of Fertilizer and Improved maize Varieties)**

| Description | Non-adopters | Adopters | Difference | t-stat |
|---|---|---|---|---|
| Labor Cost | 2170 | 2688 | 518 | 11.82*** |
| Animal Cost | 1893 | 2194 | 301 | 2.85*** |
| Fertilizer Cost | 0 | 3749 | 3749 | 45.77*** |
| Seed Cost | 201 | 474 | 273 | 37.15*** |
| Pesticide Cost | 21 | 180 | 159 | 4.71*** |
| Total Production cost | 4285 | 9285 | 5000 | 31.05*** |
| Output/ha | 24.5 | 42.4 | 17.9 | 17.5*** |
| Total Revenue | 17174 | 29652 | 12478 | 17.5*** |
| ***Total Profit*** | ***12889*** | ***20367*** | ***7478*** | ***10.84**** |

**Note**: *** indicates 1% level of significance

**Source**: Field Survey, 2018

Table 4.26 compared costs, revenue and profit of simultaneous adopters of fertilizer and improved maize varieties with non-adopters. Cost of cultivation per ha for simultaneous adopters of fertilizer and improved increased by ETB 5000 (116.68%). Though there exists a statistically significant increment in all types of production costs, the difference in total production cost is mainly resulted from fertilizer cost followed by labor cost and seed cost which accounts for 74.98, 10.36 and 5.46% respectively (see figure 4.7). On average, the maize productivity of simultaneous adopters of fertilizer and improved maize varieties was estimated to be 42.4 quintal/ha which yields an increment of 73.06% compared to non-adopters. Compared to only fertilizer adopters, this result is higher by 14.91%. Similar to the previous case, however, maize productivity for adopters of both fertilizer and improved seeds is found to be lower than the zonal average of 52.76 quintal/ha (Awi Zone Agricultural Department Office, 2018).




(a) Adopters of fertilizer (b) Adoption of fertilizer and Improved Seeds

**Figure 4.7 Contribution of Each Factor for the Difference in Total Cost of Maize Production.**

**Source:** Field Survey, 2018

Finally, simultaneous adoption resulted in an increment of total profit by 58.02% compared to non-adopters and by 13.1% compared to fertilizer adopters only. Though the cost of cultivation for simultaneous adopters of fertilizer and improved varieties of maize increases by ETB 1473 compared to only fertilizer adopters, the revenue obtained is higher than the increment in cost of cultivation which is found to be ETB 3832. This result supports the findings of Nyangena and Juma (2014) and Teklewold, Kassie, and Shiferaw (2013) which argue that adopting agricultural technologies as a package rather than rather as single element boosts productivity and profitability of farmers.

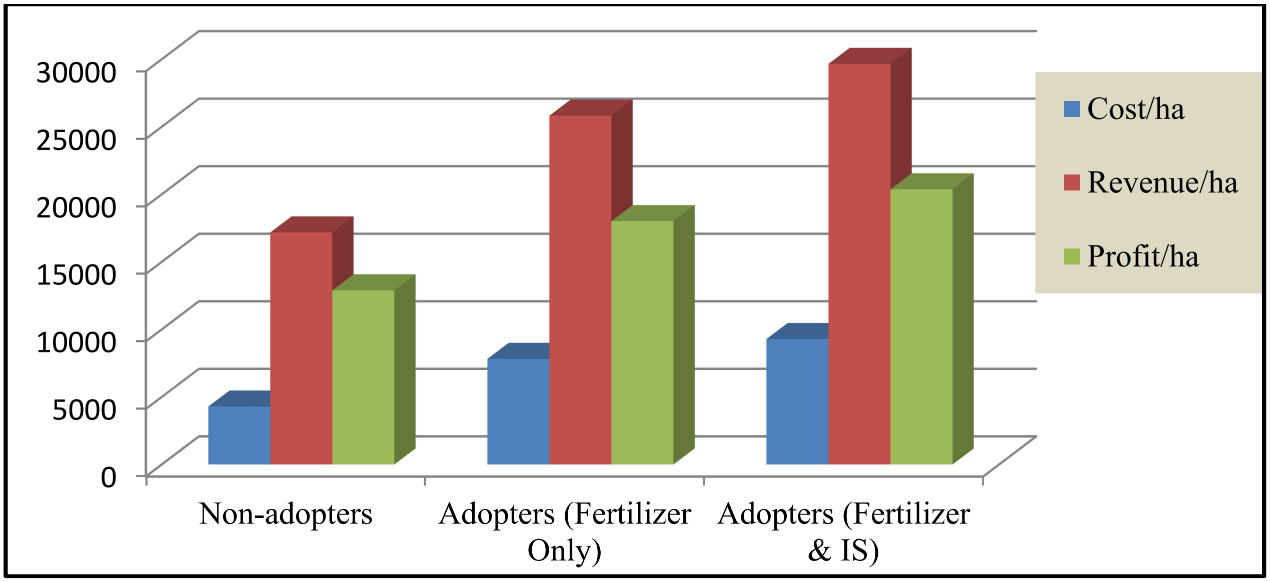



**Figure 4.8 Cost, Revenue and Profit of adopters and non-adopters of Maize producers.**

**Source:** Field Survey, 2018

Table 4.27 indicated the budgetary analysis of *teff* production. The results show that adopters of fertilizer for *teff* production spend 42% more than non-adopters. Like the case of maze production, the difference in cost of production between adopters and non-adopters of fertilizer in *teff* production is primarily and significantly resulted from the cost of fertilizer which accounts 78.5% followed by labor cost 16.8% (figure 4.9). However, the difference in animal costs, seed costs and pesticide costs between adopters and non-adopters of agricultural technologies was found to be very small.

As it is evidenced from table 4.27, fertilizer adoption improves *teff* productivity from 9.15 to 16.07 quintal per ha, yielding a rise of 75.63%. The increase in productivity further leads a rise in profitability of producers from ETB 11318 to 21604. It means that adoption of fertilizer boosts profit of *teff* producers by 90.88% (figure 4.10).

**Table 4.27 Budgetary Analysis of *Teff* Production (Adoption of Fertilizer)**

| Description | Non-adopters | Adopters | Difference | t-test |
|---|---|---|---|---|
| Labor Cost | 2458 | 2822 | 364 | 3.41*** |
| Animal Cost | 2037 | 2112 | 75 | 1.05 |
| Fertilizer Cost | - | 1701 | 1701 | 18.55*** |
| Seed Cost | 555 | 568 | 13 | 0.46 |
| Pesticide Cost | 104 | 118 | 14 | 0.27 |
| Total Production cost | 5154 | 7321 | 2167 | 10.91*** |
| Output/ha | 9.15 | 16.07 | 6.92 | 12.67*** |
| Total Revenue | 16472 | 28925 | 12453 | 12.67*** |
| ***Total Profit*** | ***11318*** | ***21604*** | ***10286*** | ***11.30**** |

**Note:** *** indicates 1% level of significance

**Source:** Field Survey, 2018

The additional profit obtained from *teff* production due to adoption of fertilizer is found to be much higher than maize because of two main reasons. Firstly, the market value of *teff* is much higher than that of maize. In this study, the price of *teff* is found to be 2.85 time the price of maize. Second, non-adopters may use more amount of manure instead of chemical fertilizer for maize production than *teff* since farmers grow maize on their land nearest to home which makes easily for manure application.

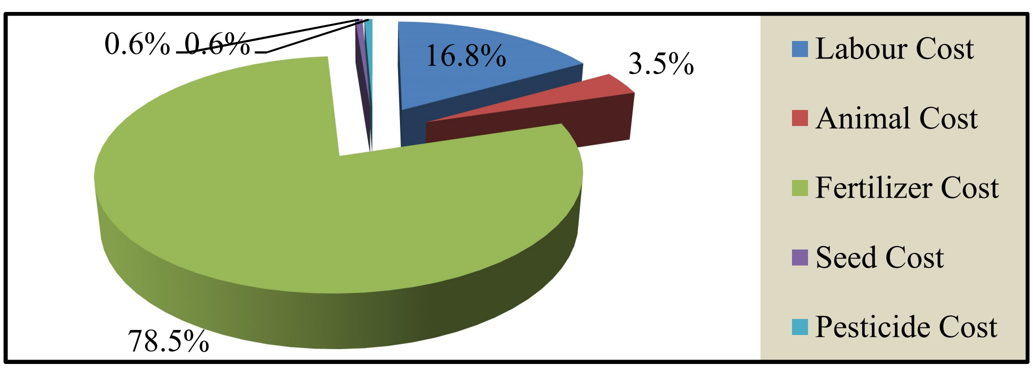



**Figure 4.9 Contribution of Each Factor for the Difference in Total Cost of *Teff* Production.**

**Source:** Field Survey, 2018

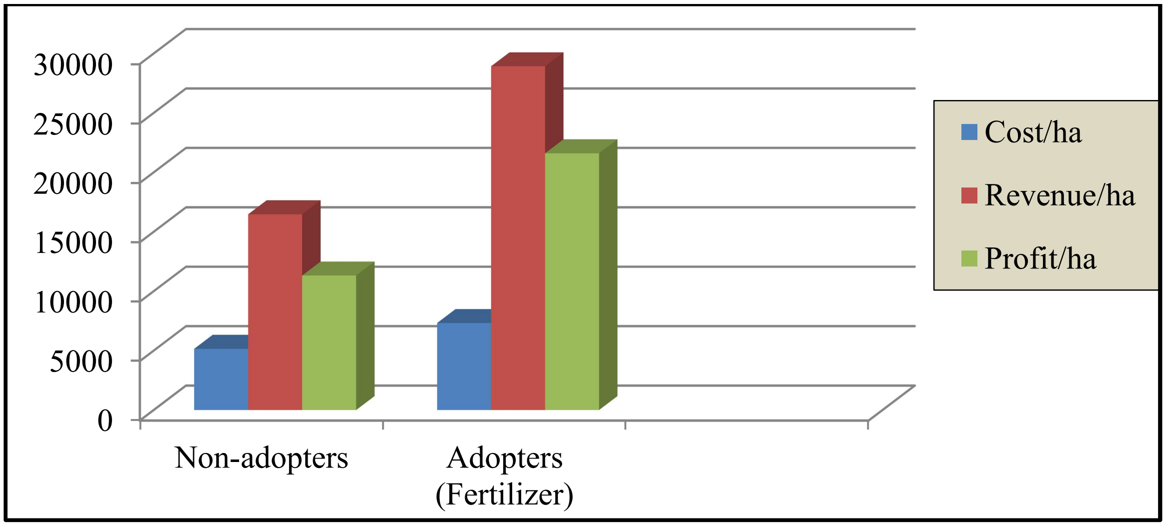



**Figure 4.10 Cost, Revenue and Profit of adopters and non-adopters of *Teff* producers.**
**Source:** Field Survey, 2018

To conclude, adoption of agricultural technologies such as fertilizer and improved seeds significantly increases total production cost both in maize and *teff* production. The rise in cost of production is primarily resulted from the cost of technologies. Moreover, in both maize and *teff* crops, the cost of labor for technology adopters is significantly higher than non-adopters. This result is not surprising in countries like Ethiopia where agriculture is labor intensive in nature and fertilizer and improved seeds are complementary rather than substitute of labor. This may be because adopters require additional labor force for the application of technologies. Similarly, studies argue that adopters use more man power for better preparation of the cultivation land, planting and weeding (Adofu et al., 2013; Akinola & Owombo, 2012; Birthal et al., 2012).

The results revealed that technology adoption significantly increases maize and *teff* productivity. Consequently, the revenue obtained from maize and *teff* production for adopters was found to be higher than non-adopters and finally resulted in an improvement in the total profit. The results are in line with other similar studies who found a positive and significant improvement in profit obtained from adoption of technology (Adofu et al., 2013; Akinola & Owombo, 2012; Devi & Ponnarasi, 2009; Myint & Napasintuwong, 2016; Pal et al., 2016).

### 4.5.3 Fertilizer and Improved Seeds Adoption and Productivity: The Blinder-Oaxaca Decomposition

In this section the difference in maize and *teff* productivity between adopters and non-adaptors of agricultural technologies is examined based on the Blinder–Oaxaca decomposition technique as discussed earlier in chapter three.

**Table 4.28 Regression Results of Maize Productivity (Case of Fertilizer)**

| Dependent: $lnY$ | Adopters ($lnY_A$) | | Non-Adopters ($lnY_{NA}$) | | Pooled ($lnY$) | |
|---|---|---|---|---|---|---|
| | Coefficients | Z-values | Coefficients | Z-values | Coefficients | Z-values |
| lnANIMAL | 0.2184 | 1.99** | 0.1888 | 2.86*** | 0.2222 | 4.08*** |
| lnLABOR | 0.2692 | 2.39*** | 0.5057 | 5.71*** | 0.3804 | 5.88*** |
| AGE | -0.0015 | -1.24 | -0.0006 | -0.55 | -0.0010 | -1.29 |
| SEX | 0.0251 | 0.33 | 0.0716 | 2.54** | 0.0633 | 2.43** |
| EDUC | | | | | | |
| Primary | 0.0666 | 1.95* | 0.0232 | 0.88 | 0.0423 | 2.09** |
| Secondary | 0.0244 | 1.05 | -0.0064 | -0.30 | 0.0094 | 0.62 |
| EXT | 0.0714 | 2.03** | 0.0500 | 2.09** | 0.0491 | 2.59** |
| DIST | -0.0005 | -0.09 | -0.0018 | -0.42 | -0.0007 | 0.21 |
| Fertilizer adoption | - | - | - | - | 0.3154 | 15.76*** |
| _cons | 0.7266 | 0.89 | -0.8737 | -1.68 | -0.3076 | -0.73 |
| Number of observations | 70 | | 110 | | 180 | |
| Adj R-squared | 0.3567 | | 0.4213 | | 0.7845 | |
| F-statistic | F(8, 61) = 5.78 | | F(8, 101) = 10.92 | | F(9, 170) = 73.39 | |
| Prob > F | 0.000*** | | 0.000*** | | 0.000*** | |

**Note:** ***, ** and * indicate level of significance at 1%, 5% and 10% respectively

**Source:** Field Survey, 2018

Table 4.28 and 4.29 displays results of the maize productivity models by adoption status along with the pooled sample regression. In this study both animal and human labors were found to be significant and positive determinants of maize productivity. In Ethiopia, like most developing countries, agriculture still remains characterized by labor intensive production. Hence, the more hours of labor and animal (oxen & horses) engaged in agriculture means better land preparation, weeding and harvesting which results in agricultural productivity increment.

Education is the other significant variable which affects maize productivity positively. This is due to the fact that education enables farm households to have more information on productive techniques. It also makes farmers more responsive to the adoption and implementation of new technologies.

Maize productivity is found to be affected by sex of the household head. Male heads were more productive than female's in all cases except for only fertilizer adopters. This may be because male household heads have more exposure to information about better farm inputs and practice and hence becomes more productive in agricultural production. The other positive and significant determinant of maize productivity is extension service. Access to extension service may increases agricultural productivity by enhancing farmers' awareness towards the importance and practice of better techniques of production and use of new technologies.

Finally, as it is shown in table 4.28 & 4.29, the coefficient of technology for the pooled regression indicates the significance influence of fertilizer and improved seeds on maize productivity.

**Table 4.29 Regression Results of maize productivity (Case of Both Fertilizer and Improved Seeds)**

| Dependent: *lnY* | Adopters ($lnY_A$) | | Non-Adopters ($lnY_{NA}$) | | Pooled ($lnY$) | |
|---|---|---|---|---|---|---|
| | Coefficients | Z-values | Coefficients | Z-values | Coefficients | Z-values |
| lnANIMAL | 0.1093 | 3.12*** | 0.1888 | 2.86*** | 0.1041 | 3.66*** |
| lnLABOR | 0.3496 | 3.60*** | 0.5057 | 5.71*** | 0.4185 | 6.07*** |
| AGE | -0.0008 | -0.79 | -0.0006 | -0.55 | -0.0006 | -0.75 |
| SEX | 0.3201 | 3.41*** | 0.0716 | 2.54** | 0.1248 | 3.62*** |
| EDUC | | | | | | |
| Primary | 0.0366 | 1.09 | 0.0232 | 0.88 | 0.02449 | 1.08*** |
| Secondary | 0.0689 | 3.16*** | -0.0064 | -0.30 | 0.0451 | 2.87*** |
| EXT | 0.0639 | 1.87* | 0.0500 | 2.09** | 0.0642 | 2.93*** |
| DIST | 0.0004 | 0.09 | -0.0018 | -0.42 | -0.0006 | -0.17 |
| Fertilizer and Improved Seed Adoption | - | - | - | - | 0.3817 | 15.18*** |
| _cons | 0.7266 | 0.89 | -0.8737 | -1.68 | -0.3076 | -0.73 |
| Number of observations | 157 | | 110 | | 267 | |
| Adj R-squared | 0.3457 | | 0.4213 | | 0.7670 | |
| F-statistic | F(8, 148) = 11.30 | | F(8, 101) = 10.92 | | F(9, 257) = 98.27 | |
| Prob > F | 0.000*** | | 0.000*** | | 0.000*** | |

**Note:** ***, ** and * indicate level of significance at 1%, 5% and 10% respectively

**Source:** Field Survey, 2018

As indicated in table 4.30, hours of animal labor, sex, secondary education and extension significantly increase *teff* productivity in the study area. The arguments behind these results are similar with the case of maize productivity. On the other hand, age of the household head affects *teff* productivity negatively for fertilizer adopters. This may be due to the fact that relatively aged farmers might be more reluctant and conservative towards adoption of new and improved techniques production. For non-adopters, labor use, sex, primary education and extension services influence *teff* productivity positively and significantly. In general, as indicated in the pooled regression result, *teff* productivity was affected by animal hours, labor use, sex, and education and fertilizer adoption positively and significantly. Age of household head affects *teff* productivity negatively.

**Table 4.30 Regression Results of *Teff* Productivity (Case of Fertilizer)**

| Dependent: $lnY$ | Adopters ($lnY_A$) | | Non-Adopters ($lnY_{NA}$) | | Pooled ($lnY$) | |
|---|---|---|---|---|---|---|
| | Coefficients | Z-values | Coefficients | Z-values | Coefficients | Z-values |
| lnANIMAL | 0.1887784 | 2.28** | 0.0273015 | 0.31 | 0.158541 | 2.49** |
| lnLABOR | 0.1140934 | 1.63 | 0.1858662 | 2.21** | 0.1284428 | 2.36* |
| AGE | -0.00449 | -2.93*** | 0.0010308 | 0.58 | -0.0030862 | -2.58** |
| SEX | 0.1068934 | 1.86* | 0.1041781 | 1.87* | 0.11521 | 2.74*** |
| EDUC | | | | | | |
| Primary | 0.0705036 | 1.65 | 0.130569 | 2.73*** | 0.0857099 | 2.59** |
| Secondary | 0.1725216 | 3.04*** | 0.1190294 | 1.32 | 0.180707 | 0.00*** |
| EXT | 0.1686706 | 3.67*** | 0.1171865 | 2.27** | 0.1504435 | 4.30*** |
| DIST | -0.0010358 | -0.13 | 0.0056673 | 0.63 | -0.0010661 | -0.17 |
| Fertilizer Adoption | - | - | - | - | 0.408633 | 11.65** |
| _cons | 0.9209983 | 1.57 | 0.6730515 | 0.98 | 0.5292907 | 1.16 |
| Number of observations | 143 | | 55 | | 198 | |
| Adj R-squared | 0.3782 | | 0.3782 | | 0.6949 | |
| F-statistic | F(8, 134) = 11.79 | | F(8, 46) = 5.27 | | F(9, 188) = 50.85 | |
| Prob > F | 0.0000*** | | 0.0001*** | | 0.0000*** | |

**Note:** ***, ** and * indicate level of significance at 1%, 5% and 10% respectively

**Source:** Field Survey, 2018

The coefficient of fertilizer adoption is found to be the most influential variable for *teff* productive, *teff* productivity (lnY) for adopters is greater than non-adopters by 0.41(50%) given all other factors of production are unchanged. This result validates the findings of (G. Hailu et al., 2016)Hailu et al. (2016) which input use (such as labor and fertilizer) and extension service affects productivity positively while age influences negatively.

Table 4.31 provides aggregate results from the B-O decomposition for maize productivity. The mean agricultural productivity of maize (lnY) was 3.19 for non-adopters while it was 3.6 for adopters of fertilizer and 3.72 for adopters of both fertilizer and improved seeds, yielding a statistically significant gap of 0.41 and 0.53 respectively. It means that, maize yield obtained by adopters of fertilizer was 50.4 % greater than non-adopters while it was 70.3 % more for adopters of both fertilizer and improved seed.

**Table 4.31 Blinder-Oaxaca aggregate Decomposition of Maize Productivity**

| Description | Fertilizer | | | Fertilizer and Improved seed | | |
|---|---|---|---|---|---|---|
| | lnY | t-statistics | Percent | lnY | t-statistics | Percent |
| Adopters | 3.596834 | 201.79*** | | 3.72117 | 210.58*** | |
| Non-adopters | 3.188664 | 222.90*** | | 3.188664 | 223.01*** | |
| Differences | 0.4081699 | 17.86*** | 50.4% | 0.532506 | 23.43*** | 70.3% |
| **Decomposition** | | | | | | |
| Explained | 0.0927161 | 4.94*** | 22.7% | 0.150718 | 7.11*** | 28.3% |
| Unexplained | 0.3154538 | 15.32*** | 77.3% | 0.381787 | 15.93*** | 71.7% |

**Note:** *** indicate level of significance at 1%

**Source:** Field Survey, 2018

The B–O decomposition further reported that 22.7% of the gap in maize productivity between adopters and non-adopters of fertilizer is resulted in because of the differences in observable characteristics (explained). This means that non-adopters productivity would increase by 22.7% if they had the characteristics as adopters. 77.3 % of the difference is unexplained (primarily due to technology adoption). For the gap in maize yield among non-adopters and simultaneous adopters of fertilizer and improved seeds, the explained part accounts for 28.3% of the gap and the remaining 71.7% is associated with the technology advantage.

**Table 4.32 Blinder-Oaxaca Aggregate Decomposition of *Teff* Productivity**

| Description | Fertilizer | | |
|---|---|---|---|
| | lnY | t-statistics | Percent |
| Adopters | 2.745772 | 128.25)*** | |
| Non-adopters | 2.197187 | (89.16)*** | |
| Differences | 0.5485857 | (16.80)*** | 73.1% |
| **Decomposition** | | | |
| Explained | 0.1399524 | ( 4.21)*** | 25.5% |
| Unexplained | 0.4086334 | (11.07)*** | 74.5% |

**Note:** *** indicate level of significance at 1%

**Source:** Field Survey, 2018

As shown in table 4.32, the average *teff* yield (lnY) for adopters and non-adopters of fertilizer were estimated to be 2.75 and 2.20 respectively having a difference of 0.55 (73.1%). This means that the average *teff* productivity of fertilizer adopters is 73% more than non-adopters. The B–O decomposition revealed that the unexplained (technology component) accounts for 74.5% of the total gap compared to 25.5% of the explained component.

Hence, the results clearly indicate that adoption of agricultural technologies resulted in significant improvement in agricultural productivity. The findings are similar with the results of Adofu, Shaibu and Yakubu (2013) and Meughoyi (2018).

Table 4.33 provides the results of the detailed decomposition analysis for maize productivity. For the purpose of interpretation, it is important to note that positive coefficients increase the productivity gap between adopters and non-adopters while negative coefficients decrease the gap. Labor, sex of the household, and extension service were found to be significant and contributed 57.1%, 9.8% and 10.8% to the total explained difference between adopters of fertilizer for maize production and non-adopters. In case of both fertilizer and improved seed adopters of maize producers, sex, education (secondary) and extension service contributed 14.45%, 6% and 10.68% respectively for the explained productivity gap while sex and secondary education constituted 60.89% and 4.83% for the unexplained gap.

**Table 4.33 Blinder-Oaxaca Detailed Decomposition of Maize Productivity**

| Variables | | Fertilizer | | Both fertilizer and Improved Seed | |
|---|---|---|---|---|---|
| | | Explained | Unexplained | Explained | Unexplained |
| lnANIMAL | | 0.0079644 | 0.1631345 | 0.0054478 | -0.4383628 |
| | | (1.38) | (0.28) | (1.18) | (-0.96) |
| lnLABOR | | 0.0529017 | -1.40668 | 0.091016 | -0.9335015 |
| | | (3.74)*** | (-1.43) | (4.88) | ( -0.98) |
| AGE | | 0.0040969 | -0.0443622 | 0.0013078 | -0.0131049 |
| | | (1.06) | ( -0.59) | (0.60) | (-0.17) |
| SEX | | 0.0090531 | -0.0426821 | 0.0217822 | 0.2328208 |
| | | (1.83)* | (-0.65) | (2.82)*** | (2.86)*** |
| EDUC | | | | | |
| | Primary | 0.0071444 | 0.0147841 | 0.0056882 | 0.0061228 (0.42) |
| | | (1.56) | (1.06) | (1.04) | |
| | Secondary | 0.0009771 | 0.007183 | 0.0090521 | 0.0184595 |
| | | (0.51) | (0.94) | (1.68)*** | (2.16)** |
| EXT | | 0.0100235 | 0.0148741 | 0.0161026 | 0.0066035 (0.24) |
| | | (1.88)* | (0.58) | (2.29)** | |
| DIST | | 0.000555 | 0.008874 | 0.0003217 | 0.0150302 (0.39) |
| | | (0.232 ) | (0.24) | (0.18) | |
| Constant | | | 1.600328 | | 1.48772 |
| | | | (1.60) | | (1.58) |
| ***Total*** | | ***0.0927161*** | ***0.3154538*** | ***0.1507184*** | ***0.3817878*** |
| | | ***(4.94)**** | ***(15.32)**** | ***(7.11)**** | ***(15.93)**** |

**Note:** ***, ** and * indicate level of significance at 1%, 5% and 10% respectively
Z-statistics are presented in parentheses

**Source:** Field Survey, 2018

Table 4.34 shows the detail decomposition analysis of gaps in *teff* productivity between the two groups; non-adopters and adopters of fertilizer. The result indicates that labor and sex significantly contributed for productivity gap. However age statistically and significant reduced the gap, contributed 65% of the unexplained component.

**Table 4.34 Blinder-Oaxaca Detailed Decomposition of *Teff* Productivity**

| Variables | Explained | Z-stat | Unexplained | Z-stat |
|---|---|---|---|---|
| lnANIMAL | 0.0057927 | 0.95 | 0 .902136 | 1.44 |
| lnLABOR | 0.0185847 | 1.76* | -0.4312056 | -0.61 |
| AGE | 0.0173735 | 1.99** | -0.2677863 | -2.78*** |
| SEX | 0.0067676 | 0.95 | 0.0017825 | 0.02 |
| EDUC | | | | |
| Primary | 0.0118675 | 1.47 | -0.0206713 | -0.91 |
| Secondary | 0.0146588 | 1.60 | 0.0032264 | 0.45 |
| EXT | 0.0631232 | 3.42*** | 0.0216889 | 0.74 |
| DIST | 0.0017844 | 0.13 | -0.0484839 | -0.57 |
| Constant | | | 0.2479468 | 0.28 |
| ***Total*** | ***0.1399524*** | ***4.21**** | ***0.4086334*** | ***11.07**** |

**Note:** ***, ** and * indicate level of significance at 1%, 5% and 10% respectively

**Source:** Field Survey, 2018

## 4.6 Determinants of Agricultural Technology adoption

Adoption of agricultural technologies can be influenced by various demographic, socio-economic and institutional factors. As it is mentioned in chapter three, in this study, logit model was employed in order to identify significant determinants of agricultural technology adoption. Two logit regression results are presented based on the type of technology. The first is concentrated on fertilizer adoption while the second regression result is related to simultaneous adoption of fertilizers and improved seeds.

Finally, Tobit model has been employed in order to identify major factors influencing use of fertilizer intensity. In this study, however, intensity of improved varieties of seed was not estimated since it is not logically convincing to sum up different varieties of improved seeds for different crops all together.

Before the regression of the models, the problem of multicollinearity was checked based on pair wise correlation matrices. The results revealed the non-existence of sever multicolloinearity since the value of pairwise correlation among explanatory variables included in the models is found to very low (see Appendix 4).

The goodness of fit of each model was checked based on diagnostic tests such the likelihood ratio test statistics, Hosmer-Lemeshow test and percentage of correctly classified observations. Moreover, since the coefficients of the estimated models are quite difficult for interpretation, marginal effects were computed and interpreted

### 4.6.1 Determinants of Fertilizer Adoption

Table 4.35 reported the estimated results of the logit model for fertilizer adoption. Goodness of fit measures confirmed the soundness of the model. The Wald test statistics indicates that the hypothesis of all coefficients is simultaneously equal to zero is rejected at 1% level of significance. The Hosmer-Lemeshow test also proved the goodness of fit of the logit model since the p-value (*0.6074)* is larger than 5% (see Appendix 5). Moreover, the logit estimates of the adoption equation correctly predict 92.33 % adopters and 50.44% of non-adopters which altogether had 80.5 % correctly classified observations (see Appendix 7).

From the total of nine variables included in the model, six of them (age of the household head, education level, family size, access to extension service, access to credit and land size) were found as significant determinants of fertilizer adoption in the study area.

Among the variables of interest in this study, age of the household head is the only significant (at 1%) variable which affects adoption of fertilizer negatively in the study area. Estimates of the marginal effect indicate that as household head’s age increases by one year, the probability of being adopter of fertilizer decreases by 0.7%. This may be due to the fact that relatively old farmers are more reluctant and conservative towards adoption of fertilizer than young farmers (Fufa & Hassan, 2006; B. K. Hailu et al., 2014).

**Table 4.35 Determinants of Fertilizer Adoption**

| Variables | Coefficients | Std. Err | Marginal effect |
|---|---|---|---|
| AGE | -0.053 | 0.012*** | -0.007 |
| SEX | 0.444 | 0 .499 | 0.066 |
| EDUC | | | |
| Primary | 0.579 | 0 .313* | 0.082 |
| Secondary | 1.164 | 0.637* | 0.150 |
| FAM | 0.435 | 0.079*** | 0.061 |
| EXT | 0.636 | 0 .275** | 0.094 |
| CRED | 1.390 | 0.277*** | 0.214 |
| DIST | -0.056 | 0.057 | -0.008 |
| LAND | 0.552 | 0.226** | 0.078 |
| OFFINC | 3.44e-06 | 0.00003 | 4.86e-07 |
| Constant | -1.159 | 0.931 | |
| Number of Observations | 400 | | |
| Pseudo $R^2$ | 0.258 | | |
| Log-likelihood | -175.87*** | | |
| Sensitivity | 92.68% | | |
| Specificity | 51.33% | | |
| Correctly classified | 81.00% | | |

**Note**: ***, ** and * indicate level of significance at 1%, 5% and 10% respectively

**Source:** Field Survey, 2018

Education is believed to improve technology adoption by promoting awareness on the importance and effective utilization of agricultural technologies. Similarly, in this study education is estimated to influence adoption of fertilizer positively and significantly. Specifically, the probability of being adopter increases by 8.2% and 15% for those farmers who attended primary and secondary education compared to illiterates respectively. This result is similar to other studies which argue that education develops the ability to adapt change, easily recognize and practices new technologies (Alene et al., 2000; Beshir et al., 2012; Croppenstedt et al., 2003; Eba & Bashargo, 2014; Kassie et al., 2011).

In line with the priori expectation, family size affects adoption of fertilizer positively and significantly. When size of the family increase by one, the probability of fertilizer adoption increases by 6.1%. The availability of larger family size enhances technology adoption since adoption requires the existence of more labor force who can engage in the agriculture production relative to non-adopters (Adofu et al., 2013; Asfaw et al., 2011; Birthal et al., 2012; Eba & Bashargo, 2014).

The other significant (at 5%) and positive determinant of fertilizer adoption in this study is extension service.  Those farmers who are contacted by an extension worker during the agricultural production year of 2017/18 were found to be more adopters of fertilizer. The study estimated that the probability of fertilizer adoption for those farm households who received extension service mainly from agricultural development agents increases by 9.4%. Many studied in Ethiopia found that access to extension service promote technology adoption by enhancing households awareness about the advantage and effective use of technologies  (Alene et al., 2000; Beshir et al., 2012; Bingxin & Alejandro, 2014; Eba & Bashargo, 2014; Kebede & Ketema, 2017).

As estimated by the logit model, accessibility of credit was found to be the most significant variable which affects adoption of fertilizer positively. The marginal effects estimated that if households have access to credit, the probability of adoption increases by 21.4%. This may be due to the fact that in general in Ethiopia, a developing country with low level of income, getting the required capital to satisfy their demand for the purchase of agricultural technology is a big challenge.  The result is consistent with other similar studies done in Ethiopia (Beshir et al., 2012; Croppenstedt et al., 2003; Eba & Bashargo, 2014; B. K. Hailu et al., 2014).

Another significant variable in this study is size of landholding. As predicted by the logit model, a one hectare increment in the size of land results in an increase of the probability of fertilizer adoption by 7.8%. In line with this study, Mariano et al. (2012) conclude that households with large land size adopt more agricultural technologies since they are less vulnerable to failure from trying new technologies than households with small land size.

However, the effects of other three variables such as sex, distance from market and off-farm income were found to be insignificant though they have taken the expected sign.

### 4.6.2 Determinants of Simultaneous Adoption Fertilizer and Improved Seeds

As discussed previously about half of farm households adopted both fertilizer and improved seeds simultaneously. Table 4.36 presents the logit estimates of the determinants of simultaneous adoption of fertilizer and improved seeds in the study area. The model is found to be statistically significant at 1 %. 81% of the observations on technology adoption were correctly classified by the model. Moreover, the Hosmer-Lemeshow test proved the goodness of fit of the model (see Appendix 6).

Like the case of fertilizer adoption, education, family size, access to extension service and access to credit were found be positive and significant determinants of simultaneous adoption of fertilizer and improved seeds while age of households influences adoption significantly and negatively

As family size increase by one member, the probability of fertilizer and improved seeds adoption rises by 6.6%. Compared to illiterates, the probability of being adopter will increase by 10 and 18.6% if farm households attended primary and secondary education respectively. Households who have access to extension service and access to credit service increase the probability of fertilizer and improved seeds adoption by 13.4 and 33.8% respectively. However, when the age of household heads increase by one year their probability of adoption reduces by 0.5%. The arguments behind these results are synonymous with the case of fertilizer adoption.

**Table 4.36 Determinants of Simultaneous Adoption of Fertilizer and Improved Seeds**

| Variables | Coefficients | Std. Err | Marginal effect |
|---|---|---|---|
| AGE | -0.026 | 0.011** | -0.005 |
| SEX | 0.503 | 0.496 | 0.091 |
| EDUC | | | |
| Primary | 0.549 | 0.262** | 0.100 |
| Secondary | 1.05 | 0.533** | 0.186 |
| FAM | 0.367 | 0.071*** | 0.066 |
| EXT | 0.717 | 0.254*** | 0.134 |
| CRED | 1.684 | 0.245*** | 0.338 |
| DIST | -0.056 | 0.049 | -0.010 |
| LAND | 0.200 | 0.207 | 0.036 |
| OFFINC | -0.00002 | 0.00002 | -4.26e-06 |
| Constant | -2.827 | 0.886 | |
| Number of Observations | 400 | | |
| Pseudo $R^2$ | 0.225 | | |
| Log-likelihood | -214.199*** | | |
| Sensitivity | 79.13% | | |
| Specificity | 68.25% | | |
| Correctly classified | 74.00% | | |

Note: *** and ** indicates level of significance at 1 and 5% respectively

**Source**: Field Survey, 2018

Similarly sex, distance from the main market and off-farm income are found to be insignificant determinants of fertilizer and improved seeds adoption in the study area. The only difference existed between the two cases lies on land size. In contrast to fertilizer adoption, the effect of land size on simultaneous adoption of fertilizer and improved seeds was found to be insignificant.

### 4.6.3 Determinants of Fertilizer Use Intensity

Tobit model is employed to figure out the extent of change in the intensity of fertilizer use for a change in explanatory variables included in the model. Robust regression was employed for the Tobit model in order to be free from the possibility of hetroschedasticity. As indicated in table 4.37, education, family size, extension and credit service influences intensity of fertilizer use positively while the effect of age of the household head is estimated to be negative.

**Table 4.37 Results of the Tobit Model**

| Variable | Coefficient | Robust Std. Err. | Marginal effect for whole respondents | Marginal effect for adopters |
|---|---|---|---|---|
| AGE | -2.328*** | 0.614 | -1.756 | -1.365 |
| SEX | 15.365 | 22.036 | 11.371 | 8.787 |
| EDUC | | | | |
| Primary | 14.667 | 12.917 | 11.047 | 8.559 |
| Secondary | 65.681*** | 20.875 | 52.795 | 42.016 |
| FAMS | 23.104*** | 4.630 | 17.422 | 13.549 |
| EXT | 47.462*** | 13.567 | 35.385 | 27.133 |
| CRED | 87.011*** | 12.694 | 65.724 | 49.913 |
| DIST | -4.931* | 2.762 | -3.718 | -2.892 |
| LAND | -6.870 | 12.346 | -5.180 | -4.028 |
| OFFINC | -0.0015 | 0.001 | -0.001 | -0.0008 |
| Constant | 4.098 | 44.42 | | |

| | | | |
|---|---|---|---|
| Number of observations | 400 | censored observations at FERTQ <= 0 | 113 |
| Pseudo $R^2$ | 0.0377 | uncensored observations | 287 |
| F-statistic (*p-value*) | 16.80(*0.000*) | right-censored observations | 0 |

**Note:** *, **, *** significance level at 10%, 5% and 1%, respectively

**Source:** Field Survey, 2018

Most of the variables which were significant under the logit model for fertilizer adoption regression were also found to be significant in the tobit model. Education, family size, extension and credit service influences intensity of fertilizer use positively while the effect of age of the household head is estimated to be negative. The results show that when the age of the household head increases by one year, use of fertilizer decrease by 1.36 kg/ha and 1.75 kg/ha for adopters and for the entire sample respectively. Secondary education increased the use of fertilizer by 42.01 kg/ha for fertilizer adopters and by 52.79 for the whole respondents. As family size increase by 1 unit, the intensity of fertilizer use raises by 13.54 kg/ha and 17.42 kg/ha for adopters and for the whole sample respectively. Moreover, provision of extension service for farm households increases the intensity of fertilizer use by 27.13 kg/ha for adopters of fertilizer and for the entire respondents by 35.38 kg/ha. More importantly, accessibility of credit increased the intensity of fertilizer use by 49.91 kg/ha for adopters and 65.72 kg/ha for the entire sample respectively. Hence, this study found that accessibility of credit is the major determinant factor not only for adoption decision but also for intensity of fertilizer use.

The difference in the results between the logit and Tobit model lies on two variables; distance from the main market and landholding size of households. The estimated results revealed that the influence of landholding size on intensity of fertilizer becomes insignificant while it affects adoption of fertilizer positively. On the other hand, distance from the main market affects intensity of fertilizer use but not probability of adoption. The Tobit model estimated that a one km increase in the distance between households residential area and the nearest market center resulted in a reduction of fertilizer use by 2.89 kg/ha for adopters and 3.71 kg/ha for the entire sample.

## 4.7 The Impact of Agricultural Technology Adoption on Poverty

In this study, consumption rather than income was used in the conduct of poverty analysis due to its convenience as discussed in chapter three. Moreover, households' consumption expenditures were adjusted to adult equivalence due to the differences in the requirement of different household members based on age and gender (see the detail at Appendix 2).

Table 4.38 presented the average annual adult equivalent consumption expenditure of surveyed households in the study area. The mean consumption expenditure per adult equivalent per annum is estimated to be ETB 8184.22. However, the result is lower than the national average per adult consumption expenditure of rural households which was estimated to be ETB 10946 (National Planning Commission, 2017).

Regarding to district disaggregation, households in Guangua district with an average annual adult consumption expenditure of ETB 8469.45 took the first rank followed by Guagusa-Shikudad district with ETB 8192.30. However, in Banja district, the average adult consumption expenditure of households was found to be the smallest, only ETB 7480.73. The existence of low level of consumption expenditure in Banja district is not a surprising result since the district is found to be the lowest in terms of important sources of agricultural production such as average landholding size and adoption of fertilizer and improved seeds.

**Table 4.38 Consumption Expenditure of Households by District**

| Districts | Obs. | Mean | Std. Dev | Min | Max |
|---|---|---|---|---|---|
| Banja | 84 | 7480.73 | 2814.73 | 3161.95 | 15131.9 |
| Guangua | 204 | 8469.45 | 3834.87 | 1095.52 | 23281.7 |
| Guagusa Shikudad | 112 | 8192.30 | 4081.96 | 3258.65 | 32360.8 |
| ***Total*** | ***400*** | ***8184.22*** | ***3729.80*** | ***1095.52*** | ***32360.8*** |

**Source:** Filed Survey, 2018

Table 4.39 indicates that the welfare of technology adopters measured by consumption expenditure per adult equivalent was significantly better than non-adopters. The average consumption expenditure for fertilizer adopters was ETB 8621.25 per annum while non-adopters had ETB 7074.25 of annual expenditure. Furthermore, households who adopted fertilizer and improved seeds simultaneous had ETB 9063.68 of annual consumption expenditure per adult equivalent while it was ETB 7202.39 for non-adopters. The results implied the importance of agricultural technologies on welfare improvement of rural households. The existence of significant difference in consumption expenditure between adopters and non-adopters of agricultural technologies resulted in disparity in households poverty measured by FGT indices (table 4.40).

**Table 4.39 Consumption Expenditure of Households by Adoption of Technology**

| Consumption Expenditure | Fertilizer | | Both Fertilizer and Improved seeds | | Total Sample HH |
|---|---|---|---|---|---|
| | Adopters | Non-adopters | Adopters | Non-adopters | |
| Mean | 8621.25 | 7074.25 | 9063.68 | 7202.39 | 8184.22 |
| t-statistics | 3.79*** | | 5.14*** | | |

**Note:** *** indicates 1% level of Significance

**Source:** Filed Survey, 2018

In order to assess the situation of poverty in the study area, it is quite important to determine the line of poverty. Total poverty is the sum of food poverty and non-food poverty. First, food poverty line was computed by selecting a set of food items commonly consumed by the poor that meets a minimum caloric requirement of 2200 kcal/day/adult. Then, the selected bundles of food items were valued at local prices. In order to account the non-food poverty line and to arrive at the absolute total poverty line, the food poverty line is divided by the food share of the poorest 25 % of the sample households (see Appendix 3 for detail).

Accordingly, the absolute poverty line in the study area is determined to be ETB 5957 which is considered as the minimum annual consumption expenditure needed for an adult to lead healthy and active life. Once the poverty line is determined, the situation of poverty in the study area was examined based on Foster-Greer-Thorbecke (FGT) poverty indices; incidence of poverty, the poverty gap, and the poverty severity.

Incidence of poverty (headcount index) is the share of population whose consumption is below the poverty line. Given the poverty line, sample households whose expenditure per adult equivalent per annum less that ETB 5957 are deemed to be poor, otherwise not. The result indicates that about 33% of the households live below poverty line which are considered as poor (table 40). In line with the existence of lower consumption expenditure, incidence of poverty in the study area is found to be higher than the national average. During 2015/16 poverty measured by head count ratio was estimated to be 25.6% for rural Ethiopia (National Planning Commission, 2017).

**Table 4.40 Poverty Measures by District**

| Poverty Measures | Districts | | | Total Sample HH |
|---|---|---|---|---|
| | Banja | Guangua | Guagusa Shikudad | |
| Head count ratio | 0.369 | 0.314 | 0.330 | 0.330 |
| Poverty gap | 0.077 | 0.051 | 0.070 | 0.062 |
| Severity gap | 0.021 | 0.016 | 0.020 | 0.018 |

**Source:** Author's computation using the FGT poverty formula, 2018

Regarding to district disaggregation, poverty is more prevalent in Banja district followed by Guagusa-Shikudad district with head count ratio of 36.9 and 33.0% respectively. However, in Guangua district, the share of poor households is found to be the smallest (31.4%).

Poverty gap measures how far consumption expenditure of the poor households is below the poverty line. In Awi zone, the poverty gap is found to be 0.062. It means that on average, 6.2 % of the poverty line is needed to bring the entire poor households at least at this poverty line. In Banja district, not only the poverty incidence but also the poverty gap is relatively high.

Poverty severity measures not only the distance separating the poor from the poverty line (the poverty gap), but also the inequality among the poor, that is, a higher weight is placed on those households further away from the poverty line. The result indicates that poverty severity is found to be 0.018. This means that there is about 1.8% of relative deprivation among the poor households in the study area.

Table 4.41 compared the incidence of poverty, the poverty gap, and the poverty severity of adopters and non-adopters. The unconditional results indicates that adopters are found to be less poor that non-adopters in all the three poverty measures. The incidence of poverty, poverty gap and severity gap of fertilizer adopters were determined to be lower than non-adopters by 15.6%, 3.7% and 1.7% respectively. On the other hand, poverty measured by head count ratio for simultaneous adopters of fertilizer and improved seeds was much lower than non-adopters (17.7%). Similarly, both poverty gap and poverty severity were also higher among non-adopters than simultaneous adopters of fertilizer and improved seeds.

**Table 4.41 Poverty Measures by Technology Adoption**

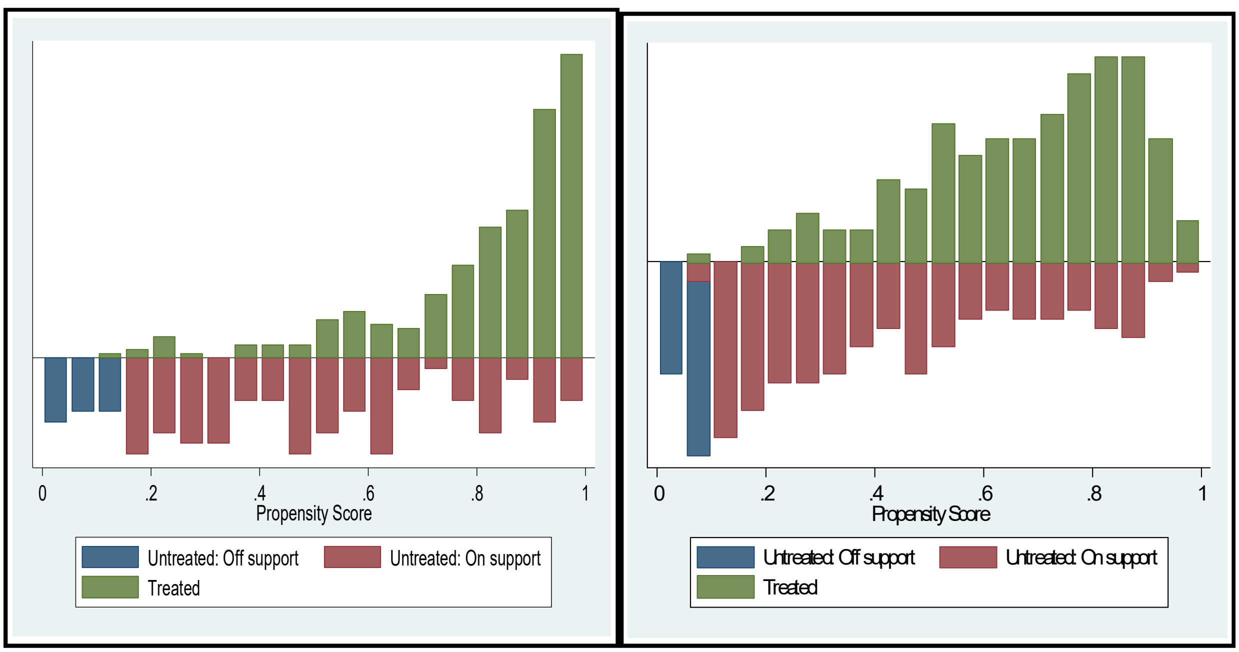
| | Fertilizer | | Fertilizer and Improved Seeds | |
|---|---|---|---|---|
| **Poverty Measures** | Adopters | Non-Adopters | Adopters | Non-Adopters |
| Head count ratio | 0.286 | 0.442 | 0.246 | 0.423 |
| Poverty gap | 0.051 | 0.088 | 0.044 | 0.081 |
| Severity gap | 0.013 | 0.030 | 0.011 | 0.026 |

**Source:** Filed Survey, 2018

To sum up, the unconditional results in table 4.39 and 4.41 validates the importance of agricultural technologies in enhancing the welfare of rural households. However, as it is explained above, a direct evaluation of differences in welfare indicators among the two groups may mislead since the differences may not solely be resulted from adoption of technology, but due to other factors too. Hence, in the next section, the poverty reduction effect of technology adoption is estimated by using the PSM approach.

As discusses earlier in chapter three, a direct comparison of the welfare of adopters and non-adopters is misleading since the differences between them may not be resulted solely from the adoption of technologies but due to other socio-economic factors also. Therefore, identifying methods which can control observable characteristics and measuring the actual effect of technology adoption is very crucial. Consequently, due to the reasons mentioned earlier, PSM method has been applied in order to analyze the true effect of technology adoption on the outcome variables. In PSM technique of analysis, the first step is the determination of propensity scores for each observation. As a result, in this study, propensity scores have been computed by using logit model as developed earlier for the two scenarios independently; one for fertilizer adoption and the other for simultaneous adoption of fertilizer and improved seeds (see table 4.35 and 4.36).

After the estimated logit models, propensity scores were predicted for each household. Once the propensity score estimation of the covariates is completed, the common support region is imposed on the propensity score distributions of both groups. Area of common support is those propensity scores within the range of the lowest and highest estimated values for households in the treatment group (Khandker et al., 2010). The results of the estimated propensity scores for the case of fertilizer adoption suggested the region of common support of [0.14108334, 0.99943489] where only 16 (4%) out of 400 observations were out of the common support. Similarly, for the case of simultaneous adoption of fertilizer and improved seeds, the estimated propensity scores suggested a region of common support of [0.09280763, 0.98548041] where only 31 (7.75%) out of 400 observations were out of the common support.




a) Fertilizer Adoption b) Both Fertilizer and Improved Seeds Adoption

**Figure 4.11 Propensity Score Distribution and Common Support.**

**Source:** Field survey, 2018

Therefore, as it is indicated in figure 4.11, there exists considerable overlap in the distribution of propensity scores of non-adopters and adopters; meaning that the common support condition is satisfied.

Furthermore, before estimating of the effect of technology adoption, the quality of alternative matching algorithms were checked based on pseudo $R^2$, likelihood ratio tests and mean standardized bias. In this study, two commonly used matching algorisms; Nearest-Neighbor Matching (NNM) and Kernel Based Matching (KBM) have been used. NNM was employed with single neighbor (NNM-1) and five nearest neighbors (NNM-5) while Kernel matching was employed with bandwidths of 0.03 (KBM-0.03) and 0.06 (KBM-0.06).

When only adoption of fertilizer is considered, the mean standardized bias was 36.2 before matching and it is reduced to ranging from 12.7 – 15.5 with a substantial reduction in standardized bias by 57.7 – 64.9%. The pseudo $R^2$ was 0.258 before matching and highly reduced ranging from 0.043 – 0.062. Moreover, likelihood ratio test indicates the insignificance of the covariates after matching (table 4.42).

**Table 4.42 Matching Quality Indicators (Fertilizer Adoption)**

| **Matching Algorithm** | | **Pseudo $R^2$** | **LR $\chi 2$** | **Mean std. bias** | **Percentage of bias reduction** |
|---|---|---|---|---|---|
| NNM-1 | Before Matching | 0.258 | 123.09*** | 36.2 | |
| | After Matching | 0.062 | 46.62 | 15.3 | 57.7 |
| NNM-5 | Before Matching | 0.258 | 123.09*** | 36.2 | |
| | After Matching | 0.048 | 22.33 | 13.0 | 64.1 |
| KBM-0.03 | Before Matching | 0.258 | 123.09*** | 36.2 | |
| | After Matching | 0.043 | 19.80 | 12.7 | 64.9 |
| KBM-0.06 | Before Matching | 0.258 | 123.09*** | 36.2 | |
| | After Matching | 0.047 | 28.33 | 13.1 | 63.8 |

**Note:** *** indicates Significant at 1%

**Source:** Field survey, 2018

Likewise, for simultaneous adoption of fertilizer and improved seeds, the mean standardized bias was considerably reduced ranging from 77.8-79.7% after matching. The pseudo $R^2$ was 0.225

before matching while it is reduced ranging from 0.011 – 0.014 after matching. Moreover, the p-values of the likelihood ratio tests after matching become insignificant.

To sum up, as indicated from table 4.42 and 4.43, the higher the reduction in the standardized mean, the lower the pseudo $R^2$ and insignificance of the likelihood ratio after matching are indicators of better quality of matching algorisms (Rosenbaum & Rubin, 1983).

**Table 4.43 Matching Quality Indicators (Adoption of Both Fertilizer and Improved Seed)**

| Matching Algorithm | | Pseudo $R^2$ | LR $\chi 2$ | Mean std. bias | Percentage of bias reduction |
|---|---|---|---|---|---|
| NNM-1 | Before Matching | 0.225 | 124.71*** | 31.5 | |
| | After Matching | 0.014 | 7.77 | 6.5 | 79.4 |
| NNM-5 | Before Matching | 0.225 | 124.71*** | 31.5 | |
| | After Matching | 0.011 | 5.22 | 6.4 | 79.7 |
| KBM-0.03 | Before Matching | 0.225 | 124.71*** | 31.5 | |
| | After Matching | 0.012 | 5.62 | 7.0 | 77.8 |
| KBM-0.06 | Before Matching | 0.225 | 124.71*** | 31.5 | |
| | After Matching | 0.047 | 4.98 | 7.0 | 77.8 |

**Note:** *** indicates Significant at 1%

**Source:** Field survey, 2018

Finally, the results of sensitivity test of estimates to hidden biases are shown in table 4.44. It revealed that the estimated results are robust which means that the results are insensitive to unobservable bias. The sensitivity test, therefore, suggest that the ATT results were obtained due to adoption of agricultural technologies rather than differences in other unobservable variables.

**Table 4.44 Results of Sensitivity Test**

| Outcome Variables | Gamma (Γ) | Fertilizer | | | | Both Fertilizer and Improved Seeds | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Q_mh+ | Q_mh- | p_mh+ | p_mh- | Q_mh+ | Q_mh- | p_mh+ | p_mh- |
| Consumption Expenditure | 1 | 2.7879 | 2.7879 | .0026 | .0026 | 3.5405 | 3.5405 | .0002 | .0002 |
| | 1.05 | 2.9611 | 2.6275 | .0015 | .0043 | 3.7230 | 3.3735 | .0001 | .0004 |
| | 1.1 | 3.1213 | 2.4696 | .0009 | .0068 | 3.8911 | 3.2082 | .0001 | .0007 |
| | 1.15 | 3.2751 | 2.3192 | .0005 | .0102 | 4.0527 | 3.0509 | .0000 | .0011 |
| | 1.2 | 3.4232 | 2.1757 | .0003 | .0148 | 4.2082 | 2.9009 | .0000 | .0019 |
| | 1.25 | 3.566 | 2.0385 | .0002 | .0207 | 4.3583 | 2.7577 | 6.6e-06 | .0029 |
| | 1.3 | 3.7039 | 1.9071 | .0001 | .0282 | 4.5034 | 2.6203 | 3.3e-06 | .0044 |
| | 1.35 | 3.8373 | 1.7809 | .0001 | .0375 | 4.6438 | 2.4889 | 1.7e-06 | .0064 |
| | 1.4 | 3.9665 | 1.6596 | .0000 | .0485 | 4.7799 | 2.3624 | 8.8e-07 | .0091 |
| | 1.45 | 4.0919 | 1.5427 | .0000 | .0614 | 4.9120 | 2.2406 | 4.5e-07 | .0125 |
| | 1.5 | 4.2137 | 1.4299 | .0000 | .0764 | 5.0404 | 2.1232 | 2.3e-07 | .0169 |
| Poverty Status | 1 | 2.7879 | 2.7879 | .00265 | .0026 | 3.9060 | 3.9060 | .0000 | .0000 |
| | 1.05 | 2.9611 | 2.6275 | .0015 | .0043 | 4.1089 | 3.7176 | .0000 | .0001 |
| | 1.1 | 3.1213 | 2.4696 | .0009 | .0068 | 4.2968 | 3.5323 | 8.7e-06 | .0002 |
| | 1.15 | 3.2751 | 2.3192 | .0005 | .0102 | 4.4770 | 3.3558 | 3.8e-06 | .0004 |
| | 1.2 | 3.4232 | 2.1757 | .0003 | .0148 | 4.6504 | 3.1873 | 1.7e-06 | .0007 |
| | 1.25 | 3.566 | 2.0385 | .0002 | .0207 | 4.8174 | 3.0262 | 7.3e-07 | .0012 |
| | 1.3 | 3.7038 | 1.9071 | .0001 | .0282 | 4.9786 | 2.8719 | 3.2e-07 | .0021 |
| | 1.35 | 3.8373 | 1.7809 | .0001 | .0374 | 5.1345 | 2.7237 | 1.4e-07 | .0032 |
| | 1.4 | 3.9665 | 1.6595 | .0000 | .0485 | 5.2853 | 2.5812 | 6.3e-08 | .0049 |
| | 1.45 | 4.0919 | 1.5427 | .0000 | .0614 | 5.4315 | 2.4440 | 2.8e-08 | .0073 |
| | 1.5 | 4.2136 | 1.4299 | .0000 | .0764 | 5.5734 | 2.3117 | 1.2e-08 | .0104 |
| | 1 | 2.5192 | 2.5192 | .0059 | .0059 | 3.7929 | 3.7929 | .0001 | .0001 |
| Total Income | 1.05 | 2.7101 | 2.3373 | .0034 | .0097 | 3.9959 | 3.6041 | .0000 | .0002 |
| | 1.1 | 2.8888 | 2.1606 | .0019 | .0153 | 4.1839 | 3.4185 | .0000 | .0003 |
| | 1.15 | 3.0604 | 1.9922 | .0011 | .0232 | 4.3644 | 3.2416 | 6.4e-06 | .0006 |
| | 1.2 | 3.2254 | 1.8315 | .0006 | .0288 | 4.5379 | 3.0729 | 2.8e-06 | .0011 |
| | 1.25 | 3.3843 | 1.6776 | .0004 | .0392 | 4.7050 | 2.9115 | 1.3e-06 | .0018 |
| | 1.3 | 3.5377 | 1.5301 | .0002 | .0453 | 4.8664 | 2.7568 | 5.7e-07 | .0029 |
| | 1.35 | 3.686 | 1.3883 | .0001 | .0556 | 5.0223 | 2.6083 | 2.6e-07 | .0045 |
| | 1.4 | 3.8296 | 1.2519 | .0001 | .0673 | 5.1732 | 2.4655 | 1.2e-07 | .0068 |
| | 1.45 | 3.9687 | 1.1206 | .0000 | .0804 | 5.3195 | 2.3280 | 5.2e-08 | .0099 |
| | 1.5 | 4.1038 | .99377 | .000 | .0949 | 5.4614 | 2.1954 | 2.4e-08 | .0141 |

**Source:** Field survey, 2018

Now we are in a position to examine the effect of fertilizer and improved seeds adoption on poverty reduction based on their consumption expenditure and incidence of poverty. Table 4.45 presents the estimated average treatment effect for the treated (ATT) due to adoption of fertilizer and improved seeds. The results show that adoption of chemical fertilizer and improved seeds resulted in a positive and significant effect on households' consumption expenditure. Based on four algorithms, the ATT increased ranging from ETB 1542-1654 due to fertilizer adoption at 1% level of significance. On the other hand, simultaneous adoption of fertilizer and improved seed improved annual consumption expenditure per adult equivalent by ETB 1700-1818 depending on the various matching algorithms used. The results are consistent with other similar studies such as Sahu and Das (2016) in India, Budhathoki and Bhatta (2016) in Nepal, Afolami, Obayelu, and Vaughan (2015) in Nigeria, and Mekonnen (2017) and Jaleta, Kassie, Marenya, Yirga, and Erenstein (2018) in Ethiopia which found a positive and significant impact of agricultural technology adoption on consumption expenditure of rural households,

**Table 4.45 Effect of Fertilizer and Improved Seeds on Farmers' Consumption Expenditure**

| Matching | Fertilizer | | | Both Fertilizer and Improved Seeds | | |
|---|---|---|---|---|---|---|
| Algorithm | ATT | Std. Err. | t-stat | ATT | Std. Err. | t-stat |
| NNM-1 | 1615.15 | 552.24 | 2.92*** | 1700.29 | 488.76 | 3.46*** |
| NNM-5 | 1591.58 | 514.28 | 3.09*** | 1742.50 | 464.14 | 3.75*** |
| KM-0.03 | 1654.08 | 519.59 | 3.18*** | 1747.19 | 470.04 | 3.72*** |
| KM-0.06 | 1542.28 | 488.59 | 3.16*** | 1817.72 | 447.91 | 4.06*** |

**Note:** *** indicates 1% significance level

**Source:** Field Survey, 2018

The impacts of fertilizer and improved seeds on incidence of poverty are reported in Table 4.46. The results indicate that adoption of agricultural technologies reduces the incidence of poverty in the study area. This result is not surprising since technology adoption resulted in improvement in the consumption expenditure of households as it is indicated in table 4.45. Depending on the matching algorithms used, the incidence of poverty for fertilizer adopters were lower than non-adopters ranging from 17.4-18.2%. On the other hand, the effect of simultaneous adoption of fertilizer and improved were estimated to be 18.8-20.0%. Many similar studies such as Mendola (2007) in Bangladesh, Wu, Ding, Pandey, and Tao (2010) in china, Kassie et al. (2011) in Uganda, Asfaw et al. (2012) in Tanzania, and Zeng et al. (2015) and Verkaart et al. (2017) in Ethiopia revealed the importance of agricultural technologies for reduction of poverty.

**Table 4.46 Impact of fertilizer and improved seeds on farmers' incidence of poverty**

| Matching Algorithm | Fertilizer | | | Both Fertilizer and Improved Seeds | | |
|---|---|---|---|---|---|---|
| | ATT | Std. Err. | t-stat | ATT | Std. Err. | t-stat |
| NNM-1 | -17.4% | 0.097 | -1.79* | -18.8% | 0.076 | -2.46** |
| NNM-5 | -18.2% | 0.089 | -2.04** | -19.8% | 0.071 | -2.77*** |
| KM-0.03 | -17.6% | 0.090 | -1.94* | -19.9% | 0.072 | -2.75*** |
| KM-0.06 | -17.9% | 0.087 | -2.06** | -20.0% | 0.069 | -2.91*** |

**Note:** *, **, ***, indicates 10, 5 and 1% level of significance respectively

**Source:** Field survey, 2018

The situation of poverty and distribution of income may not only be influenced by adoption of technology but its intensity of utilization too. In this study, the impact of fertilizer intensity on the outcome variables was estimated by using the dose response function. Figure 4.12 depict the dose response function results which relate intensity of fertilizer utilization with annual household income, consumption expenditure and incidence of poverty. As shown from the figure, the annual households' income and the average consumption expenditure per adult equivalent significantly increases with the intensity of fertilizer adoption. On the other hand, the average probability of incidence of poverty declines with the intensity of fertilizer utilization.

Moreover, the results of the marginal effects revealed that the increment in households' income increase with increasing trend. Moreover, increase in the intensity of fertilizer use significantly and sharply reduces incidence of poverty in farm households (reduce poverty at an increasing rate). The results of this study are consistent with similar studies such as Kassie et al. (2014) and Shiferaw et al. (2014) which revealed that intensity of technology adoption significantly increases consumption expenditure and reduce probability of food insecurity.

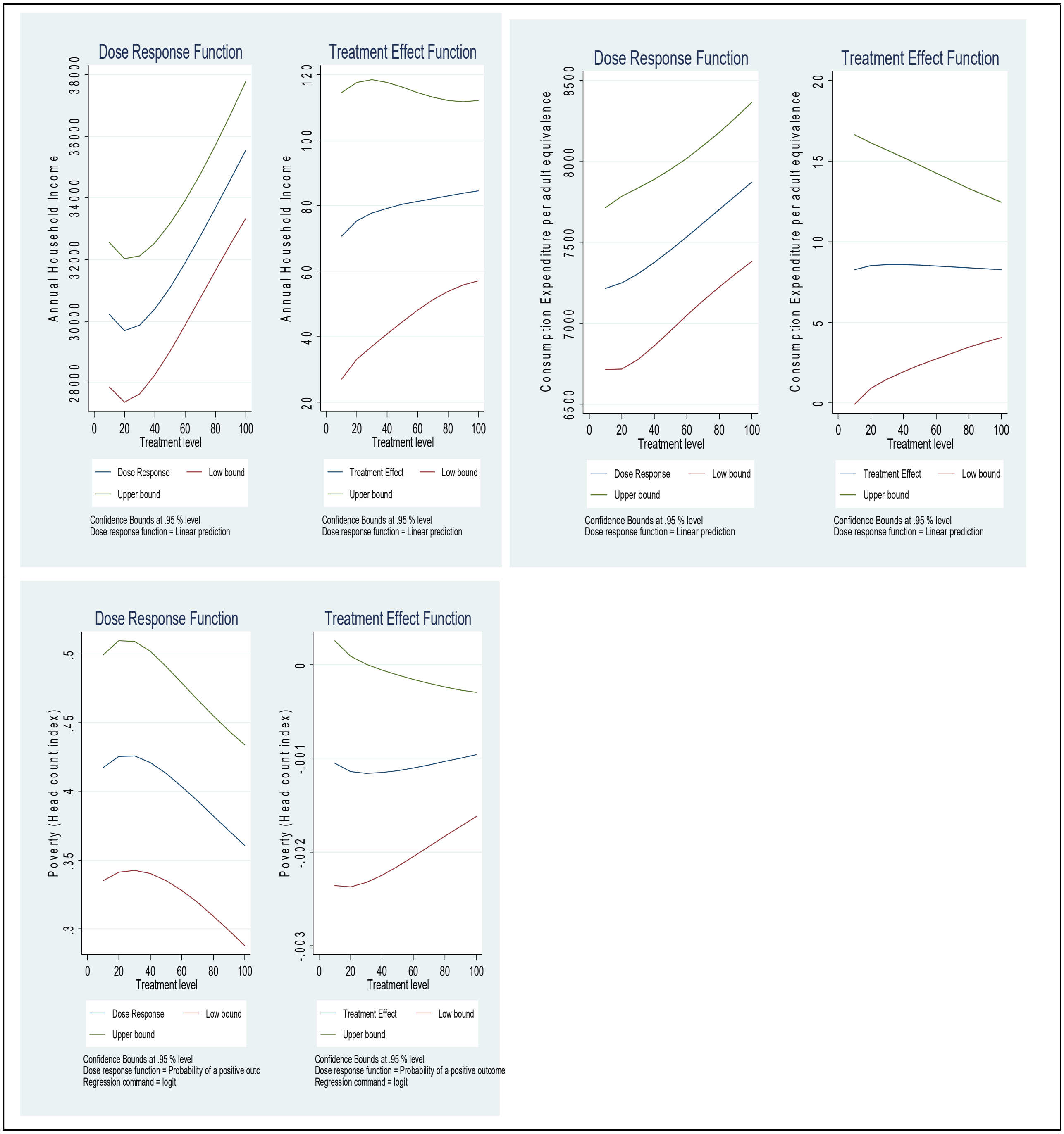



**Figure 4.12 Dose response functions (Average treatment effects)**

**Source**: Own depict based on field survey, 2018

## 4.8 The Impact of agricultural Technology Adoption on Income Distribution

There is growing consensus that assessments of economic performance should not focus solely on overall income growth, but also take into account income distribution (Hoeller et al., 2014). According to War & Coxhead (1992), a more equitable distribution of income is a major policy concern so that policy makers need to know the likely effects of technology adoption on the income of households. In this section, therefore, the distribution of income in the study area is examined. Moreover, the impact of agricultural technologies such as fertilizer and improved varieties of seeds has been evaluated.

**Table 4.47 Income of Households by Sources**

| Sources of Income | Mean | Std. Dev | Min | Max |
|---|---|---|---|---|
| Crop income | 24529.97 | 30876.14 | 0 | 73650 |
| Livestock Income | 11413.02 | 9056.567 | 0 | 58625 |
| Off-farm Income | 4535.05 | 5396.965 | 0 | 26000 |
| ***Total Income*** | ***40478.04*** | ***32866.58*** | ***9600*** | ***97930*** |

**Source:** Field survey, 2018

Table 4.47 presents the average income of households in the study area by their sources of income. The average income of a household in the study area is found to be ETB 40478 which composed of three main sources of income; crop income, Livestock income and off-farm income. As indicated in figure 4.13, crop income is the major source of income for rural farmers which account 60.6% of their total income. Livestock income comprises the second largest sources of income which took 28.8%. However, off-farm income contributes only 11.2% which is the lowest among other sources of income.

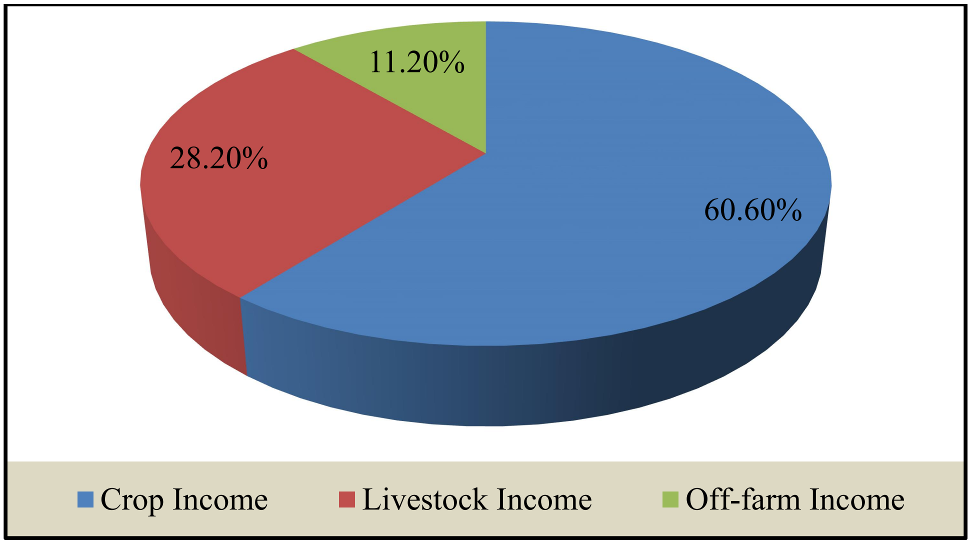



**Figure 4.13 Shares of Each Sources of Income from the Total Income**

**Source:** Field survey, 2018

Regarding to district disaggregation, as it shown in table 4.48, the total income of households who lived in Guangua district is better than the rest of the districts. This may be due to the existence of better adoption of agricultural technologies and larger land size among others. Like the case of consumption expenditure and poverty, Banja district is found to be the lowest in terms of the average income of households.

**Table 4.48 Income of Households by District**

| Districts | Mean | Std. Dev | Min | Max |
|---|---|---|---|---|
| Banja | 32455.48 | 12815.11 | 12090 | 69640 |
| Guangua | 44021.76 | 43589 | 10345 | 97930 |
| Guagusa Shikudad | 40040.35 | 14607.1 | 9600 | 81210 |

**Source:** Field survey, 2018

One of the most common measures of income distribution is the Lorenz curve. Hence, in this study distribution of income among rural households is considered based on Lorenz curve and reported in figure 4.14. When each income component is considered, higher income inequality is observed in case of off-farm income because 42% of the total farm households were not participated in off-farm activities (see table 4.15). Relative to other sources of income crop income is fairly distributed among rural households. The aggregate distribution of income of households is relatively better than other sources of income. This implies that households which have low income in one source of income may have better level of income from other sources (Lin, 1999). This is supported by the decomposition of the Gini coefficient (table 4.49).

**Table 4.49 Gini Coefficients by Income Components**

| Source of Income | Sk | Gk | Rk | Share | % Change |
|---|---|---|---|---|---|
| Crop Income | 0.6060 | 0.3671 | 0.8382 | 0.6920 | 0.0860 |
| Livestock Income | 0.2820 | 0.4165 | 0.6008 | 0.2619 | -0.0201 |
| Off-farm Income | 0.1120 | 0.6167 | 0.1797 | 0.0461 | -0.0659 |
| ***Total Income*** | ***1.0000*** | ***0.2695*** | ***1.0000*** | ***1.0000*** | ***0.0000*** |

**Source:** Field survey, 2018

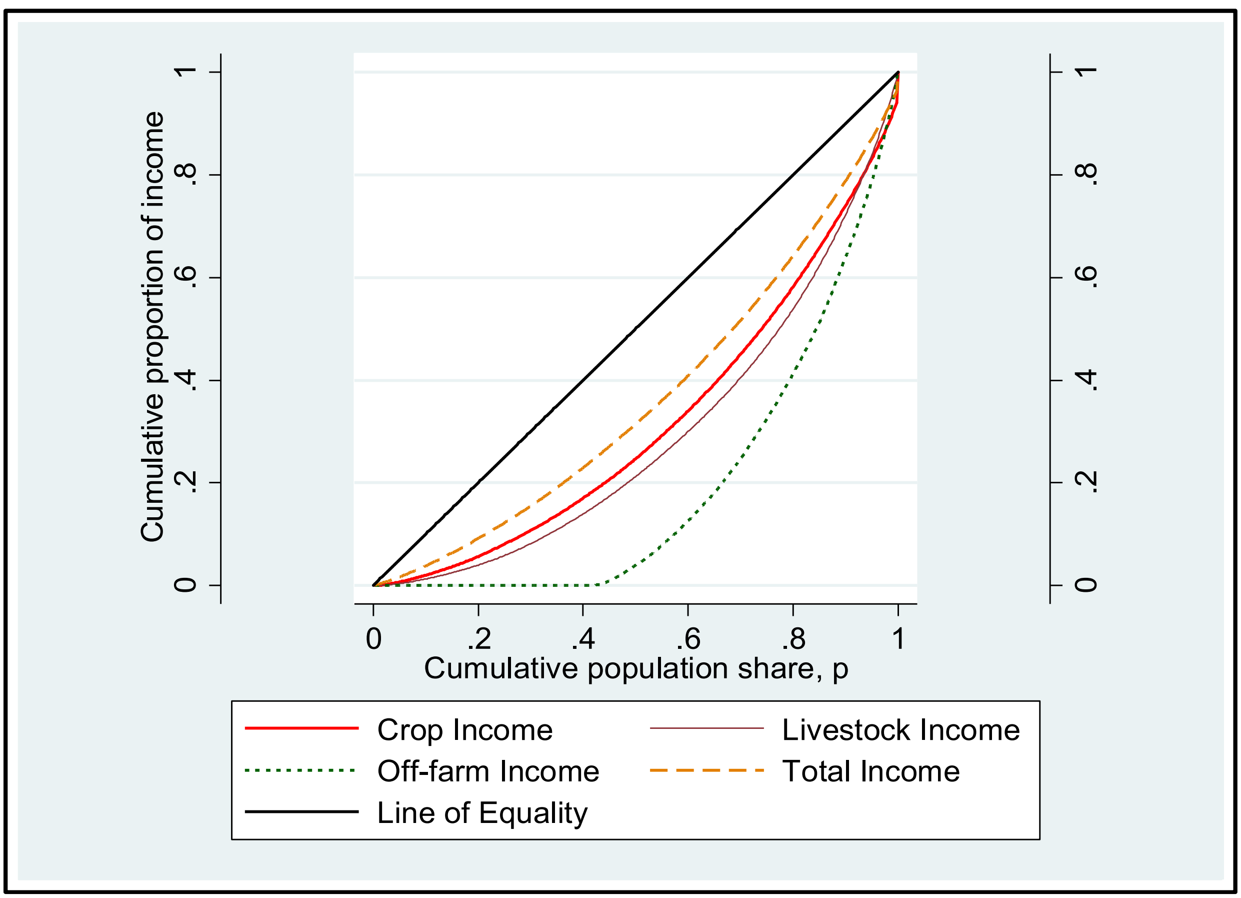



**Figure 4.14: Lorenz Curve Comparison by Sources of Income**

**Source:** Field Survey, 2018

Table 4.49 reports the results of Pyatt, Chen, and Fei, (1980) decomposition of the aggregate Gini coefficient based on sources of total income of households in the study area. The Gini coefficient of total household income was estimated to be 0.269. The result is not far from the national average Gini coefficient for Ethiopian rural households. In 2015/16, Gini Coefficient measured by the income (consumption) inequality in Ethiopia was found to be 0.284 for rural households (National Planning Commission, 2017). Similarly, a study by Gatiso and Wossen, (2015) estimated the aggregate income Gini coefficient in rural Ethiopia to be 0.274. In line with the result of this study, the Gini coefficient based reports of UNDP grouped Ethiopia as a country with very low income inequality (UNDP, 2016).

The second column indicates the share of each income component from the total aggregate income of households (Sk). As discussed earlier, in this study, crop income is found to be the major sources of income followed by livestock income. As reported in column 3, off-farm income is the most unequally distributed (Gk=0.6167) source of income followed by livestock income (Gk=0.4165). Relatively crop income is the most equally distributed income source (*Gk* = 0.3671). However, crop income contributes the largest share in income inequality (69.2%) followed by livestock income (26.19%). The share of off-farm income to total income inequality was appeared to be the lowest with only 4.61%.

**Table 4.50 Income of Households by Sources and Technology Adoption**

| | **Fertilizer** | | | **Fertilizer and Improved Seeds** | | |
|---|---|---|---|---|---|---|
| **Sources of Income** | Adopters | Non-adopters | t-stat | Adopters | Non-adopters | t-stat |
| Crop income | 27261.47 | 17592.45 | -2.84*** | 30111.5 | 18298.74 | -3.88*** |
| Livestock Income | 12488.55 | 8681.37 | -3.85*** | 13903.78 | 8632.331 | -6.06*** |
| Off-farm Income | 4472.021 | 4695.13 | 0.37 | 4233.033 | 4872.222 | 1.18 |
| ***Total*** | ***44222.04*** | ***30968.96*** | ***-3.68**** | ***48248.32*** | ***31803.29*** | ***-5.15**** |

**Note:** *** Indicates 1% level of significance

**Source:** Field Survey, 2018

Moreover, column 6 presents the elasticity of Gini for each sources of income. Crop income is found to be an inequality increasing source of income (8.6%). In contrary, off-farm income was the main inequality decreasing sources of income with elasticity of -6.59%. The reason may be due to larger participation of the poor in off-farm activities.

Table 4.50 compares the income of adopters and non-adopters of agricultural technology by income components. It indicates the existence of significant difference in total income between adopter and non-adopter households. In the case of only fertilizer adoption, the income of adopters is higher than non-adopters by ETB 13253 (42.79%). On the other hand, simultaneous adoption of fertilizer and improved seeds improves households' income by ETB 16445 (51.71%). The total income gap between adopters and non-adopters is primarily resulted from the difference in crop income followed by livestock income. This may indicate that use of fertilizers and improved seeds results in improvement in households income through increment in agricultural productivity. However, the difference in off-farm income between adopters and non-adopters was found to be insignificant.

Like the case of poverty, the unconditional results presented in table 4.46 confirmed the significant impact of technology adoption on income inequality.  However, evaluating the true effect of technology adoption becomes crucial since the gap may not solely be resulted from adoption but also other factors too. Therefore, the impact of fertilizer and improved seeds adoption on income and its distribution is evaluated by using PSM approach.

Table 4.51 presents ATT of fertilizer and improved seed adoption on households' income which was estimated based on the PSM technique described above. The estimated ATT revealed that adoption of chemical fertilizer and improved seeds resulted in a positive and significant (at 1%) effect on the income households. The income of fertilizer adopters was higher than non-adopters range from ETB 8369 to 10710 based on alternative matching algorithms. Similarly, simultaneous adoption of fertilizer and improved seeds resulted in an increment in total income of households' range from ETB 11293 to 13667. The findings this study is consistent to many similar studies which conclude that adoption technologies improves the income of households by enhancing agricultural productivity (Ding et al., 2011; Huang et al., 2015; Kassie et al., 2011; Lin, 1999; Mendola, 2007; Sofolume et al., 2013).

**Table 4.51 Impact of Fertilizer and Improved Seeds on Households' Income**

| **Matching Algorithm** | **Fertilizer** | | | **Both Fertilizer and Improved Seeds** | | |
|---|---|---|---|---|---|---|
| | ATT | Std. Err. | t-stat | ATT | Std. Err. | t-stat |
| NNM-1 | 8369.37 | 3414.94 | 2.45** | 11293.29 | 3558.64 | 3.17*** |
| NNM-5 | 10300.62 | 4106.44 | 2.51** | 13543.10 | 3869.60 | 3.50*** |
| KM-0.03 | 10710.37 | 4121.96 | 2.60*** | 13667.47 | 3882.95 | 3.52*** |
| KM-0.06 | 9094.67 | 3487.21 | 2.61*** | 13238.83 | 3612.44 | 3.66*** |

**Note:** ** and *** indicates 5% and 1% level of significance

**Source:** Field Survey, 2018

As it is discussed in the methodology section, the impact of technology on income distribution was computed as the difference in Gini Coefficients with and without technology adoption. The distribution of income with technology adoption is easy since it is computed based on the observable income of households. However, in order to estimate Gini Coefficients without technology adoption, first the impact of technology on the total income was estimated.

Then the estimated income effect was subtracted from the total income of technology adopters in order to obtain the counterfactual income which represents income of technology adopters had it not been adopted. Finally, the effect of agricultural technology on income inequality was examined based on Lorenz curve and Gini Coefficients.

Figure 4.15 & 4.16 depicts the effect of technology on income distribution based on Lorenz curve. In each figure three alternative Lorenz curves are identified; one is constructed based on the observable income of rural households (with technology adoption) while the other two Lorenz curves were derived based on the counterfactual income (without technology adoption) depending on two matching algorithms, NNM-5 and KBM-0.06.

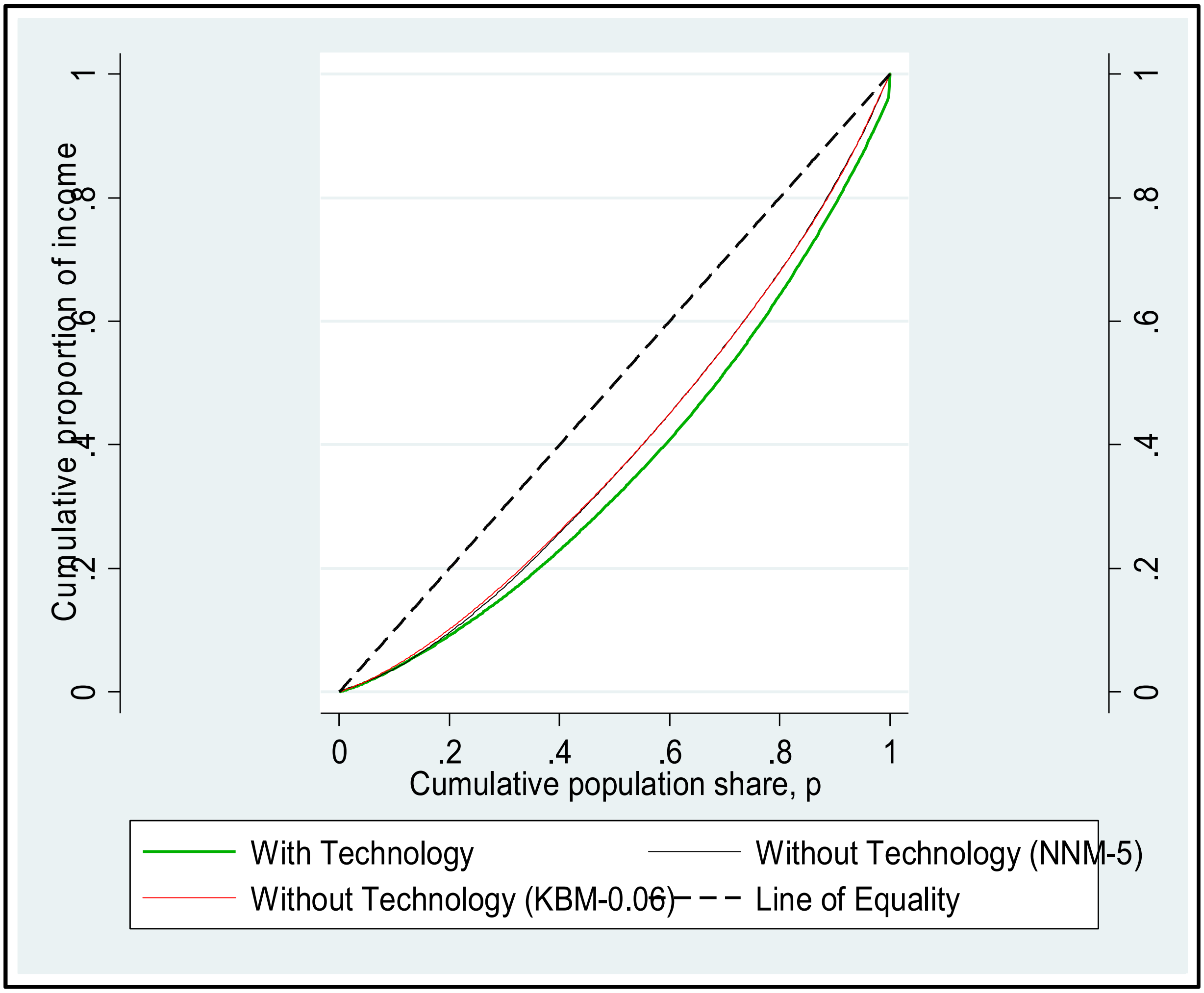



**Figure 4.15 Lorenz Curve Comparisons With and Without Fertilizer Adoption**

**Source:** Field Survey, 2018

Figure 4.15 compares the distribution of income before and after adoption of fertilizer among rural households. As it is indicated from the Lorenz curves, in both the matching algorithms, the distribution of income without fertilizer adoption is found to be better than with technology adoption. Similarly, Lorenz curves in figure 4.16 indicates that income inequality worsens with simultaneous adoption of fertilizer and improved seeds in the study area since the Lorenz curve with technology adoption far away from the line of equality more than other Lorenz curves without adoption of technology. Therefore, the Lorenz curve measurement of income distribution revealed that adoption of agricultural technology increases total income inequality among rural farmers in the study area.

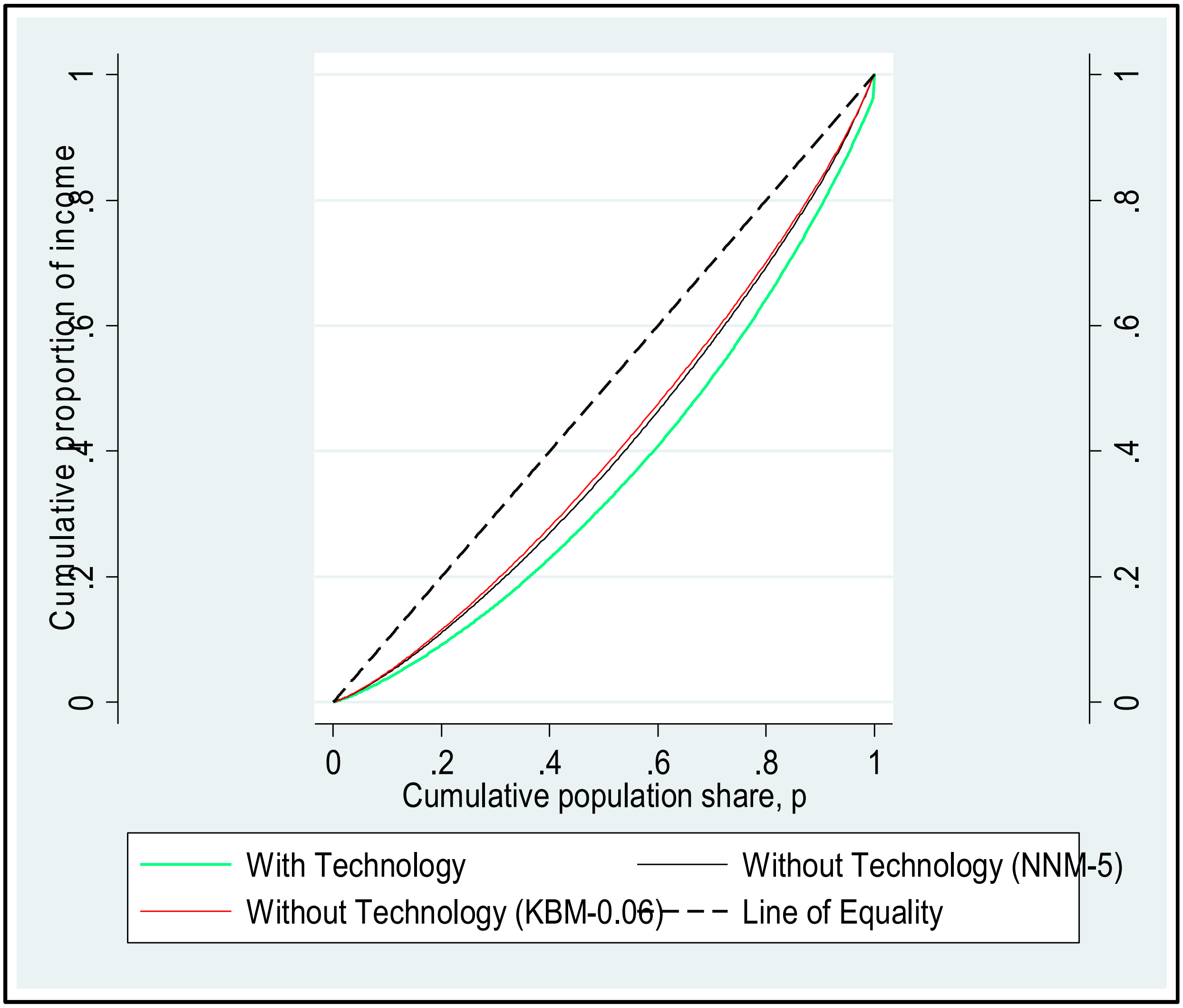



**Figure 4.16 Lorenz Curves With and Without Adoption of Fertilizer and Improved Seeds**

**Source:** Field Survey, 2018

Finally, the effect of fertilizer and improved seeds adoption on income inequality was estimated based on Gini coefficient. The estimated Gini coefficients on observed income (with technology adoption) and the counterfactual income (without technology adoption) based on four alternative PSM algorithms are presented in table 4.52. It is found that that adoption of fertilizer resulted in widening of income distribution where Gini coefficients increased ranging from 0.017 to 0.055. On the other hand, simultaneous adoption of fertilizer and improved seeds resulted in an increase in income inequality measured by Gini coefficient ranging from 0.047 to 0.087 depending on the alternative matching algorithms.

**Table 4.52 The Impact of Fertilizer and Improved seeds on Distribution of Income**

| Matching algorithm | Gini coefficient (With Technology) | Gini Coefficient Without Technology (Fertilizer) | Gini coefficient Without Technology (Fertilizer and Improved Seeds) |
|---|---|---|---|
| NNM-1 | 0.26945 | 0.25277 | 0.22178 |
| NNM-5 | 0.26945 | 0.21808 | 0.19666 |
| KM-0.03 | 0.26945 | 0.22797 | 0.20173 |
| KM-0.06 | 0.26945 | 0.21475 | 0.18245 |

**Source:** Field Survey, 2018

This result may not be surprising because as it is shown in the previous discussions, technology adoption resulted in a significant increase in total income and crop income was found to be the main income inequality increasing sources of income which is directly affected by technology adoption. Hence, this finding may lead us to the conclusion that adoption of agricultural technologies increases income inequality in which the income resulted from agricultural technology adoption was unequally distributed implying that higher-income farmers benefited more than small-income (Freebairn, 1995; Huang et al., 2015; Sahoo, 2014).

In contrary to Lin (1999) finding, in this study, even though livestock income and off-farm income were found as inequality decreasing sources of income their effect didn't offset the inequality increment from crop income since their contribution in the total income is small.

Moreover, the impact of agricultural technology adoption on only crop income distribution was estimated and presented in table 4.53. The PSM results indicated that when only crop income is considered, the impact of technology adoption on crop income distribution is found to be more substantial compared to its impact on total income. This is due to the fact that technology adoption highly and directly affects crop income than other sources of income. It estimated that fertilizer adoption resulted in high income inequality ranging from 0.041 -0.083 and simultaneous adoption of fertilizer and improved seeds worsen distribution by about 0.083-0.097 based on different matching algorithms.

**Table 4.53 The Impact of Fertilizer and Improved seeds on Distribution of Crop Income**

| Matching algorithm | Gini coefficient (With Technology) | Gini Coefficient Without Technology (Fertilizer) | Gini coefficient Without Technology (Fertilizer and Improved Seeds) |
|---|---|---|---|
| NNM-1 | 0.36393 | 0.32332 | 0.30452 |
| NNM-5 | 0.36393 | 0.30262 | 0.28510 |
| KM-0.03 | 0.36393 | 0.31580 | 0.29099 |
| KM-0.06 | 0.36393 | 0.28135 | 0.26645 |

**Source:** Field Survey, 2018

# CHAPTER FIVE

# SUMMARY, CONCLUSION AND RECOMMENDATIONS

## 5.1 Introduction

Agricultural growth is seen as a best strategy for achieving food security and reducing poverty since it is the source of livelihood for the larger share of the population of developing countries. Agriculture remains an important sector in the Ethiopian economy which accounts for 36.7% of the GDP and generates 88.8% of export earnings. Its growth is a major driver of poverty reduction in Ethiopia since the bulk of the rural population derives its livelihood from agriculture and poverty is by and large a rural phenomenon. The growth of agriculture, however, is recently believed to be possible only through the adoption of productivity enhancing technologies since expansion of farming area is hardly possible.

Various Literatures on Green Revolution argue that the adoption of agricultural technologies such as fertilizers and improved seeds have been essential for the decline of poverty by increasing agricultural productivity. Hence the main objective of this study is to analyze the economic benefits of agricultural technology adoption and its impact on poverty reduction and income inequality among households at Awi Administrative Zone, Ethiopia. In this study, two common agricultural productivity enhancing technologies, that is, chemical fertilizer and improved seeds have been examined.

To this end, three districts were randomly selected and investigated; namely Banja, Guangua and Guagusa-Shikudad. By using appropriate sample size determination formula, 400 sample households were selected from six kebeles, two kebeles from each district based on their population proportion and survey data was collected through structured questionnaire. Moreover, data was collected from interview of heads and experts of agricultural offices of the selected districts.

The purpose of this chapter is, therefore, to present the overall summary of the results of the study, conclusions and recommendations together with highlighting gaps for future research.

## 5.2 Summary

This study is conducted in order to achieve four specific objectives; to estimate the economic benefit of agricultural technology adoption, to identify determinants of agricultural technology adoption, to analyze the impact of technology adoption on poverty reduction and to examine the impact of technology adoption on income distribution. Hence, Summary of the study is made available in line with the specific objectives as follows.

### 5.2.1 Economic Analysis of Agricultural Technology Adoption

This study tried to examine the economic impact of fertilizer and improved seed adoption on maize and *teff* crops, the main agricultural crops in the study area. Budgetary analysis technique was employed for maize and *teff* crops independently in order to estimate the difference in costs and returns between adopters and non-adopters. Moreover, Blinder–Oaxaca decomposition technique was carried out to determine productivity differences between adopters and non-adopters.

The study revealed that 46.59% of maize producers adopted both fertilizer and improved seed and 20.77% applied only fertilizer. Even though 73.3% farmers adopted fertilizer, improved seed were applied only by 3.88% of *teff* producing farmers. In all the cases, the cost of production is higher for technology adopters compared to non-adopters. However, the difference in cost of production is mainly resulted from the cost of fertilizer which accounts 75% - 87% of the difference in total cost of production between adopters and non-adopters.

On average, maize yield in quintal/ha was estimated to be 24.5, 36.9 and 42.4 for non-adopters, adopters of fertilizer and simultaneous adopters of fertilizer and improved seeds respectively. Consequently, adoption of agricultural technology brought an increase in profit of 37.7% for fertilizer adopters and 58% for adopters of both fertilizer and improved seeds compared to non-adopters. Fertilizer adopter *teff* producers gained additional yield of 6.92 quintal/ha than non-adopters which resulted in increase of profit by 91%.

Moreover, the results from B-O decomposition reported that maize productivity of fertilizer adopters was 50.4 % greater than non-adopters while it was 70.3 % more for adopters of both fertilizer and improved seed. It further revealed that 77.3% and 71.7% of the difference in maize productivity was found due to differences in the yield of the characteristics (mainly technology adoption) for adopters of fertilizer and simultaneous adopters of fertilizer and improved seeds. The average *teff* productivity of fertilizer adopters is 73% more than non-adopters which the unexplained (technology component) accounts for 74.5% of the total gap while 25.5% of the gap is the explained component.

### 5.2.2 Determinants of Agricultural Technology adoption

In the study area 71.75% and 52.75% of farmers applied chemical fertilizer and improved seeds in at least one of their crops during the agricultural season of 2017/18 with 12.44 and 9.69 average years of experience in practicing these technologies, respectively. However, more than half of them (53.66%) applied chemical fertilizer below the recommended rate.

Adoption of agricultural technologies can be influenced by various demographic, socio-economic and institutional factors. In this study two dependent variables (adoption of fertilizer and simultaneous adoption of fertilizers and improved seeds) were used and their determinants have been estimated independently by the help of logit model. Moreover, factors affecting the intensity of fertilizer use were investigated by using tobit model.

Regarding to determinants of fertilizer adoption, six out of nine variables were found to be significant. As a result, education, family size, access to extension service, access to credit and size of land holding were found to be significant variables which affect adoption of fertilizer positively. However, age of the household head is the only significant variable which affects adoption of fertilizer negatively in the study area.

Similarly, simultaneous adoption of fertilizer and improved seeds were determined by education, family size, access to extension service and access to credit significantly and positively while age of households head affects adoption negatively. Hence, variables which affect agricultural technology adoption in the study area are the same in the two scenarios (adoption of fertilizer; simultaneous adoption of fertilizer and improved seeds) except in one variable (size of land holding) which is significant in the former scenario while it becomes insignificant in the latter case.

Finally, intensity of fertilizer use was influenced by education, family size, extension service and accessibility of credit positively. In contrary, age and distance from the market were significant variable which affects both adoption decision and fertilizer use intensity negatively.

### 5.2.3 The Impact of Agricultural Technology on Poverty Reduction

Poverty keeps tough problem of the developing world. In this study poverty in measured based on households' consumption expenditure and FGT poverty indices. Based on the cost of 2,200 kcal per day per adult food consumption with an allowance for essential nonfood items, the poverty line in the study area was estimated to be ETB 5957 per annum. Based on the estimated line of poverty, in the study area, about 33% of the households live below the poverty lines which are considered as poor. Moreover, the poverty gap and severity gap in the study area were determined to be 6.2% and 1.8% respectively.

In this paper the impact of agricultural technology adoption (chemical fertilizer and improved seeds) on poverty reduction was examined based on PSM approach and the dose reponse function. The results of the PSM model estimated that the annual consumption expenditure of fertilizer adopters increased by ETB 1542-1654 as compared to non-adopters. Moreover, simultaneous adoption of fertilizer and improved seeds resulted in ETB 1700-1818 increase in consumption expenditure per adult equivalent. Similarly, adoption of fertilizer in a reduction in poverty measured by headcount index by 17.4-18.2% depending on different matching algorithms. On the other hand, simultaneous adoption of fertilizer and improved seeds were estimated to reduce rural poverty by 18.8-20.0%. In the same vein, results of the dose-response functions revealed that an increase in the intensity of fertilizer utilization improves farm households' income and their consumption expenditure which further resulted in the reduction in the incidence of poverty.

### 5.2.4 The Impact of Agricultural Technology Adoption on Income Distribution

Many development economists believe that the impact of policies and programs should not only be considered from the view point of overall income increment but also their effect on income distribution. Even though the impact of agricultural technology adoption on productivity and poverty reduction is well recognized, its impact on income distribution in ambiguous.

Distribution of income was measured by both the Lorenz curve and Gini coefficient. Both measures revealed the existence of some level of income inequality among rural households but not sever compared to the experience of other countries (UNDP, 2016). Specifically, the Gini coefficient of total household income in the study area was found to be 0.269. Among the other sources of income, crop income contributed the largest share in income inequality.

This study analyzed the impact of agricultural technology on income distribution by using PSM approach. The results indicated that after adoption of fertilizer, total income inequality measured by Gini coefficient increased range from 0.017 - 0.055. On the other hand, simultaneous adoption of fertilizer and improved seeds resulted in an increase in income inequality by about 0.047-0.087 depending on alternative matching algorithms. Moreover, when only one source of income i.e. crop income is considered, the impact of technology adoption on crop income distribution is found to be more substantial. It estimated that fertilizer adoption resulted in a rise in Gini coefficient ranging from 0.041 -0.083 while simultaneous adoption of fertilizer and improved seeds increase Gini coefficient by about 0.083-0.097.

## 5.3 Conclusion

This study revealed that adoption and use intensity of agricultural technologies such as fertilizer and improved seeds were mainly influenced by age, education, family size, access to extension service and access to credit ( the results of both the logit and tobit models are highly consistent). Moreover, all the employed models such as the budgetary analysis technique, B-O decomposition method, PSM model and the Dose-response function results consistently indicated the importance of adoption of agricultural technologies in improving the welfare of farm households. The study found that adoption of fertilizer and improved seeds reduced rural poverty by increasing consumption expenditure and households' income. This was mainly achieved through the increment in productivity and profitability of technology adopter households. However, it simultaneously worsen distribution of income implying that large farmers were more benefited from adoption than the poor.

## 5.4 Recommendation

In generally, this study revealed the importance of agricultural technology adoption such as chemical fertilizer and improved seeds in improvement of agricultural productivity, enhancement of consumption expenditure and hence significant reduction in rural households' poverty.

Hence, the recommendation here is that, more efforts should be exerted by the government, NGOs and other concerned bodies in order to enhance adoption of agricultural technology by rural households. As a result, this study recommends the concerned authorities to focus on the main influential factors affecting adoption of agricultural technology in order to enhance farmers' adoption of technologies. Hence, the government and other concerned authorities should focus on improving adoption of technologies through provision of formal education, increasing their accessibility for extension and credit services.

In this study, formal education and access to extension service influenced farmer's adoption decision positively and significant. This indicates the importance of expanding extension services provided by development agents to enhance farmers' awareness about its benefit and efficiently use of these technologies. Moreover, it should be noted that not only their accessibly but also their frequency of visiting farms become equally vital in order to maximize the benefits of farmers from technology adoption.

Even though accessibility of credit was found to be one of the significant variables which influence farmer's adoption decision; nearly half of the farmers had not the access. Therefore, agricultural cooperatives, microfinance and other financial institutions should avail credit for rural farmers at the right time and at low/fair rate of interest. Moreover, the procedure of getting credit such as group lending and requirement of minimum saving in financial institutions should be reconsidered.

However, at the same time proper measures should be taken to distribute the benefits of technologies proportionately for the farm households since adoption of technology worsen distribution of income. Hence, the government and other concerned authorities should focus on improving adoption of technologies by the small (poor) households through provision of formal education, increasing their accessibility for extension and credit services for them.

## 5.5 Limitation and Suggestion for Further Studies

Even though this study achieved its own objectives, there are other relevant issues that are not addressed in this study and recommended for future research. The focus of this study was on two main agricultural technologies (fertilizer and improved seeds), hence there is a need to investigate the effect of other agricultural technologies such as pesticides, irrigation and mechanization. Moreover, it will be more relevant if the same study is conducted in other districts of Awi zone, other zones and regions in Ethiopia.

This study has employed PSM approach in order to evaluate the poverty and inequality effect of fertilizer and improved seeds adoption which entertain observable characteristics only. Therefore, future studies which take in to account differences in unobservable characteristics may be needed.

This study mainly focus on chemical fertilizer. Hence, further studies on organic fertilizer by relating to the nature of soil is importnant to increase the benefit of farm households from adoption.

Finally, though the study found that adoption of productivity enhancing technologies (fertilizer and improved varieties of seeds) improves productivity and reduces rural poverty, its long-run effect on the quality of soil should be studied further.

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# APPENDICIES

## Appendix 1 Results of Reliability Test

```
. alpha FERT HYVS FERTQ AGE SEX EDUC FAM EXT CRED LAND DIST OFFINC CONSUMP POVSTATUS TOTALINC, std item

Test scale = mean(standardized items)
```

| Item | Obs | Sign | item-test correlation | item-rest correlation | average interitem correlation | alpha |
|---|---|---|---|---|---|---|
| FERT | 400 | + | 0.6381 | 0.5440 | 0.1626 | 0.7311 |
| HYVS | 400 | + | 0.7504 | 0.6790 | 0.1538 | 0.7178 |
| FERTQ | 400 | + | 0.7654 | 0.6975 | 0.1526 | 0.7160 |
| AGE | 400 | + | 0.7449 | 0.6723 | 0.1542 | 0.7185 |
| SEX | 400 | + | 0.2948 | 0.1609 | 0.1898 | 0.7663 |
| EDUC | 400 | + | 0.5293 | 0.4179 | 0.1713 | 0.7431 |
| FAM | 400 | + | 0.4329 | 0.3101 | 0.1789 | 0.7531 |
| EXT | 400 | + | 0.5086 | 0.3945 | 0.1729 | 0.7453 |
| CRED | 400 | + | 0.4469 | 0.3255 | 0.1778 | 0.7517 |
| LAND | 400 | + | 0.3071 | 0.1740 | 0.1888 | 0.7652 |
| DIST | 400 | - | 0.1519 | 0.0131 | 0.2011 | 0.7790 |
| OFFINC | 400 | - | 0.1656 | 0.0270 | 0.2000 | 0.7778 |
| CONSUMP | 400 | + | 0.4566 | 0.3362 | 0.1770 | 0.7507 |
| POVSTATUS | 400 | - | 0.4073 | 0.2819 | 0.1809 | 0.7556 |
| TOTALINC | 400 | + | 0.5964 | 0.4951 | 0.1659 | 0.7358 |
| Test scale | | | | | 0.1752 | 0.7611 |

## Appendix 2 Conversion Factor Used to Calculate Adult Equivalence (AE)

| Age category in years | Conversion Factor | |
|---|---|---|
| | **Men** | **Women** |
| 0-1 | 0.33 | 0.33 |
| 1-2 | 0.46 | 0.46 |
| 2-3 | 0.54 | 0.54 |
| 3-5 | 0.62 | 0.62 |
| 5-7 | 0.74 | 0.70 |
| 7-10 | 0.84 | 0.72 |
| 10-12 | 0.88 | 0.78 |
| 12-14 | 0.96 | 0.84 |
| 14-16 | 1.06 | 0.86 |
| 16-18 | 1.14 | 0.86 |
| 18-30 | 1.04 | 0.80 |
| 30-60 | 1.00 | 0.82 |
| >60 | 0.84 | 0.74 |

**Source:** Dercon (1997)

## Appendix 3 Computation of Poverty Line

| Food Items | Average consumption/adult equivalent/kg/year of food items (A) | Calorie value /kg (B) | Total calories consumed/ adult equivalent/ year (C=A*B) | Scaling up/down of A ($D^4$=(8030000/ 14590052.4612128)*A | Mean price of each food items/kg (E) | Monetary value of yearly consumption/ adult equivalent (F=D*E) |
|---|---|---|---|---|---|---|
| *Teff* | 44.65996357 | 3450 | 1540768.743 | 24.57972707 | 20 | 491.5945415 |
| Maize | 128.4880113 | 3630 | 4664114.81 | 70.71658812 | 7 | 495.0161169 |
| Wheat | 57.0716111 | 3440 | 1963263.422 | 31.41078748 | 11 | 345.5186622 |
| Barley | 44.78078492 | 3390 | 1518068.609 | 24.64622412 | 10.5 | 258.7853533 |
| Finger millet | 54.479444 | 3360 | 1830509.319 | 29.98412353 | 8 | 239.8729883 |
| Chickpeas | 9.01327253 | 3700 | 333491.0836 | 4.960679793 | 22 | 109.1349554 |
| Beans | 13.15414962 | 3420 | 449871.9172 | 7.239714989 | 20 | 144.7942998 |
| Peppers | 5.239899085 | 3180 | 166628.7909 | 2.883909415 | 40 | 115.3563766 |
| Potato | 133.694313 | 750 | 1002707.347 | 73.58200638 | 5 | 367.9100319 |
| Onion | 6.32664511 | 480 | 30367.89653 | 3.482027249 | 10 | 34.82027249 |
| Garlic | 0.685386554 | 1390 | 9526.873095 | 0.377219619 | 22 | 8.29883161 |
| Coffee | 2.4142302 | 20 | 482.84604 | 1.328731926 | 100 | 132.8731926 |
| Cooking Oil | 3.543360612 | 8840 | 313233.0781 | 1.950177067 | 51 | 99.45903041 |
| Salt | 5.383275977 | 00 | 0 | 2.962820471 | 10 | 29.62820471 |
| Sugar | 2.082520682 | 4000 | 83300.82728 | 1.146167303 | 24 | 27.50801527 |
| Spices | 13.95649158 | 3410 | 475916.3627 | 7.681303933 | 30 | 230.439118 |
| meat | 5.059119336 | 2620 | 132548.9266 | 2.784412762 | 150 | 417.6619143 |
| Eggs | 0.551837226 | 1580 | 8719.028174 | 0.303717409 | 0.1265 | 0.038420252 |
| Butter | 0.929226001 | 7160 | 66532.58164 | 0.511422752 | 160 | 81.82764035 |
| Total | | | 14590052.46 | | | 3630.53796 |
| Food Poverty Line | | | | | | 3631 |
| The share of the poorest 25% food expenditure | | | | | | 0.6095 |
| ***Total Poverty line*** | | | | | | ***5957*** |

**Source:** Estimated from own survey, 2018

[4] 2200 kcal/day*365

## Appendix 4 Multicollinearity Test for the Logit and Tobit Models

```
pwcorr FERT AGE SEX EDUC FAM EXT CRED LAND DIST INCOFF, star(0.05)
```

| | FERT | AGE | SEX | EDUC | FAM | EXT | CRED |
|---|---|---|---|---|---|---|---|
| FERT | 1.0000 | | | | | | |
| AGE | -0.2155* | 1.0000 | | | | | |
| SEX | 0.1550* | -0.0268 | 1.0000 | | | | |
| EDUC | 0.1784* | -0.1244* | 0.0216 | 1.0000 | | | |
| FAM | 0.2920* | 0.1552* | 0.2056* | -0.0023 | 1.0000 | | |
| EXT | 0.2286* | -0.1737* | 0.0321 | 0.1383* | 0.0306 | 1.0000 | |
| CRED | 0.3254* | -0.0702 | 0.1123* | 0.0644 | 0.0506 | 0.2074* | 1.0000 |
| LAND | 0.1451* | 0.1995* | -0.0133 | -0.0135 | 0.1435* | 0.0212 | 0.0827 |
| DIST | -0.0027 | -0.0781 | -0.0190 | 0.0092 | 0.0755 | 0.0658 | -0.0008 |
| INCOFF | -0.0186 | 0.0113 | -0.0684 | -0.0137 | -0.0231 | 0.0700 | -0.0824 |

| | LAND | DIST | INCOFF |
|---|---|---|---|
| LAND | 1.0000 | | |
| DIST | -0.0840 | 1.0000 | |
| INCOFF | -0.0023 | -0.3664* | 1.0000 |

**Appendix 5 The Hosmer-Lemeshow goodness of fit test (for the Logit Model in Table 4.35)**

```
. estat gof, group(10)

Logistic model for FERT, goodness-of-fit test

  (Table collapsed on quantiles of estimated probabilities)

       number of observations =       400
             number of groups =        10
      Hosmer-Lemeshow chi2(8) =         6.36
                  Prob > chi2 =         0.6074
```

**Appendix 6 The Hosmer-Lemeshow goodness of fit test (for the Logit Model in Table 4.36)**

```
. estat gof, group(10)

Logistic model for HYVS, goodness-of-fit test

  (Table collapsed on quantiles of estimated probabilities)

       number of observations =       400
             number of groups =        10
      Hosmer-Lemeshow chi2(8) =        15.39
                  Prob > chi2 =         0.0520
```

## Appendix 7 Correctly Predicted Observations (for the Logit Model in Table 4.35)

```
. estat classification

Logistic model for FERT

              -------- True --------
Classified |         D            ~D  |      Total
-----------+--------------------------+-----------
     +     |       266            55  |        321
     -     |        21            58  |         79
-----------+--------------------------+-----------
   Total   |       287           113  |        400

Classified + if predicted Pr(D) >= .5
True D defined as FERT != 0
--------------------------------------------------
Sensitivity                     Pr( +| D)   92.68%
Specificity                     Pr( -|~D)   51.33%
Positive predictive value       Pr( D| +)   82.87%
Negative predictive value       Pr(~D| -)   73.42%
--------------------------------------------------
False + rate for true ~D        Pr( +|~D)   48.67%
False - rate for true D         Pr( -| D)    7.32%
False + rate for classified +   Pr(~D| +)   17.13%
False - rate for classified -   Pr( D| -)   26.58%
--------------------------------------------------
Correctly classified                        81.00%
--------------------------------------------------
```

## Appendix 8 Correctly Predicted Observations (for the Logit Model in Table 4.36)

```
. estat classification

Logistic model for HYVS

              -------- True --------
Classified |         D            ~D  |      Total
-----------+--------------------------+-----------
     +     |       167            60  |        227
     -     |        44           129  |        173
-----------+--------------------------+-----------
   Total   |       211           189  |        400

Classified + if predicted Pr(D) >= .5
True D defined as HYVS != 0
--------------------------------------------------
Sensitivity                     Pr( +| D)   79.15%
Specificity                     Pr( -|~D)   68.25%
Positive predictive value       Pr( D| +)   73.57%
Negative predictive value       Pr(~D| -)   74.57%
--------------------------------------------------
False + rate for true ~D        Pr( +|~D)   31.75%
False - rate for true D         Pr( -| D)   20.85%
False + rate for classified +   Pr(~D| +)   26.43%
False - rate for classified -   Pr( D| -)   25.43%
--------------------------------------------------
Correctly classified                        74.00%
--------------------------------------------------
```

## **Appendix 9 Sensitivity Test (** Only Fertilizer Adoption)

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

Mantel-Haenszel (1959) bounds for variable CONSUMP

Gamma         Q_mh+     Q_mh-     p_mh+     p_mh-
-------------------------------------------------
    1       2.78794   2.78794   .002652   .002652
 1.05       2.96109   2.62753   .001533     .0043
  1.1        3.1213   2.46957     .0009   .006764
 1.15       3.27515   2.31921   .000528   .010192
  1.2       3.42323   2.17575   .000309   .014787
 1.25         3.566   2.03855   .000181   .020747
  1.3       3.70389    1.9071   .000106   .028254
 1.35       3.83729    1.7809   .000062   .037464
  1.4       3.96652   1.65956   .000036   .048502
 1.45        4.0919   1.54269   .000021   .061453
  1.5       4.21367   1.42998   .000013   .076361

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)
```

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

Mantel-Haenszel (1959) bounds for variable POV

Gamma         Q_mh+     Q_mh-     p_mh+     p_mh-
-------------------------------------------------
    1       2.78794   2.78794   .002652   .002652
 1.05       2.96109   2.62753   .001533     .0043
  1.1        3.1213   2.46957     .0009   .006764
 1.15       3.27515   2.31921   .000528   .010192
  1.2       3.42323   2.17575   .000309   .014787
 1.25         3.566   2.03855   .000181   .020747
  1.3       3.70389    1.9071   .000106   .028254
 1.35       3.83729    1.7809   .000062   .037464
  1.4       3.96652   1.65956   .000036   .048502
 1.45        4.0919   1.54269   .000021   .061453
  1.5       4.21367   1.42998   .000013   .076361

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)
```

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

Mantel-Haenszel (1959) bounds for variable INCTOTAL

Gamma         Q_mh+     Q_mh-     p_mh+     p_mh-
-------------------------------------------------
    1       2.51918   2.51918   .005881   .005881
 1.05       2.71009   2.33735   .003363    .00971
  1.1       2.88887   2.16062   .001933   .015362
 1.15       3.06042   1.99225   .001105   .023172
  1.2       3.22539   1.83147   .000629   .028796
 1.25       3.38432   1.67761   .000357   .039198
  1.3       3.53772   1.53007   .000202   .045325
 1.35         3.686   1.38835   .000114   .055637
  1.4       3.82956   1.25199   .000064   .067336
 1.45       3.96873   1.12058   .000036    .08044
  1.5       4.10382   .993771    .00002   .094945

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 10 Sensitivity Test (   Both Fertilizer and Improved Seeds)

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

Mantel-Haenszel (1959) bounds for variable CONSUMP

Gamma         Q_mh+     Q_mh-     p_mh+     p_mh-
-------------------------------------------------
    1       3.54053   3.54053     .0002     .0002
 1.05       3.72307   3.37352   .000098   .000371
  1.1       3.89114   3.20818    .00005   .000668
 1.15       4.05267   3.05093   .000025   .001141
  1.2       4.20824   2.90098   .000013    .00186
 1.25       4.35833   2.75769   6.6e-06   .002911
  1.3       4.50339   2.62048   3.3e-06    .00439
 1.35        4.6438   2.48885   1.7e-06   .006408
  1.4       4.77991   2.36236   8.8e-07   .009079
 1.45       4.91201   2.24061   4.5e-07   .012526
  1.5        5.0404   2.12326   2.3e-07   .016866

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)
```

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

Mantel-Haenszel (1959) bounds for variable POV

Gamma         Q_mh+     Q_mh-     p_mh+     p_mh-
-------------------------------------------------
    1       3.90601   3.90601   .000047   .000047
 1.05       4.10898   3.71769    .00002   .000101
  1.1       4.29677   3.53229   8.7e-06   .000206
 1.15       4.47702   3.35578   3.8e-06   .000396
  1.2       4.65038   3.18733   1.7e-06   .000718
 1.25       4.81742   3.02624   7.3e-07   .001238
  1.3       4.97864   2.87187   3.2e-07    .00204
 1.35       5.13447    2.7237   1.4e-07   .003228
  1.4       5.28533   2.58122   6.3e-08   .004923
 1.45       5.43154   2.44403   2.8e-08   .007262
  1.5       5.57344   2.31172   1.2e-08   .010396

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)


. mhbounds INCTOTAL , gamma(1 (0.05) 1.5)

Mantel-Haenszel (1959) bounds for variable INCTOTAL

Gamma         Q_mh+     Q_mh-     p_mh+     p_mh-
-------------------------------------------------
    1       3.79298   3.79298   .000074   .000074
 1.05       3.99596   3.60414   .000032   .000157
  1.1       4.18396   3.41846   .000014   .000315
 1.15        4.3644   3.24165   6.4e-06   .000594
  1.2       4.53792    3.0729   2.8e-06    .00106
 1.25       4.70509    2.9115   1.3e-06   .001798
  1.3       4.86642   2.75684   5.7e-07   .002918
 1.35       5.02234   2.60835   2.6e-07   .004549
  1.4       5.17327   2.46557   1.2e-07    .00684
 1.45       5.31954   2.32806   5.2e-08   .009954
  1.5       5.46147   2.19545   2.4e-08   .014066

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 11 Survey Questionnaire to be filled by Rural Households

**Dear Respondents,**

This questionnaire is designed to gather relevant data on households' behavior towards agricultural technology adoption and its impact on poverty and income inequality at Awi Administrative Zone, Ethiopia. The expected information will be used to conduct a research for the partial fulfillment of Ph.D Degree in Economics at Delhi Technological University. Hence, I confirm you that all data will be used for academic purpose and analyzed anonymously through the authorization of the university.

Thank you in advance for your honest cooperation!!

**Address and Questionnaire ID**

| | |
|---|---|
| Name of District | |
| Name of Kebele | |
| Household ID | |

**Part I: Socio-Demographic Characteristics of the household**

| № | Name of HH members | Age in years/ Month | Sex 0=female 1=Male | Marital Status 0=Married 1=Non-married | Educational level; 0=illiterate 1=primary education 2=secondary education 3=Higher education |
|---|---|---|---|---|---|
| 1 | $FM^{5}_{1}$ (HH Head) | | | | |
| 2 | $FM_2$ | | | | |
| 3 | $FM_3$ | | | | |
| 4 | $FM_4$ | | | | |

[5] FM = Family Member

| | | | | | |
|---|---|---|---|---|---|
| 5 | $FM_5$ | | | | |
| 6 | $FM_6$ | | | | |
| 7 | $FM_7$ | | | | |
| 8 | $FM_8$ | | | | |
| 9 | $FM_9$ | | | | |
| 10 | $FM_{10}$ | | | | |
| 11 | $FM_{11}$ | | | | |
| 12 | $FM_{12}$ | | | | |
| 13 | $FM_{13}$ | | | | |

**Part II: Land Resource Ownership and Farming System**

1. Do you have land for cultivation? 1. Yes 2. No
2. If yes for $Q_1$, what is the total size of your current land holding?

| № | **Land Types** | **Land Size in Hectare** |
|---|---|---|
| 1 | Cultivated Land | |
| 2 | Non Cultivated land<br>(such as Grazing Land, forest land, fallow land, etc) | |
| | **Total Land Holding** | |

3. If "yes" for $Q_1$, how do you rate the average fertility level of your cultivated land?
   1 High 2. Low 3. Medium
4. If "no" for $Q_1$, how do you earn your livelihood? ____________________________
   1. Work on rented land 2. Gift from relatives 3. Others (specify)_____________
5. What type of animal you use for tillage? 1. Ox 2.Horse 3. Donkey 4. Other________
6. Are your animals enough for the farming activities? 1. Yes 2. No
7. If no, how do you get additional animals for farming activities?
   1. Hiring 2. Coupling with others 3. Borrow from friends or relatives
   4. Exchanging by labor 5. Others (specify) _____________________________________
8. Do you use other methods rather than animals for farming purpose such as tractors? Specify, if any _____________________________________________________________

**Part III: Access to Market and Agricultural Extension Services**

1. How many kilometers is your home away from the nearest local market? __________
2. How long will it take to reach to the nearest market (in minutes)? _________________
3. Has your household received extension services which provide advice on crop production?

   1. Yes  2. No
4. If your answer is “Yes” for Q.3, for what activities they provide the service?

   1. The use of improved seeds  2. The application of fertilizers  3. Ploughing

   4. snowing  5. Harvesting  6. Others, specify ______________________________
5. Have you got sufficient extension services? 1. Yes  2. No
6. Is there development agent in your village?  1. Yes  2. No
7. If your answer is “Yes” for Q. 6, how frequently they visited your farm in last year? _______

**Part IV: Use of Fertilizer**

1. Did you use chemical fertilizers for your farm last year?  1. Yes  2. No
2. If yes, indicate the amount you used in the last year in the following table

| S.No | Type of Crops | Type of Chemical Fertilizers | | | | | |
|---|---|---|---|---|---|---|---|
| | | Urea in kg | Value in birr | DAP in kg | Value in birr | Others ( ) | Value In Birr |
| 1 | | | | | | | |
| 2 | | | | | | | |
| 3 | | | | | | | |
| 4 | | | | | | | |
| 5 | | | | | | | |
| 6 | | | | | | | |
| Total | | | | | | | |

3. If your answer is “yes” for Q.1, for how many years have you been using fertilizer? _______
4. If your answer is “no” for Q.1, what is/are your reason/s?

   1. Not useful  2. Too expensive  3. Not available  4. Harmful to the soil

   5. Others (specify) ___________________________________

**Part V: Use of Improved Seeds**

1. Do you use improved seeds on your farm in the last year? 1. Yes 2. No
2. If yes, list them in the following table

| № | Types of crops which improved seeds were Applied | improved seeds used in kg | Value of improved seeds in Birr | Traditional seed used in kg | Value of Traditional seed Birr |
|---|---|---|---|---|---|
| 1 | | | | | |
| 2 | | | | | |
| 3 | | | | | |
| 4 | | | | | |
| 5 | | | | | |
| 6 | | | | | |
| **Total** | | | | | |

3. If your answer is "no" for Q.1, state your reason/s? 1. Lack of Information 2. Not available 3.Too expensive 4. Other reasons ________________________________
4. If your answer is "yes" for Q.1, for how many years have you been using improved seeds? __

**Part VI: Accessibility of Credit**

1. Do you have access to credit for the purchase of fertilizer and/or HYVs? 1. Yes 2. No
2. If your answer is "yes" for Q.1, which is/are your source/s of credit?
   1. Cooperatives 2. Microfinance 3. Friends and relatives 4. Local Money Lenders
   5. Others (specify) ________________________________
3. If your answer for Q.1 is "no", why?
   1. Lack of asset for collateral 2. No source of credit 3. Fear of inability to pay back 4.
   4. High rate of Interest 5. Others (specify) ________________________________
4. Does the government provide subsidy for the purchase of fertilizer and/or Improved seeds?
   1. Yes 2. No

## Part VII: Use of Irrigation

1. Are you using irrigation for your farm? 1. Yes 2. No
2. If your answer is "yes" for Q.1, how much percent of your land is irrigated? ___________
3. If you use irrigation, what type is it? 1. Modern[6] 2. Traditional[7] 3. Both
4. If you do not use any irrigation activities, state your reasons? 1. Lack of awareness
   2. No water available 3. Lack of finance 4. Other reasons (specify) _____________

## Part VII: Off-farm Income

1. Do you or any member of your family have off-farm job? 1. Yes 2. No
2. If your answer is "yes" for Q.1, how often you or your family engaged in off-farm activities?
1. Seasonal 2. Through the year 3. Other, specify _____________________
3. If your answer for Q.2 is "seasonal", when is the appropriate time? 1. Meher 2. Belg
4. If your answer is "yes" for Q.1, indicate the type of work and annual income received?

| No | Type of Activities | | Amount earned (ETB) |
|---|---|---|---|
| 1. | Employment in another's farm | | |
| 2. | Employment in non-agriculture (Daily labor/ monthly paid) | | |
| 3. | Handcrafts (weaving, pottery, metal works, carpenter, etc) | | |
| 4. | Livestock trade | | |
| 5. | Pity trade (grain, vegetables, fruits, etc.) | | |
| 6. | Trade of fire and construction wood and grass, charcoal | | |
| 7. | Land rent | | |
| 8. | Rent of animals | | |
| 9. | House rent | | |
| 10. | Remittance | | |
| 11. | Others | | |
| | | | |
| | Total | | |

[6] Drip irrigation, sprinkler mechanism, canal irrigation system etc

[7] tanks, ponds, diverting stream/ river

5. If no, what are the reasons not to participate in off -farming activities?
   1. No employment opportunity  2. Wages are too low  3. Jobs are too far away
   4. Not interested in nonfarm activities  5. Others (specify) ____________________________

**Part IX: Livestock Production**

1. Do you possess Livestock? 1. Yes  2. No
2. If yes, indicate the number of livestock you owned.

| № | Types of Livestock | Number owned to date | № | Types of Livestock | Number owned to date |
|---|---|---|---|---|---|
| 1 | Oxen | | 10 | Goats(adult) | |
| 2 | Improved cows | | 11 | Local Bee hives | |
| 3 | local cows | | 12 | Modern Bee hives | |
| 4 | Bulls | | 13 | Hen | |
| 5 | Heifer | | 14 | Horse | |
| 6 | Calves | | 15 | Mule | |
| 7 | Sheep(young) | | 16 | Donkeys (young) | |
| 8 | Sheep(Adult) | | 17 | Donkeys(Adult) | |
| 9 | Goats(young) | | 18 | Others Specify | |

3. How much amount of income have you obtained from livestock production in last year? Indicate based on the following table.

| S.No. | Sales of Animals | | Income earned in birr/year |
|---|---|---|---|
| 1. | Sale of livestock | | |
| 2. | Sale of skins | | |
| 3. | Sale of Milk | | |
| 4. | Sale of Butter | | |
| 5. | Sale of Eggs | | |
| 6. | Sale of Manures | | |
| 7 | Others | | |
| **Total** | | | |

**Part X: Cost of Production and Income from Crop production (Meher Season)**

| Name of Crops | Area cultivated (Hectare) | Seed cost (in Birr) | | Chemical Fertilizer cost (in Birr) | Manure cost (in Birr) | | Oxen/horse cost[1] (in Birr) | Labor cost [2] (in Birr) | | Irrigation cost (in Birr) | Pesticide cost (in Birr) | Other costs (in Birr) | Total output in kg | Price/ kg | Consumed Output in kg |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Own | buy | | Own | buy | | Own | buy | | | | | | |
| *Teff* | | | | | | | | | | | | | | | |
| Barley | | | | | | | | | | | | | | | |
| Wheat | | | | | | | | | | | | | | | |
| Maize | | | | | | | | | | | | | | | |
| Finger millet | | | | | | | | | | | | | | | |
| Chickpeas | | | | | | | | | | | | | | | |
| Beans | | | | | | | | | | | | | | | |
| Gibto | | | | | | | | | | | | | | | |
| Oats | | | | | | | | | | | | | | | |
| Neug | | | | | | | | | | | | | | | |
| Rape seed | | | | | | | | | | | | | | | |
| Head Cabbage | | | | | | | | | | | | | | | |
| Ethiopian Cabbage | | | | | | | | | | | | | | | |
| Tomatoes | | | | | | | | | | | | | | | |
| Peppers | | | | | | | | | | | | | | | |
| Potato | | | | | | | | | | | | | | | |

| Name of Crops | Area cultivated (Hectare) | Seed cost (in Birr) | | Chemical Fertilizer cost (in Birr) | Manure cost (in Birr) | | Oxen/horse cost[1] (in Birr) | Labor cost [2] (in Birr) | | Irrigation cost (in Birr) | Pesticide cost (in Birr) | Other costs (in Birr) | Total output in kg | Price/ kg | Consumed Output in kg |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Own | buy | | own | buy | | Own | buy | | | | | | |
| Garlic | | | | | | | | | | | | | | | |
| Onion | | | | | | | | | | | | | | | |
| Sweet potatoes | | | | | | | | | | | | | | | |
| Avocados | | | | | | | | | | | | | | | |
| Bananas | | | | | | | | | | | | | | | |
| Lemons | | | | | | | | | | | | | | | |
| Oranges | | | | | | | | | | | | | | | |
| Mangoes | | | | | | | | | | | | | | | |
| Papayas | | | | | | | | | | | | | | | |
| Pineapples | | | | | | | | | | | | | | | |
| Chat | | | | | | | | | | | | | | | |
| Sugar Cane | | | | | | | | | | | | | | | |
| Coffee | | | | | | | | | | | | | | | |
| Hops | | | | | | | | | | | | | | | |
| Others | | | | | | | | | | | | | | | |
| | | | | | | | | | | | | | | | |

Note: [1]Oxen/horse cost=number of Oxen/horse used during production *Working Days*Estimated unit cost/day

[2] labor cost=the total amount of labor used in production (ploughing, weeding, trashing….)*working days*Estimated wage/day

## Part XI: Cost of Production and Income from Crop production (Belg[8] Season)

| Name of Crops[9] | Area cultivated (Hectare) | Seed cost (in Birr) | | Chemical Fertilizer cost (in Birr) | Manure cost (in Birr) | | Oxen/horse cost (in Birr) | Labor cost (in Birr) | | Irrigation cost (in Birr) | Pesticide cost (in Birr) | Other costs (in Birr) | Total output in kg | Price/ kg | Consumed Output in kg |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Own | buy | | Own | buy | | own | buy | | | | | | |
| | | | | | | | | | | | | | | | |
| | | | | | | | | | | | | | | | |
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[8] Belg Season refers to harvesting period from the months of March to August

[9] Households will be asked same types of crops listed at Meher season and those which were produced will be recorded

**Part XII: Household Consumption Expenditure**

Please state your household's food and non-food expenditures during the last Year.

| № | Types of Expenditure | Own Production | | Purchased | | Total Consumption (Birr) |
|---|---|---|---|---|---|---|
| | | Quantity in kg | Value (Birr) | Quantity in kg | Value (Birr) | |
| Food Expenditure | | | | | | |
| 1 | *Teff* | | | | | |
| 2 | Maize | | | | | |
| 3 | Wheat | | | | | |
| 4 | Barley | | | | | |
| 5 | Finger millet | | | | | |
| 6 | Chickpeas | | | | | |
| 7 | Beans | | | | | |
| 8 | Gibto | | | | | |
| 9 | Peppers | | | | | |
| 10 | Potato | | | | | |
| 11 | Sweet potato | | | | | |
| 12 | Onion | | | | | |
| 13 | Garlic | | | | | |
| 14 | Tomatoes | | | | | |
| 15 | Sugar cane | | | | | |
| 16 | Coffee | | | | | |
| 17 | Cooking Oil | | | | | |
| 18 | Salt | | | | | |
| 19 | Sugar | | | | | |
| 20 | Lentils | | | | | |
| 21 | Spices | | | | | |
| 22 | Honey | | | | | |

| № | Types of Expenditure | Own Production | | Purchased | | Total Consumption (Birr) |
|---|---|---|---|---|---|---|
| | | Quantity in kg | Value (Birr) | Quantity in kg | Value (Birr) | |
| 23 | Fruits (banana, Pineapples, mangoes, lemon…) | | | | | |
| 24 | Beef | | | | | |
| 25 | Sheep | | | | | |
| 26 | Goat | | | | | |
| 27 | Chicken | | | | | |
| 28 | Eggs | | | | | |
| 29 | Milk | | | | | |
| 30 | Butter | | | | | |
| 31 | Others(specify | | | | | |
| | | | | | | |
| | | | | | | |
| | **Non-food Expenditure** | | | | | |
| 1 | Clothing & footwear | | | | | |
| 2 | Medication | | | | | |
| 3 | Education expense (school fees, education materials such as books, pen, pencil & bag, dormitory rent ….) | | | | | |
| 5 | Social obligations (Edir, wedding, etc) | | | | | |
| 6 | Cleaning materials (soap, | | | | | |
| 7 | Household durables such as Mobile phone, radio, Furniture (bed, chair, table…), jewelry | | | | | |
| 8 | Transport | | | | | |
| 9 | Leisure (drinks, candies, lotteries etc.) | | | | | |
| 10 | Contribution to associations(women, youth , farmers and others) | | | | | |
| 11 | Energy consumption( Kerosene, match, etc) | | | | | |
| 12 | Other (specify), | | | | | |
| | | | | | | |

# Appendix 12 Interview Questions for Heads and Experts of Agricultural Offices

**Dear Heads/Experts,**

These Interview questions are prepared to gather relevant data on agricultural technology adoption at Awi Administrative Zone, Ethiopia. The expected information will be used to conduct a research for the partial fulfillment of Ph.D Degree in Economics at Delhi Technological University. Hence, I confirm you that all data will be used for academic purpose and analyzed anonymously through the authorization of the university.

Thank you for your cooperation in Advance

1. What are the main agricultural technologies adopted by farmers in your district?
2. How do you observe and rate the technology adoption behavior of farm households?
3. What kind of supports does your office provide in order to motivate farmers to adopt more technologies?
4. How frequently does your office provide extension services to farm households? What types of extension services are provided?
5. Where farmers purchase HYVs of seeds and fertilizers? Is the supply these inputs available for farmers adequately at the right time?
6. What types of credit arrangements are available for farmers in your district?
7. What are the major credit related problems in the community and how do you help in solving them, if any?
8. Do farmers apply adequate chemical fertilizer based on the standard stated by the region? If not, what are the major reasons for the farmers to apply below the standard? What are the possible consequences?
9. Does the government provide subsidy for the purchase of HYVs and fertilizers? If yes, how much is it?
10. Do you think that adoption of technologies reduce poverty? How? Reason out based on your observation from the real experience of farmers?

11. Are there agricultural cooperatives at the Kebeles? If yes, what are the major supports provided by these agricultural cooperatives?
12. Do you believe that agricultural technologies adopted by poor and rich farmers equally? If not, who is more benefited? Rich/poor farmers? Why?
13. Which are the main challenges that hampered farmers' adoption of agricultural technologies in your district?
14. What should be done by farmers, developmental agents, administrators, financial institutions and others to enhance agricultural production?

# LIST OF PUBLICATIONS

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