ADDIS ABABA UNIVERSITY
COLLEGE OF BUSINESS AND ECONOMICS
DEPARTMENT OF ECONOMICS

Effects of Locus of Control and Aspiration on Agricultural Technology Adoption: The Case of Jabi-Tehnan District, Northern Ethiopia

A thesis submitted to the College of Business and Economics of Addis Ababa University in partial fulfillment for the Degree of Master of Science in Economics (Natural Resource and Environmental Economics)

By: Asefa Belay

Advisor: Gebeyehu Manie (PhD)

June, 2021
Addis Ababa, Ethiopia

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This is to certify that the thesis prepared by **Asefa Belay** entitled: **Effects of Locus of Control and Aspiration on Agricultural Technology Adoption: The Case of Jabi-Tehnan District, Northern Ethiopia**, and submitted in partial fulfillment of the requirements for the Degree of Master of Science in Economics (Natural Resource and Environmental Economics) complies with the regulations of the University and meets the accepted standards concerning originality and quality.

Signed by the Examining Committee:

Eternal Examiner ______________________Signature ____________Date________________

Internal Examiner ____________________ Signature_____________Date________________

Advisor ___________________________Signature____________Date_________________

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Acronyms and Abbreviations

BA: Behavioural Attitude, attitude towards behaviour

BI: Behavioural Intension

BMPs: Best Management Practices

CAP-Africa: Combating Arthropod Pests for Better Health, Food and Resilience to Climate Change

CAPI: Computer-Assisted Personal Interviewing

CASCAPE: Capacity Scaling Up of Evidence Based Best Practice in Agricultural Production in Ethiopia.

CSA: Climate Smart Agriculture

DOI: Diffusion of Innovation Model

EUT: Expected Utility Theory

FAO: Food and Agricultural Organization

ICIPE: International Centre of Insect Physiology and Ecology

IPC: Internal Chance and Powerful Others Scale

LOC: Locus of Control

MDGs: Millennium Development Goals

NPC: National Planning Commission of Ethiopia

PBC: Perceived Behavioural Control

PPT: Push Pull Technology

PT: Prospect Theory

SDGs: Sustainable Development Goals

SLT: Social Learning Theory

SN: Subjective Norm

SSA: Sub-Saharan Africa

SSIAU: Social Sciences and Impact Assessment Unit

TAM: Technology Acceptance Model

TBA: Theory of Planned Behaviour

TRA: Theory of Reasoned Action

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Abstract

Agricultural productivity in sub-Saharan Africa (SSA) including Ethiopia remains low; and one primary reason is low adoption of agricultural technologies. The external reasons (e.g., credit constraints) why farmers do not adopt productivity-increasing technologies have been documented extensively. However, there are limited studies on the potential role of behavioral and psychological factors, which are factors internal to the decision makers, in influencing technology adoption decisions. In this study, we examine the effects of locus of control and aspiration of farming households on technology adoption decisions in Northwest Ethiopia. We use a household survey data collected from Jabi-Tehnan district of the Amhara Regional State, Ethiopia. The data is collected by the Social Sciences and Impact Assessment Unit of the International Centre of Insect Physiology and Ecology (icipe). We use binary logistic regression model to estimate the effect of locus of control and aspiration on adoption decision of agricultural technologies: fertilizers, irrigation, pesticides*, and push-pull technology. To estimate the intensity of adoption, we also use ordered logistic model. We find that households with higher internal locus of control and high aspiration levels have higher propensity to adopt agricultural technologies. In contrast, households with high external locus of control have low propensity to adopt agricultural technologies. In terms of intensity of adoption, households with high internal locus of control and high aspiration level are associated with adoption of higher number of agricultural technologies and more use of inputs per hectare. In contrast, households with high external locus of control are associated with adoption of lower number of technologies and less use of inputs per hectare. Besides, access to extension service, access to credit, land size and information (for new technologies) are found to be the main factors affecting adoption decision and intensity of adoption. The findings suggest that interventions that improve farmers' internal locus of control and aspiration for a better future may promote the adoption of agricultural technologies. Particularly, effectively utilizing the agricultural extension system for the purpose of enhancing farming households' psychological or non-cognitive skills and improving aspiration level may facilitate the promotion of agricultural technologies, as the extension system is a bridge between farmers and agricultural technologies.*

Key Words: Locus of control, Aspiration, Technology Adoption, Jabi-Tehnan, Ethiopia

CHAPTER ONE

INTRODUCTION

1.1. Background of the study

Agricultural productivity growth in sub-Sahara Africa (SSA) is considered as a critical strategy for the region's future overall development (Dawson et al., 2016; Otsuka and Larson 2016). However, agricultural productivity in SSA remains low (Bjornlund et al., 2020; AASR, 2018), and much of the growth occurred in the past is from an expansion of cultivated land (Arslan et al., 2020; Dawson et al., 2016; Evenson & Gollin, 2003). Lack of productive and appropriate agricultural technologies is one primary reason. Other factors (economic, social and institutional) also hinder adoption of agricultural technologies (Walker & Alwang, 2015; Wiggins, 2015; Asenso-Okyere & Jemaneh, 2012). Besides, agricultural productivity in SSA is highly constrained by climate change, ineffective policies, weak institutions, and pests and diseases (Arslan et al., 2020; AASR, 2018; Yalew et al., 2018).

For these reasons, substantial agricultural productivity differences exist across countries, particularly between developed and less developed countries (Gollin et al., 2014). In their data, Gollin et al. (2014) found the United States produce more than 100 times as much agricultural output per worker as the SSA countries including Ethiopia. After the start of the green revolution in 1960s, Kawagoe et al. (1985) found the productivity gap further widened, particularly labour productivity. While Lagakos and Waugh (2013) argue what explains these gaps is still an open question, Gollin et al. (2014) stated that the gap is not the result of mere poor quality of agricultural data in developing countries; and the difference in adoption of productivity enhancing inputs possibly explain the disparity.

In SSA, persistent poverty and widespread food insecurity (also a high population growth) are two serious concerns (Gassner et al., 2019). These issues were core in the past development plans and still the top issues in the current Sustainable Development Goals (SDGs) for they were partially achieved in the past (Arslan et al., 2020; MDGs, 2015). These challenges of SSA countries are similar with that of many of the Asian countries faced until the mid-1960s (Otsuka & Larson, 2013). However, in many of the Asian and Latin America countries, green revolution strategies transformed their rural economies and wiped out the fears of food insecurity and hunger (Otsuka & Muraoka, 2017; Dawson et al., 2016). The key to the success of the green revolution was effective adoption of agricultural technologies, mainly fertilizers and improved seeds (Walker & Alwang, 2015; Gollin et al., 2005). In contrast, despite significant efforts, green revolution in SSA has failed to achieve the same objectives (Pingali, 2012). Low adoption and lack of integration of package of technologies and improved management practices are potential reasons for the failure, among others (Otsuka & Muraoka, 2017; Evenson and Gollin 2003).

The promotion of productive agricultural technologies in SSA is therefore a key for boosting agricultural productivity (Arslan et al., 2020; Glover et al., 2016). Because the livelihood of the population (about 80% of extreme poor living in rural (FAO, 2019)) in this region largely depends on agriculture, and agricultural technologies can be an engine in poverty reduction, ensuring food security (Arslan et al., 2020; Chavas & Nauges, 2020; Gollin et al., 2005). Without adoption of agricultural technologies, there is no impact (Walker & Alwang, 2015).The expected outcomes from the technologies are premised on their adoption (Bukchin & Kerret, 2018). However, technology adoption in SSA still remains relatively low (Bukchin & Kerret, 2020a; Louhichi et al., 2019), being one primary reason for the differences and low agricultural productivity in the region (Bold et al., 2017; Foster & Rosenzweig, 2010).

Several micro and macro level adoption studies have been undertaken and provide a broad range of factors as reasons, ranging from socio-economic, institutional, individual characteristics, agro-ecological conditions to policy related issues. However, why low adoptions of agricultural technologies is still an empirical question (Abay et al., 2018; Bold et al., 2017; Mwangi & Kariuki, 2015; Suri, 2011). These studies provided various explanations for low technology adoption.

Recent studies hypothesized that psycho-behavioral aspects related to decision makers, which have less attention in past studies, are considered as potential factors in individuals' decisions and choices including technology adoption. Farmers are not passive recipients of technologies; thus, farmers' personal resources (positive emotion, character strength, hope, and self-control) affect their adoption decisions (Bukchin & Kerret, 2018; 2020a; 2020b). Besides, decision makers' hope (Goldin, 2015), aspiration (Bernard et al., 2014), and knowledge and trust (Eidt et al., 2012) has also considered as a critical factors in explaining adoption decisions. Like these and other psycho-behavioural factors, locus of control and aspiration of individuals could have a great role in explaining the low adoption rates and adoption decisions.

In Ethiopia, use of modern inputs remain limited despite overtime growth (Louhichi et al., 2019; and Shita et al., 2018). Traditional seeds and farming systems are still predominant (Louhichi et al., 2019; and Yalew et al., 2018). Abay et al. (2018) stated that in past studies, these problems are commonly attributed to supply-related constraints. Paradoxically, this is occurring while Ethiopia has been implementing several cereal intensification programs since 1960 that promote the adoption of modern technologies (particularly chemical fertilizer and improved seeds) (Bachewe et al., 2018). For this reason, beside to external constraints of farmers, locus of control and aspiration could explain such low rate of adoptions and they could play important role in the promotion and adoption of agricultural technologies.

Locus of control is a concept developed to measure the degree to which individuals believe that they have control over events that affect their lives (Rotter 1966; 1990). Locus of control could be important for understanding a wide range of economic decisions including adoption of technologies, and its significance on individuals' decision and behavior has been explored in multiple studies (Taffesse & Tadesse, 2017; Abay et al, 2017; Cobb-Clark, 2015). For instance, Abay et al. (2017) and Taffesse & Tadesse (2017) stated that locus of control and related psychological traits may serve as a complementary pathway to influence farmers' choices and adoption of technologies. On the other hand, aspiration is the desire to achieve something, indicating forward looking or future oriented goals (Ray, 2002; Bernard & Taffesse, 2014; Mekonnen & Gerber, 2016). Mekonnen & Gerber (2016) document that aspiration and agricultural innovations are strongly associated. Bukchin & Kerret (2018) also stated that curious people wish to explore innovations and seek new experiences and activities.

Considering the previous literature, this thesis investigates the effect of locus of control and aspiration on farming households' agricultural technology adoption decisions using data from Northwest Ethiopia. Understanding the implication of farmers' locus of control and aspiration remains important to design appropriate policy that could tackle low technology adoption problems. In Ethiopia, the agricultural extension system allocates huge effort in persuading farmers to adopt technologies, and thus enhancing farmers' psychological capital (non-cognitive skills) through this system may promote adoption and perhaps play part in mitigating external constraints that farmers are facing.

1.2 Statement of the problem

Adoption of technological innovations in agriculture has attracted considerable attention among development economists (Feder et al., 1985). Explaining and improving prediction of farmers' behaviour relating to technology adoptions is a major focus of research and important concern yet (Streletskaya et al., 2020; Dessart et al., 2019; Momani et al., 2017).

Despite the overtime increase in accessibility, use of agricultural technologies remains low in developing countries (Feyisa, 2020; Takahashi et al., 2019; Walker & Alwang, 2015); and the heavy reliance on traditional production methods made the level of productivity low (Mwangi & Kariuki, 2015). There is also heterogeneity among adopters in terms of choice and intensity of adoption (Fentie & Beyene, 2018; Bukchin & Kerret, 2018). Consequently, why individuals prefer some technologies to other technologies, why some accept certain technologies while others reject them, and why some technologies diffuse more quickly than others could be interesting policy-relevant questions.

However, despite extensive research works undertaken, why low adoption rates in SSA is still a question, and there exists little coherent understanding of technological change in the region (Abay et al., 2018; Bold et al., 2017; Glover et al., 2016).

In the empirical literature, heterogeneity in net return (Suri, 2011; Foster & Rosenzweig, 2010); missing markets, risk and uncertainty, lack of credit and knowledge(information), behavioral constraints, inappropriate polices, and low quality of inputs (Bold et al., 2017 and Janvry et al., 2016); and weak extension system (Takahashi et al., 2019) are mentioned as explanations for the low rate of adoption in SSA. Janvry et al. (2016, p. 3) argue that deficit in effective supply ("the joint occurrence of local availability of technologies and information about them") well explains the low rate of adoption in SSA. Methodological issues, particularly with the concept and measurements of adoption has also mentioned as one possible explanation for the existing little understanding of agricultural technology change in Africa (Glover et al., 2019; Glover et al., 2016; Foster & Rosenzweig, 2010). Nevertheless, many of them failed to converge towards a consistent explanation for why farmers choose to adopt technologies or not (Montes de Oca Munguia, Llewellyn, 2020). Past empirical studies also mainly focused on socio-economic and institutional factors. Key determinants of adoption decisions such as farmer's belief, attitude, perceptions and other psycho-behavioral aspects were not adequately explored (Olum et al., 2020; and Zeweld et al., 2018).

There are few studies that show the role of psycho-behavioural factors on technology adoption decisions (Dessart et al., 2019; Taffesse & Tadesse, 2017; and Abay et al., 2017). Bukchin & Kerret (2020b; 2018), Abay et al. (2017), Taffesse & Tadesse (2017), Mekonnen & Gerber (2016), and Mwangi & Kariuki (2015) state in common that still much remains unknown about adoption of agricultural technologies. They highlighted the importance of the incorporation of farmers' intrinsic and behavioral factors as determinants of technology adoption. Dessart et al. (2019), Bukchin & Kerret (2018) and Abay et al. (2016) in their review found that economic, social, and geographic barriers or commonly observable attributes and characteristics of farmers alone fail to provide a comprehensive explanation for adoption decisions and the heterogeneity in adoptions. Besides, Taffesse & Tadesse (2017) revealed that the existing literatures on "locus of control" and its predictive value in the case of developing countries (particularly their rural areas) is yet to be explored.

Furthermore, Mekonnen & Gerber (2016) stated the effect of aspiration on farmers' technology adoption remains still not uncovered. In adoption studies, existing few empirical studies on the effect of psycho-behavioural factors including locus of control and aspiration acknowledge the predicting potential of these factors in agricultural technologies adoption. For instance, Dessart et al. (2019) identified behavioural factors significantly influencing farmers' decisions to adopt specific sustainable practices. Bukchin & Kerret (2020b; and 2018) provide theoretical and empirical arguments for the correlation between personal resources (such as self-control skills and hope) and adoption decisions. They found the relative effect of farmers' hope on drip irrigation adoption to be greater than the effect of other previously studied factors. Janvry et al. (2016) also acknowledge the role of farmers' behaviour in adoption decisions.

From the discussions so far, three key points emerge. First, despite increments over time, agricultural technologies adoption in SSA is low and why it is still low particularly for those profitable technologies is a puzzle. Second, there exists inadequate empirical literature on the effects of psycho-behavioural attributes of the farmers like locus of control and aspiration on adoption decisions. Third, existing empirical studies point out the potential role of locus of control and aspiration. Thus, having the evidence of scantly available empirical literature on the effect of locus of control and aspiration on technology adoption on the one hand, and the predicting capacity of these factors to individuals' choices and decision making on the other hand, it is important to consider these two attributes alongside with the deemed external factors in technology adoption studies.

Thus, by focusing on two psycho-behavioural attributes of farmers (locus of control and aspiration) towards agricultural technologies adoption, this study will give additional insights to the scantly available empirical evidence, and substantiate the previous findings and will have a policy relevance particularly in the promotion of agricultural technologies.

1.3 Research Questions

The research questions that this study aims to address include:

i) Will farming households' locus of control accelerate or constrain the adoption of agricultural technologies?
ii) What is the effect of farming households' aspiration on their technology adoption?
iii) What are the main factors influencing agricultural technology adoptions in the study area?

1.4 Objective of the Study

1.4.1 General Objective

The overall objective of this study is to examine the effects of farming households' locus of control and aspiration on their technology adoption decisions.

1.4.2 Specific Objectives

The specific objectives of this study are:

i) To examine the effect of farming households' locus of control on their technology adoption decisions,
ii) To analyse the effect of farming households' aspiration on their technology adoption decisions, and
iii) To identify the major factors influencing farmers' agricultural technologies adoption.

1.5 Hypothesis of the Study

The hypotheses of this study are:

i) Individuals' internal locus of control have a positive effect in multiple decision outcomes (Taffesse & Tadesse, 2017; Abay et al. 2017; Cobb-Clark, 2015). Thus, we hypothesize that farming households' internal locus of control positively relates with their technology adoption decisions. In contrast, individuals' external locus of control has a negative effect on multiple decisions and respective outcomes. Thus, we hypothesize that farming households' external locus of control negatively correlates with their technology adoption decisions.

ii) Individuals aspiration for a better life outcomes have a positive effects on desired outcome (Bernard & Taffesse, 2014 and Mekonnen & Gerber, 2016). We hypothesize that farming households' aspiration positively associates with their technology adoption decisions.

1.6 Significance of the Study

The promotion and adoption of productive and efficient technologies is an important feature of the development process (Foster & Rosenzweig, 2010). Thus, a better understanding of constraints to technological adoption decision is an essential component of the promotion of agricultural technologies and increased agricultural productivity (Arslan et al., 2020 and Mwangi & Kariuki, 2015). In Ethiopia, like in other SSA countries, poverty eradication is the principal development agenda of the government (NPC, 2017). The government has integrated the United Nations development plans (MDGs, and SDGs) with its national development plans. The top two goals of the current SDGs are ending poverty and ending hunger, achieving food security and improved nutrition. To achieve these goal a particular attention is given to the strategy of transforming the agricultural sector and increasing the productivity of small-holder farmers by technological adoption (NPC, 2017).

Therefore, understanding farming households' intention to adopt agricultural technologies and factors influencing their decision-making is important for enacting more realistic agricultural policies and interventions aiming at improving the productivity of the farming households and the agricultural sector. The study highlights the possible ways of making interventions in promoting the adoption of agricultural technologies in the study area. More generally, it contributes to the scantly available empirical literatures on the effects of psycho-behavioural attributes of farming households on their agricultural technology adoption decisions. By examining the effect of locus of control and aspiration on farmer's adoption decisions and then providing explanation, the study highlights agricultural policy implication particularly in the effort to promote adoption of agricultural technologies.

1.7 Scope of the study

This study mainly focuses on the effects of two important psycho-behavioural attributes of farmers (locus of control and aspiration) on their adoption of agricultural technologies. Thus, concepts and measurements related with locus of control and aspiration and their effects on technology adoption, and theories and models related with agricultural technology adoption are discussed in this paper. However, other psycho-behavioural factors (such as perception of farmers about the technology, risk and uncertainty) deemed to affect agricultural technology adoptions are not covered. In terms of geographic coverage and data usage, this study is undertaken in the Jabi-Tehnan district of the Amhara National Regional State of Ethiopia and mainly rely on a cross-sectional data.

1.8 Organization of the study

The remaining parts of this thesis are as follow: Chapter two, reviews the theoretical and empirical literature, which consists the concept and measurement of technologies adoption, locus of control and aspiration, theories and models of technology adoption, and empirical studies of technology adoption. Chapter three describes the data source and type, study area, details of measurement tools, model specification and estimation techniques. The fourth chapter present the data and discussion of results. Chapter five, the final chapter consists a summary and policy implications of the study.

CHAPTER TWO

LITERATURE REVIEW

In this chapter, we review the theoretical and empirical literatures related with technology adoption, locus of control and aspiration.

2.1. Theoretical Literature Review

2.1.1. Concept and Measurements of Locus of Control

The concept of locus of control was first introduced in 1966, by Julian Rotter (Halpert & Hill, 2012). Rotter defined locus of control as a generalized attitude, belief, or expectance regarding the nature of the causal relationship between individuals' own behavior and its consequences (Rotter, 1966 and 1990). It measures the degree or extent to which individuals perceive their behaviour and its outcome is contingent on their own behavior and or is determined by external forces (Rotter, 1990; and Levenson, 1981).

Over time, many similar concepts have developed to explain the influences or controls that individuals and events have or the interactions and the causal associations among them. There was a proliferation of terms related with or to express to what Rotter introduced as locus of control (LOC) and more than 100 definitions of LOC exist in the literature (Nowicki & Duke, 2016). For instance, self-esteem, self-efficacy, perceived behavioral control, self-control and motivation are among the terms alternatively used. Therefore, it is important to note that there exists a meaning difference among these concepts. Nowicki & Duke (2016), Rotter (1990), and Palenzuela (1984) noted that there exist problems in applying the concept LOC as suggested by Rotter's 1996 and 1990 publications.

Apart from its conceptual meaning, measurements to elicit LOC have also developed. To measure LOC, an internal – external (I-E) scale was developed by Rotter (1966). Later, this scale was further developed by Levenson (1973), in which case, LOC comprises three dimensional measures namely internal scale, chance scale and powerful others scale, and is elicited using a Likert Scale. Levenson (1973) used an example dataset to validate and justify the split of the scale in to three-dimensional scale. However, many ways of measuring LOC have developed over time, for instance, twenty-eight measures of LOC are described by Halpert & Hill (2012).

To use LOC and possibly other related concepts in applied works, Rotter (1990) proposed some requirements accounting for the practical value of the concepts. These include a precise definition of the concept (particularly subjective variables), an impediment of the concept in a broad theory, measurement principles of the concept derived from its foundation theory. In this regard, for instance, Cobb-clark (2015) applied these suggestions in his study of LOC and labor market. He first discussed the conceptual origin of LOC, and then its relationship with related concepts, such as self-control and motivation.

In this study, we apply the two measurement scales: Rotter (1966) I-E scale and Levenson (1973) three scale. The Rotter's scale is constructed by letting the individuals choose between two subjective statements (forced choice format) and then grouping them as having internal LOC or external LOC (a binary measure).The Levenson's three scales are expressed as a discrete and limited variables, elicited using fifteen questions (five for each of the three dimensions) with Likert six-point scale responses.

2.1.2. The Concept and Measurements of Aspiration

Aspiration is defined by Debraj Ray as "the social grounding of individual desires" and considered as a multidimensional concept for the reason that peoples aspire to different things: for a better standard of living, dignity, good health, recognition, and political power, among others (Ray, 2002, p. 1-2). Bernard & Taffesse (2014; 2012) have made a detailed exploration on the definition of aspiration and issues of its measurement. Finally, they designed and provided a measurement instrument for aspiration. They have also tested the usability, reliability and validity of the measurement instruments using data from Ethiopia.

After undertaking review on the definitions and ways of understanding aspirations, Bernard & Taffesse (2014) defined aspiration as "*something that signifies some aim or target and a desire or wish to attain that goal. The meaning also suggests, rather implicitly, that some effort would be exerted to realize the desired aim/target. Moreover, an aspiration may or may not reflect the feasibility of the corresponding target. In short, aspirations combine or summarize the preferences maintained, the beliefs held, and possibly the constraints acknowledged by an individual about aspects of the future*" (Bernard & Taffesse, 2012, p. 3; and 2014, p. 198).

Based on this definition, Bernard & Taffesse (2014) made three distinctive features about aspirations. First, aspirations are future oriented; second, aspirations are motivators; and third, aspirations are an ambition to reach a multi-dimensional life outcomes.

Since aspiration is not directly observed, Bernard & Taffesse (2012; and 2014) devised two alternatives of measuring it. The first measure is by integrating the assumptions about the set of aspiration determinants or the pattern of choice made by the individual. The second measure is by directly asking individuals about their aspiration level using designed questions for this particular purpose and then constructing an aspiration index. Bernard & Taffesse (2014) stated that both methods need to be considered carefully in using them for they have some difficulties, however, relatively the second method is easier and provides a good measurement if implemented carefully (see details in Bernard & Taffesse, 2014; 2012). In this thesis, we use the second approach.

2.1.3. Definitions and Measurements of Technology Adoption

Technology adoption is not new in the literature; however, it is worthy to go through the definitions and the measurements given that there is still confusion on its meaning and nature. In this regard, technology and technologies adoption are defined by different scholars differently.

Perhaps, the first definition of technology adoption is by Roggers (1962) who defined it as "a mental process an individual passes from first hearing about an innovation to final adoption" as quoted by (Feder et al., 1985, p. 256). According to Roggers, a technology or innovation is defined as "an idea, practice, or object that is perceived by individuals as new or other units of adoption ", and diffusion as "the process in which innovation is communicated through certain channels over time among members of social system" (Rogers, 1983, p. 11, p.5). Roggers used the words "technology" and "innovation" as synonyms and defined technology as "the design for instrumental action that reduces the uncertainty in the cause-effect relationship involved in achieving a desired outcome" (Rogers, 1983, p. 13). Moreover, the term technology is defined in a book by Enos & Park (1988, p. 9) as the general knowledge or information that help some tasks to be accomplished, some service rendered, or some products manufactured.

Alternatively, technology is defined as "the means and methods of producing goods and services, including methods of organization as well as physical technique" and agricultural technology as "means and methods of producing crops and livestock" (Loevinsohn et al., 2013, p. 2-3).

Following this, Loevinsohn et al. (2013, p. 3) defined adoption as “the integration of a new technology in to existing practice; usually proceeded by a period of ‘trying’ and some degree of adaptation”. Thus, adoption refers both to rate and intensity or extent (Bonabana-Wabbi, 2002, p. 24).
However, commonly in a broader sense, technology or innovation can refer to “any new idea or means” to the population, including both that are abstract and concrete (Bonabana-Wabbi, 2002, p. 23 and Straub, 2009, p. 626). It is also important to note that adoption and diffusion are different concepts. Straub (2009) stated adoption as choices an individual made to accept or reject a particular innovation and diffusion as how an innovation spreads over time. Thus, adoption is a micro perspective while diffusion is a macro one (Straub, 2009).

In a review studies, Janvry et al. (2016), Sunding & Zilberma (2001), Feder & Umali (1993), and Feder et al. (1985) emphasized the need for a precise quantitative definition of adoption in theoretical and empirical analysis. They suggest that the definition must make distinction between individual (farm-level) adoption and aggregate level adoption (regional or national).

In the literature, the most widely used indicators of adoption is discrete variable: a dummy variable that measure whether individuals (farmers) are actually adopting and using (adopters) or not (non-adopters) a technology under consideration. However, this measure of adoption is criticized by many scholars, for instance, Glover et al. (2019) and Glover et al. (2016) stated the conception of adoption in empirical studies is flawed as it is too binary and linear: being a possible reason for little understanding of technological change in Africa as this approach curtails the important aspects of technological change. Sumberg (2016) also states at least three criticism for binary measure of adoption: it does not reflect the realities of technological change; it ignores how a particular technology is used such as the rate, timing and method of input application; and calls into question the robustness of the treatment group classification and runs the risk of systematically overestimating the importance of adoption, while underestimating the impacts of the new technology.

An alternative adoption indicator is a continuous measure, explaining the degree or extent of adoption that is to what extent a divisible technology is used (taking from zero to some positive values) (Sunding & Zilberma, 2001). In this thesis, we use three alternative measures of adoption:

a binary measure, a continuous measure, and a limited discrete measure such as the number of technologies adopted by farmers.

2.1.4. Theories and Models of Technology Adoption

Even though there are many theories and models that explain adoption of technologies, some of the most widely used are theory of reasoned action, theory of planned behavior, innovation diffusion theory, technology acceptance model, and social cognitive theory (Vaz et al., 2020; Lalani et al., 2016). In economics, expected utility theory and prospect theory are widely used in choice and decision making involving risk and uncertainty (Harrison & Rutström, 2009).

To begin with, expected utility theory (EUT) is a theory first proposed by Bernoulli (1954) which estimates the likely utility of actions or events with risk and uncertainty (Starmer, 2000 and Sebora & Cornwall, 1995). In studies of agricultural economics including innovations adoption, risks and uncertainties are central features because they are intrinsic to agricultural production and they play a key role in farmer's decision making (Bocqueho et al., 2014). EUT states that the decision maker chooses between risky or uncertain prospects by comparing their expected utility (Mongin, 1997) and has been a major theory in decision making analysis (Schoemaker, 1982). In this theory, farmers are assumed to be rational decision makers (expected utility maximizers). This theory has three fundamental assumptions: consistency of preferences for alternatives; linearity in assigning of decision weights to alternatives; and judgment in reference to a fixed asset position (Sebora & Cornwall, 1995).

Although there are many extensions or new versions of EUT including Von Neumann-Morgenstern utility theory, the basic formula eliciting EUT is given as follow. Let $P = (X_1, P_1; X_2, P_2 \ldots;\ X_n, P_n)$ be any finite prospect, where a prospect is "a list of consequences (outcomes of a choice) with associated probabilities" (Starmer, 2000), then preferences over finite prospects are represented as:

$$\text{EUP} = \sum_{i=1}^{n} P_i U(X_i) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

Where, P_1 is probability of occurrence of outcome X_i.

However, despite having some advantages, this theory is criticized for many reasons. For instance, Bocqueho et al. (2014), Starmer (2000), and Sebora & Cornwall (1995) noted that there exists substantial evidence that individuals do not necessarily behave according to the key assumptions underlying EUT. They also document that empirical testing of EUT against alternative theories for decision-making under risk has provided evidence in favor of the alternative theories.

Due to these criticisms of EUT, Kahneman & Tversky (1979) proposed the prospect theory (PT) as alternative theory of choice under risk. This theory distinguishes two phases in the choice making process: an early phase of editing, which includes a preliminary analysis of the offered prospects and yielding a simpler representation of these outcomes and evaluation phase, in which the edited prospects (outcomes) are evaluated and the prospect (outcome) of highest value is chosen (Kahneman & Tversky, 1979). The basic equation of the theory is given by Kahneman & Tversky (1979) as follow.

If (x, p; y, q) is a regular prospect, a combination of outcome x with probability p and outcome y with probability q, then the over value of a prospect, V is given as:

$$V(x,p;\ y,q) = \pi(p)v(x) + \pi(q)v(y) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (2)$$

Where, π is a subjective weight to probabilities, so π(p) and π(q) are decision weights, which reflects the impact of p on the over-all value of the prospect. On the other hand, v is assigned to all outcomes, v(x) and v(y) reflect the subjective value of that outcomes. In PT, outcomes are defined relative to a reference point, which serves as the zero point of the value scale. Hence, v measures the value of deviations from that reference point, i.e., gains and losses (Kahneman & Tversky, 1979). Equation (1) generalizes expected utility theory by relaxing the expectation principle (Kahneman & Tversky, 1979).

Both EUT and PT are used for analyzing decisions under risk and uncertainty. However, there exists a strict difference between them. EUT does not distinguish between gains and losses; assumes preferences as consistent; and outcomes have objective probabilities, while in PT outcomes are classified as either gains or losses with respect to a reference point and there is weighting of probabilities or outcomes have subjective probabilities. PT features two key factors in explaining EU anomalies, namely reference dependence and probability weighting. Probability weighting refers to people's tendency to distort objective probabilities, which is accounted for in PT through a nonlinear valuation of outcomes with respect to objective probabilities. Assuming PT instead of EU potentially leads to a very different understanding of farmers' decisions, and fits the agricultural context particularly well as farmers are likely to have reference points for outcome valuation and there is a growing body of empirical evidence that farmers rely on subjective probabilities rather than objective probabilities (Bocqueho et al., 2014).

Another dominant theory of behaviour is theory of reasoned action (TRA), introduced by Martine Fishbein in the 1960s, and further developed by Fishbein and Ajzen in 1975 (Madden et al., 1992). It predicts how individuals behave and explains the relationship between attitude and behaviour. This theory has two main constructs or variables, namely attitude towards the behavior and subjective norm, where a construct *is defined as "a latent variable that can be defined in conceptual terms but cannot be directly measured or measured without error"* (Sok et al., 2020, p. 6)). Attitude is an individual's positive or negative feelings about performing a certain behavior while subjective norm is individuals' perception of the social pressure (mostly from peoples who are important to individuals) of performing (or not performing) the behavior in consideration (Fishbein & Ajzen, 1975).

TRA is not a specific model rather a general model designed to explain almost any human behavior (Momani et al., 2017 and Sarver, 1983). It asserts that individual's propensity to perform certain behavior is determined directly by the individual's behavioral intention (BI) while BI (an intention to behave in certain way), in turn, is determined by individuals' attitude towards that behavior (BA) and subjective norms (SN). According to this theory, external factors (factors not included in the model) such as demographic characteristics, personality characteristics of the individual, nature of the behavior under consideration not directly rather indirectly affect behavioral intension and then actual performance of behavior.

The other related theory is theory of planned behavior (TPB), an extension of TRA by Icek Ajzen in 1985 (Ajzen, 1991). The two theories explain individuals' behavior in the same manner except that TPB in its framework added the perceived behavioral control (PBC) as an additional characteristics (Sok et al., 2020 ;Patel & Connolly, 2007). PBC is a measure of individuals' control that they perceive they have about performing the behavior under consideration. It is influenced by the availability of resources, opportunities and skills (Taherdoost, 2018). In the case of TPB, BI is determined by three variables namely: BA, SN, and PBC, while in the case of TRA, BI is determined by just two variables: BA and SN. The addition of PBC to the model of TPB was designed to account for situations where performance of a behaviour is not entirely under the individuals' volitional control (Ajzen, 1991).

According to the TPB, no other predictors should have a direct effect on intentions. To the extent that other factors (background factors) are found to influence behaviour, according to TPB, they do it indirectly by their effects on behavioural, normative and/or control beliefs. This is known as the sufficiency assumption (Sok et al., 2020). However, TPB in principle is open to the addition of other predictors if they can be shown to influence intentions in a consistent and substantial way across a variety of behaviour (Sok et al., 2020; and Ajzen, 1991). Additional predictors including demographic characteristics, individuals' or the social group properties (such as gender, age, education, personality traits, values, risk-taking propensity, intelligence, sensation seeking, religion, culture), and other related attributes are expected to influence intentions and behaviour only indirectly by their effects on predictors of behavioural intension or by moderating the relations among the theory's constructs (Ajzen, 2011).

The two theories, TRA and TPB can be simplified as fellow:

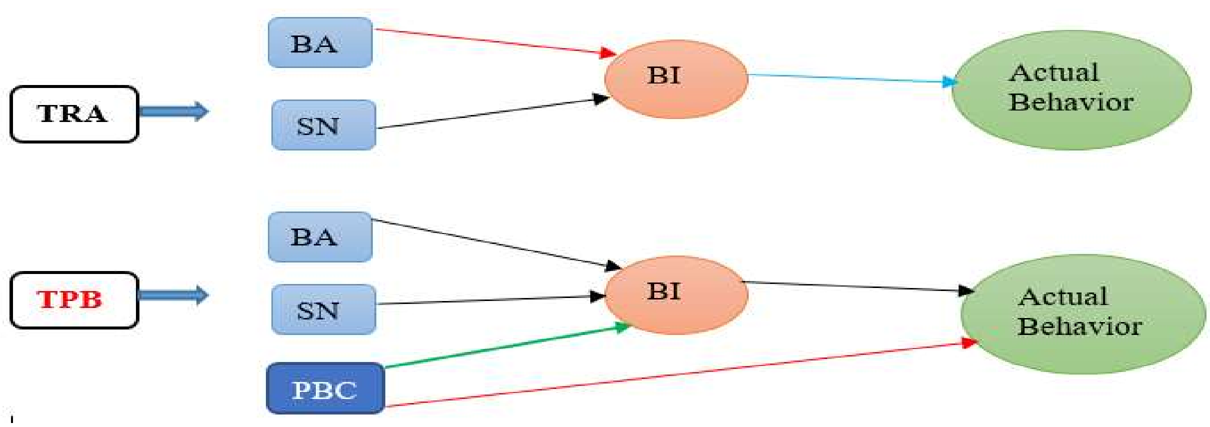

Figure 1: Conceptual frameworks of TRA and TPB

Source: Madden et al. (1992)

Figure 1 shows the major difference between TRA and TPB. PBC is included in TPB as an exogenous factor that has a direct and indirect effect on behaviour. More generally, according to the two theories, the more favorable BA and SN towards a behavior, and the higher the PBC an individual have, the stronger will be an individual's intension to actually perform certain behavior under consideration (Ajzen, 1991).

Technology acceptance model(TAM), first developed by Davis (1986) is another known adoption model. Davis proposed this model taking TRA as a his reference paradigm (Davis, 1986). According to this theory, the key determinant of technology adoption (particularly information technologies) are usefulness and ease of use. The higher the perceived usefulness and ease of use of the innovation, the larger will be the degree of its acceptance.

In a simplified way, TAM is depicted below.

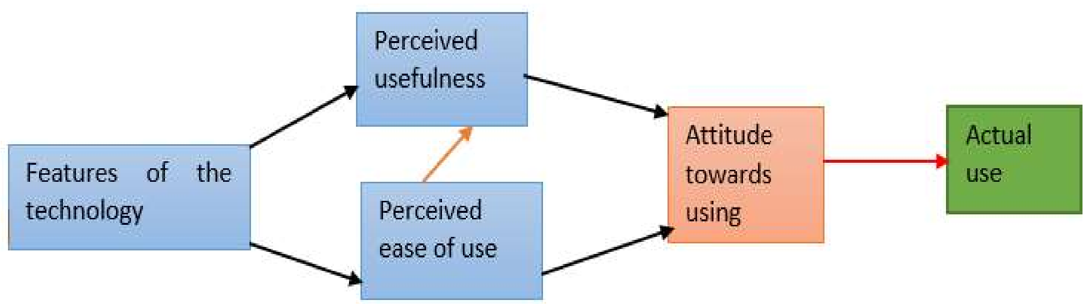

Figure 2: TAM of Davis (1986, p. 24)

Thus, the attitude towards using (like behavioural intentions in TRA and TPB) is the immediate determinant of actual use of technology. Attitude toward using, in turn, is a function of two major beliefs: perceived usefulness and perceived ease of use, while perceived ease of use has a causal effect on perceived usefulness. In TAM, the attitude towards behaviour, BA in TRA and TPB is replaced by two acceptance measures called perceived usefulness and perceived ease of use while the subjective norm, SN construct is excluded.

Last but not least, Diffusion of innovation theory (DOI) is a theory initially proposed by Roggers in 1962 is also dominant theory of innovation adoption (Rogers, 1983). This theory is formulated from diffusion studies focusing on individual differences in innovativeness (Momani, et al., 2017). It tries to predict over time, why and how any kind of innovation gets spread. Roggers' diffusion theory proposes five attributes that explain for why some innovations spread while others fail (Rogers, 1995; 1983). These are relative advantage, compatibility with existing values and practices, simplicity and ease of use (complexity), trialability and observability of results. According to this theory, the more favorable measures of these five attributes of an innovation, the greater will be the rate of adoption of the innovation under consideration. More generally, DOI seeks to explain adoption behaviour against personal characteristics and endowments (Rogers, 1995).

The theories and adoption models discussed above are not the only theories/models that are used in adoption studies. There are many other theories including social cognitive theory which is discussed in the next section (For detail reviews, see Momani et al., 2017; Taherdoost, 2018; and Patel & Connolly, 2007).

Overall, despite having their own limitations, these theories using their constructs or variables could explain individuals' behavior and their degree of acceptance to new technologies. Importantly, most of these theories focused on psychological and behavioral characteristics of individuals or user of technology under consideration (Momani, et al., 2017).

Regarding the approaches followed by researchers studying farmers' decisions of technology adoptions, Vaz et al. (2020) mentioned at least two common approaches. The first approach is to use the standard economic perspective (considering farmers as profit maximizers') and the second approach to use socio-psychological theories such as TRA and TPB. TRA and TPB has been applied for understanding farmers' behaviour in adoption of certain technologies. For instance, Vaz et al. (2020), Daxini et al. (2019), Bagheri et al. (2019) applied the TPB for understanding farmers' intension to adopt on-farm silos, to follow a nutrient management plan, and to adopt integrated crop management practices, respectively. On the other hand, Lada et al. (2009) and Rehman et al. (2007) applied TRA for understanding the intention to use halal products and the uptake of new technologies on dairy farms, respectively. In these studies, the adoption decision was taken or assumed as a human behavior or action.
In empirical applications, there are specific procedures (guidelines) to be followed in each theory. For instance, in a critical review on the application of TPB to farmer behaviour, Sok et al. (2020) stated that the guidelines on how to apply TPB are widely ignored, resulting in serious conceptual

and methodological problems. For a good practice in applying the TPB, Sok et al. (2020) recommend to follow and fulfil the guidelines of the theory. The guidelines include fulfilling the principle of compatibility and assumption of sufficiency, pilot study and identification of influential beliefs and additional predictors of intention (background factors), and analyzing the relative impact of TPB constructs on intention. Furthermore, Rehman (2007) mentioned at least four procedures in applying TRA. These are identification of behaviors to be examined (e.g. technology adoption in this case), identification of main outcome beliefs and referent groups with respect to the behavior under consideration, development of structured interview schedule or questionnaires depending on the theory being applied (Silva et al., 2020), and finally analysis of attitudinal and normative data.

However, as Montes de Oca Munguia et al. (2021) and Straub (2009) document there is no single model for understanding the adoption process. For instance, Straub (2009) stated that no single theory accounts for all the three predictors of behavioral change (which he stated as contextual, cognitive and affective factors) in adoption theories. Furthermore, Momani et al. (2017) stated that there is no single theory that considers all behavioral factors for there is complexity of behavior research.

Therefore, in studying the behavior of farmers in adopting technologies, an independent reliance on a single theory may not be necessary and mandatory. For instance, if we want to employ the TRA alone for investigating farmers' behavior in adopting agricultural technologies, our analysis may lack important factors to be considered such as PBC. Momani et al. (2017) stated that the theory does not refer for key factors such as fear (risk and uncertainty), mood, threat and previous experience that possibly affect behavioral intention (to adopt a technology or not). In line to this, Dessart et al. (2019) mentioned that their study was not built on a specific theoretical framework (such as the TPB or PT) to map behavioural factors influencing farmer decision-making for the reason that lack of a unified theory would inevitably restrict the range of factors considered.

Related to the above arguments, it could be for this reason that some theories have developed by extracting the main variables and features from the previous theories and then making decompositions or combinations to form new theories and models. To give examples, as Momani et al. (2017) stated, the TAM and TPB were combined and formed Combined TAM and TPB by

Taylor and Todd in 1955. Furthermore, in an applied work, Ambrosius et al. (2015) used four theories to conceptualize farmers decision making and then developed a theoretical framework to model farmers' strategic decision making.

From the review, TPB seems a good approach for predicting human behaviour as it allows an addition of variables into the main conceptual framework of the theory. However, it has complexity and requires a lot of procedures, particularly, in examining the effect of additional variables (background factors) on a behaviour. Perhaps, for this reason, Burton (2004) stated that many empirical studies mention the use of the TPB, not because they actually relied on it to design and guide their research, but merely to justify their approach.

Therefore, given the non-independency of these theories (Momani et al., 2017), the procedures required in applying each theory, and the nature of this study in to account, no single theory is directly applied in this study. Montes de Oca Munguia et al. (2021), however, stated that the existence of the variety of models is a strength rather than a weakness. Because, each model has been built to answer different questions, analyzing adoption in specific settings or at different scales, using different assumptions, data, and methods (Montes de Oca Munguia et al., 2021). In this thesis, we consider the theoretical propositions given by some of these theories (such as statements on how different factors affect adoption decision) in formulating the conceptual and theoretical framework linking technology adoption decision and its determinants including LOC and aspiration.

2.1.5. The Theoretical Foundation on the Linkage between Locus of Control and Technology Adoption

Feder et al. (1985) on their review study criticize that much of the technology adoption studies they reviewed lack theoretical foundations from which a structural relationship can be specified. Further, Rotter (1990) noted that although the majority of studies with LOC have dealt with applied problems, it is important to recognize that the concept originated from both theoretical and empirical concerns. Thus, we provide an explanation for the theoretical foundations on the linkages between LOC and aspiration with technology adoption.

The concept LOC emerged from Rotter's theory of social learning (Cobb-Clark, 2015). Thus, clearly, social learning theory is the foundation for the concept or the broad theory up on which

LOC rely. The social learning theory (SLT) is a model for predicting behavior like the previous discussed theories. Social learning theory argues personality which is internal to the individual is not independent of the environment. It states that behavior cannot be considered merely as an automatic response to an objective set of environmental stimuli. Thus, according to this theory, in understanding behavior we must take into account both the individuals with their life history of learning and experience and the environment that is those stimuli that the individuals are aware of and responding to (Rotter, 1954).

Basically, Rotter's theory of social learning, for predicting behavior has four main components. Namely, behavior potential, expectancy, reinforcement value and psychological situation (Rotter,1954)). His predictive formula is set as below.

$$BP = f(E \text{ and } RV)$$

Where**,** BP is behavior potential, which is the likelihood or probability of engaging in a particular behavior; E is expectancy which is the subjective probability that given behavior will result in certain reinforcement (i.e., punishment or reward); and RV is reinforcement value which is the subjective value to an outcome of a given behavior. The fourth component of the formula not explicitly incorporated above is psychological situation, which is a measure of the subjective interpretation of the environment. Although having different frameworks, SLT explains behaviour in slightly same manner TRA and TPB do. Because BP in SLT is the same with BI in TRA and TPB; RV in SLT is similar (but not identical) with BA in TRA and TPB; and psychological situation in SLT somehow relates with SN in TRA and TPB.

In general, the formula implies that the probability of engaging in a certain behavior is a function of the subjective probability that the given behavior will result in an outcome and the subjective value of that outcome. In his theory, Rotter emphasized that behavior is not only influenced by the reinforcement but also by the individual's perception about the relationship between behavior and the reinforcement. This is what Rotter called locus of control. Accordingly, if individuals believe that their skills and efforts will determine outcomes, then they will have a probability of participating in selection of and performing certain actions and behaviors that will determine the outcomes. Thus, LOC is a measure of degree of control peoples' have over the events related to their life. The important thing about LOC is that it can be used to predict peoples' behavior across situations as it is a generalized expectancy (Rotter, 1990).

After recognizing the difficulty of identifying the channels through which LOC affects technology adoption, Abay et al. (2017) provided three theoretical possible mechanisms through which it could affect technology adoption. The first mechanism is that LOC affects the saving behavior of individuals, and this in turn affects individual's agricultural investment. The second way is that there is an interaction between cognitive and non-cognitive abilities (such LOC) of individuals. Hence, LOC may influence individuals' decision making including agricultural investment by shaping the interaction between cognitive and non-cognitive skills of peoples. In this way, internal LOC may compensate the constraints of factors like poverty on cognitive skills and quality of decision making. The third way is through its implication on aspiration formation, that peoples with internal LOC will aspire for better outcomes, thus LOC might improve farmer's agricultural investment decisions. Contrary, aspiration failure is associated with under investments. Thus, it is deemed LOC relates with technology adoption decision even in an unobservable way.

2.1.6. The Theoretical Foundation on the Linkage between Aspiration and Technology Adoption

Regarding the theoretical foundation on the link between aspiration and technology adoption, Mekonnen & Gerber (2016) made the pioneering work. They connected aspiration and technology adoption based on the theoretical model of Dalton et al. (2016), a model for the effects of aspiration on economic outcomes such as poverty. The model by Dalton et al. (2016) has three key premises. The first is that aspiration level is a reference point and affects the utility from realized outcomes. This implies that utility is a function of aspiration. The second premise states that aspiration level and effort level are jointly determined in equilibrium or aspiration level is a function of effort level. The third is that though aspiration and effort are jointly determined, the model assumed individuals take aspiration as given to determine the optimal effort level. Taking only the first two key premises, Mekonnen & Gerber (2016) expressed agricultural innovation as a proxy for effort. The reason is innovations are efforts exerted to achieve a certain outcomes (Mekonnen & Gerber, 2016).

However, like that of LOC, the mechanisms through which aspiration affects technology adoption may be multiple: directly and indirectly through its determinants such as LOC, self-esteem, trust in others, and subjective well beings (Mekonnen & Gerber, 2016).

2.2. Empirical Literature Review

In this section, we review empirical studies related with LOC, aspiration, and technologies adoption.

2.2.1. Studies on Agricultural Technology Adoption

Albeit in different ways, in terms of methodology, scope, content, study area, factors considered, and intensity of analysis, the available empirical literature on factors affecting the adoption of technologies is many. Arslan et al. (2020) made a meta-analysis by bringing 168 selected studies of adoption of improved agricultural technologies in Africa. They found that socio-demographic factors and resource endowment (related to income and wealth) factors to be the most frequently studied factors. They document that in the literature eleven factors in common are found to increase adoption in general, across studies and themes. These are factors related to wealth (land size, livestock assets, off-farm income, overall income, and wealth index); factors relate to policy tools (access to extension, access to information, farmer group participation, and access to credit); and finally, exposure to high temperatures and secure land tenure.

A study by Abegunde et al. (2020) on adoption of climate smart agricultural(CSA) practices in South Africa found that farm-income, educational status, farming experience, size of farmland, agricultural production activity, contact with agricultural extension, exposure to media, membership of an agricultural association or group and the perception of the impact of climate change positively and significantly correlated with CSA adoption. These findings are supported by findings of Milkias & Abdulahi (2018), a study on determinants of adoption improved maize variety in Toko Kutaye, a district in Ethiopia. In contrast, off-farm income and distance of farm to homestead were negatively and significantly related with the CSA level of adoption in South Africa (Abegunde et al., 2020).

Another empirical study on technology adoptions made by Ousmane & Nafiou (2019) in Nigeria show that agricultural technology adoption decisions by farming households were determined by the age and education level of the farm household head, the size of the farm household, the membership of agricultural cooperative, the number of plots owned, the level of farm household income and wealth, the plot size, the types of soil on the plot, the plots location (located on the valley and gentle slope), and the land tenure status. Relatedly, they mentioned that the effect depends on the type of technology being considered.

Liu et al. (2018) made extensive review of studies with the aim of identifying factors influencing farmers' adoption of best management practices (BMPs) in developed and developing countries. They noted that most studies of BMPs are made at micro level and macro level studies are limited. They acknowledge the progress of recent studies for dealing with factors which have not been examined before, such as the influence of social norms and peer pressure, information and awareness, geographic regions, policies, markets and business, uncertainty and risks, and farmers' time preference.

From their review, Liu et al. (2018) found that characteristics of BMPs(observability, location, ease of use, time requirement, cost-effectiveness, flexibility of conservation standards, relative advantage conferred to the farm), individual characteristics of farmers(such as age, experience, education, risk preference) play important roles in the adoption decision making process. However, findings of effect of farmers' age, experience, education, and gender on adoption decision are mixed. In addition, they noted that although uncertainty and risk are important in agricultural producers' decision-making, they are rarely investigated in the literature because of the complexities of estimation. Finally, they emphasized the importance of information and enhancing trust of farmers to use the various information sources in conservation adoption as they found that different types of farmers are motivated by different strategies at different stages of adoption.

Bold et al. (2017) investigated whether a low quality of inputs explains the existing low adoption of agricultural technologies in Uganda. In local markets of Uganda, Bold et al. (2017) found that 30% of nutrients missed in fertilizer and estimated hybrid maize to contain less than 50% authentic seeds. They confirmed that the use of such low-quality inputs resulted in low average returns (close to zero). They argue, this in turn, explains the low up takes of agricultural technologies by smallholder farmers as the technologies available in local markets are simply of too low quality and to be profitable. Moreover, they found the large heterogeneity in quality of agricultural inputs not correlated with price. In contrast, they estimated that if authentic technologies replaced these low-quality products, then average returns for smallholder farmers would be over 80%. Finally, Bold et al. (2017) document low quality of agricultural technologies in deed explains the low adoption of agricultural inputs by smallholder farmers.

Kassie et al. (2015) examined the adoption decision of a portfolio of sustainable intensification practices by small holder farmers in eastern and southern Africa using a multivariate probit model. They found social capital and networks, quality of extension services, reliance on government support during crop failure, incidence of pests and diseases, resource constraints, tenure security, education, and market access as the major factors influencing adoption of sustainable intensification practices in Ethiopia, Kenya, Malawi, and Tanzania. They document the existence of complementarity between some practices implying the adoption of one practice can possibly increase the probability of adopting another agricultural sustainable practice. This is supported by the findings of Abay et al. (2018) and Teklewold et al. (2013). They also stated that social and economic factors (profitability and risk implications), changes in inputs and output prices, and weather variability influence adoption decisions.

Mwangi & Kariuki (2015) made extensive analysis on studies of factors affecting adoption of new agricultural technology by smallholder farmers in developing countries. They stated perception of farmers towards a new technology as a key precondition for adoption to actually happen. The other principal determinant factors mentioned are: technological factors(trialability, suitability and appropriateness); economic factors(farm size, net gain to adoption, high cost and unavailability of seeds, income, wealth(off farm income); institutional factors(social group membership, social network, learning externalities, acquisition of information, access to extension, access to credit); and household specific factors(education, age, gender, household size). Finally, they stated that the determinant factors do not always have the same effect on adoption, rather the effect varies depending on the type of technology being considered/introduced.

Foster & Rosenzweig (2010) made a review of micro studies on adoption of agricultural technologies. In doing their review, Foster & Rosenzweig (2010) mentioned the difference in adoption and use of technologies account for the major differences in per capita GDP across countries, and on the other hand, they document return to technology, wealth, education, learning(more related to information on the technology), and risk(due to incomplete insurance and credit constraints) as major determinants of agricultural technologies adoption. Finally, they mention the existence of inconsistent finding across studies on the effect of these variables on adoption decisions. This study is also supported by a review study, Feyisa (2020) that there is heterogeneity in findings of studies in the case of Ethiopia.

Foster & Rosenzweig (2010) acknowledge recent literature for its focus on the role of learning on adoption decision. However, they recognize the complexity of adoption process (particularly related with measurements) and difficulty of inferences as there are common unobservable factors affecting adoption decisions.

The last but not least, and an old review of studies on agricultural innovations adoption was made by Feder et al. (1985). On this review study, the main factors found to limit technology adoption rates were farm size, tenure arrangement, labor availability, credit constraints, risk and uncertainty, human capital, and sociological and other factors. On the relationship between these potential explanatory variables and technology adoption, Feder & Umali (1993) and Feder et al. (1985) mentioned the existence of inconsistent and conflicting findings from different studies. This was also supported in recent studies by Montes de Oca Munguia, Llewellyn (2020), Shita et al. (2018) Mwangi & Kariuki (2015) that there is no convergence towards a consistent explanation of what determines agricultural technology adoption.

In the Ethiopian case, Feyisa (2020) made a meta-analysis on studies of agricultural technologies adoption using a random effect model. From his review, he found that age of the household head, education level, farm size, livestock holding, and access to extension services, access to credit services, cooperative membership, and distance from the market as significant factors in influencing agricultural technology adoption. Finally, Feyisa (2020) stated despite studies indicate the determinants of agricultural technology adoption, their practical applicability at the national level is limited due to heterogeneity in findings of these studies.

Kebede (2020) made an empirical analysis using logistic regression on determinants of adoption of improved wheat technology in Liben Jewi, a district in Oromia Region, Ethiopia. His findings show that farm size, livestock ownership, extension contact and access to credit positively related with adoption of wheat technology. In contrast, age, distance from market and distance from farmers training center are found to have a negative influence in adoption decisions.

Another review study by Shita et al. (2018) was made with the objective of reviewing factors affecting the adoption of agricultural technologies in Ethiopia. From their review, they recognized that past studies in Ethiopia mainly focused on adoption of fertilizers and improved seeds varieties. They stated studies in the past identified different variables affecting adoption decisions depending on their study area and the type of technology they studied while the principal variables to affect agricultural technologies adoption were accessibility of credit, farm size, education level, oxen ownership, and distance to the market.

One more study by Teklewold et al. (2013) was made on adoption of multiple sustainable agricultural practices in Ethiopia using multivariate and ordered probit models. Their findings show the existence of correlation or complementarity between sustainable agricultural practices. This complementarity between technologies/inputs is consistent with findings of a recent study by Abay et al. (2018). Finally, findings of Teklewold et al. (2013) show that both the probability and the extent of adoptions are affected by diverse factors among other by household's trust in government support, credit constraints, spouse education, rainfall and plot-level disturbances, household wealth, social capital and networks, labour availability, plot and market access.

As it can be inferred from the above-discussed empirical literature and reviews, the factors commonly mentioned to affect technology adoption in most of the studies can be included within the domains of household specific and demographic factors, socio–economic factors, institutional factors, technology related factors, and pshyco-behahvioural factors. The household specific and demographic factors may comprise factors like age, gender, education (schooling), farming experience and leadership experience, while socio-economic factors may include income from farming, off-farm income, total wealthy, farm-size, household size, membership on farming cooperatives and other institutions. On the other hand, institutional factors may include access to information, access to credit, access to extension services, access to market (distance to market), land tenure or property right, and availability of inputs/technologies. The technology (itself) related factors include factors such as easiness of the technology, compatibility, trialability and cost of the input/technology, and net gain from adoption etc. Finally, the domain pshyco-behahvioural factors may include households' perception and knowledge about the input/technology, attitude, belief, trust, risk preference, self-efficacy, personality traits, aspiration, and locus of control (control belief) etc. There are agro-climatic related factors such as type and fertility of soil and rainfall amount, temperature etc.

However, the categorization of the factors made above and made in other review studies is not mutually exclusive and might not be inclusive. In line to this, Bonabana-Wabbi (2002, p. 27) stated that although there are many categories of factors influencing technology adoption, "there is no clear distinguishing feature between variables in each category". Rather, categorization is done to suit the current technology being investigated, the location, and the researcher's preference, or even to suit client needs. On his way, Bonabana-Wabbi (2002) stated that the factors affecting adoption decision of farmers can be classified into two broad groups: incentives (reasons for) and disincentive s(reasons against) adoption.

Finally, following their findings of inconsistent results on the effects of potential variables on technology adoption in different areas and countries, Feder et al. (1985) stated that these conflicting findings might be because of differences in social, cultural and institutional environment. Relatedly, Abay et al. (2018) and Suri (2011) document unobserved heterogeneity in farmers and heterogeneity in net return, respectively can account for the inconsistent findings and low uptake of agricultural technologies in developing countries. Others studies such as Glover et al. (2019), Glover et al. (2016), Sumberg (2016), and Foster & Rosenzweig (2010) mention methodological issues as one reason for the inconsistent findings and little understandings of technologies adoption, particularly in SSA. The statements about the inconsistent findings of studies informs that relying on a single study of adoption and making inference about the whole might not be necessarily relevant.

2.2.2. The Effects of Locus of Control and Aspiration on Technology Adoption

Apart from the theoretical suggestions for the existence of linkages between LOC and aspiration with agricultural investment, there are some supportive empirical evidence as well. There are studies which mainly focus on the effect of internal characteristics of farmers' themselves on their technology adoption decisions. Some of these include the effect of farmers' personal characteristics like self-control and hope (Bukchin & Kerret, 2020a; 2020b; and 2018); the effect of farmers' human capital (Huffman, 2020); the effect of efficacy, risk aversion, attitude, knowledge and perception (Zeweld et al., 2018; Meijer et al., 2015) and the effect of motivation (Herath, 2010), on agricultural technology adoption decisions.

To the best of my knowledge, there are only three empirical studies that analyzed the effect of LOC and aspiration on technology adoption in developing countries. These are Taffesse & Tadesse (2017), Abay et al. (2017), and Mekonnen & Gerber (2016). Using a large survey from rural Ethiopia, Taffesse & Tadesse (2017) measured LOC of individuals (farmers') using fifteen questions designed to elicit locus of control. Then, they investigated the correlation of farmers' LOC and other covariates with agricultural technology adoption decisions using an ordered probit model. Technology adoption was measured using a discrete measure constructed to capture the extent of adoption of two familiar inputs, fertilizers, and improved seeds in Ethiopia. On the other hand, LOC was measured using binary scale (either or question) and Likert format. Finally, they found the existence of external LOC in large numbers of rural farmers in Ethiopia. Specifically, their findings show that both lower internal LOC and higher external LOC lead to less propensity to adopt agricultural technologies while both high internal and low external LOC associates with high input usages.

The other study by Abay et al. (2017) is made with the objective of investigating the implication of farmers' LOC on their technology adoption decisions focusing on three important inputs adoptions: chemical fertilizers, improved seeds and irrigations, with data from rural Ethiopia. They made a good examination of the issue particularly in terms of data employment (large sample coverage) and utilization of alternative econometrics approaches to probe the robustness of their results. The most important element of their investigation was they measured hypothetical demand of farmers or "stated willingness" and analyzed the link between LOC and this hypothetical demand for new agricultural technologies. They stated that this approach enabled them to minimize some of the possible occurrence of endogeneity and reverses causality problems, and highlight the state of future agricultural investments. In their findings, they mentioned that farmers with internal LOC are more likely to adopt agricultural technologies including chemical fertilizers, improved seeds, and irrigational practices than farmers having external LOC.

One more related study is Mekonnen & Gerber (2016) made on the effect of aspirations on technology adoptions in rural Ethiopia. Aspiration was measured as index of weighted values of four indicators of aspiration: farmers' wealthy, income, education and social status, constructed by Bernard & Taffesse (2014). In their regression, Mekonnen & Gerber (2016) used an aspiration gap instead of aspiration, for which Ray (2002, p. 3) defined aspiration gap as "the difference between someone's aspired level of standard living and his current standard of living(Ray,2002, p. 3). Chemical fertilizers, improved seeds and pesticides were used as indicators of technology adoption. They that farmers with narrow aspiration gap or with very large aspiration gap are associated with low level of technological adoption rates. In other words, when the aspirations gap is either too narrow or too wide, the authors observed aspirations failure and people giving up. The reason is because when the aspirations gap is too narrow, the reward is considered too small for the effort, and when it is too wide, the gap will remain large regardless of the amount of effort put in. On the other hand, farmers with moderate aspiration gap are found to have more propensity to adopt agricultural inputs.

From these three studies review, LOC and aspiration are strongly correlated with technology adoption decisions. From the empirical studies on the effect of LOC, in most cases, internal LOC relates with positive outcomes and external LOC with negative outcomes, however, this does not necessarily mean the relations are this way. Rinn & Boazman (2014) stated that even though experiencing both internal and external LOC have pros and cons, ultimately, having internal LOC is the healthier. From the empirical reviews technology adoption was measured in most cases as a simple binary concept. However, adoption is a process and this approach has criticized for it does not completely reflect what exactly technology adoption is (Glover et al., 2019; Glover et al., 2016; Sumberg, 2016; Feder & Umali, 1993; Feder et al., 1985). Besides, past studies in Ethiopia mainly focused on adoption of fertilizers and improved seeds varieties (Shita et al., 2018).

In this study, we use alternative technologies such as irrigation, fertilizer (Urea and DAP), pesticides and push pull technology as a measure of agricultural technology adoption. We also reason use alternative measures, technology adoption as continues variable (measured as technology input per plot) and as a count measure (measured as the number of technologies used) in addition to the dummy measure.

2.3. Conceptual framework

The conceptual framework which defines the relevant variables (the outcome and explanatory variables) and maps the explanatory variables relating to the outcome variable is given in figure 2.1. As already mentioned in the theoretical literature part, there is no single theory or model that considers all factors deemed to have an influence on farmers' decision making towards technology adoption for there is complexity of behavior research (Momani et al., 2017; Straub (2009). Moreover, in applying theories of adoption, there are strict requirement and guidelines to be followed. Instead, using the combination of these different theories in defining the underlining relationships between the different factors (including locus of control and aspiration) and technology adoptions is more important.

Loevinsohn et al. (2013, p. 2) stated that "the decision of farmers about whether and how to adopt new technology are conditioned by the dynamic interaction between characteristics of the technology itself and the array of conditions and circumstances". Empirical studies agree that agricultural technologies' adoption is influenced by several interrelated components within the decision environment in which farmers operate. Thus, relying on these statements, the conceptual framework below explains that factors affecting the adoption of agricultural technologies could be grouped in to three broad categories for the sake of simplicity. These are factors related to the adopters (farmers themselves), characteristics of the technology under consideration and institutional or structural factors.

The factors mostly cited in the theoretical and or empirical literature as determinants of agricultural technologies adoption are included in the figure below keeping in mind the main objective of this study is to examine the effect of the two factors, LOC and aspiration which are included in the psycho-behavioural category.

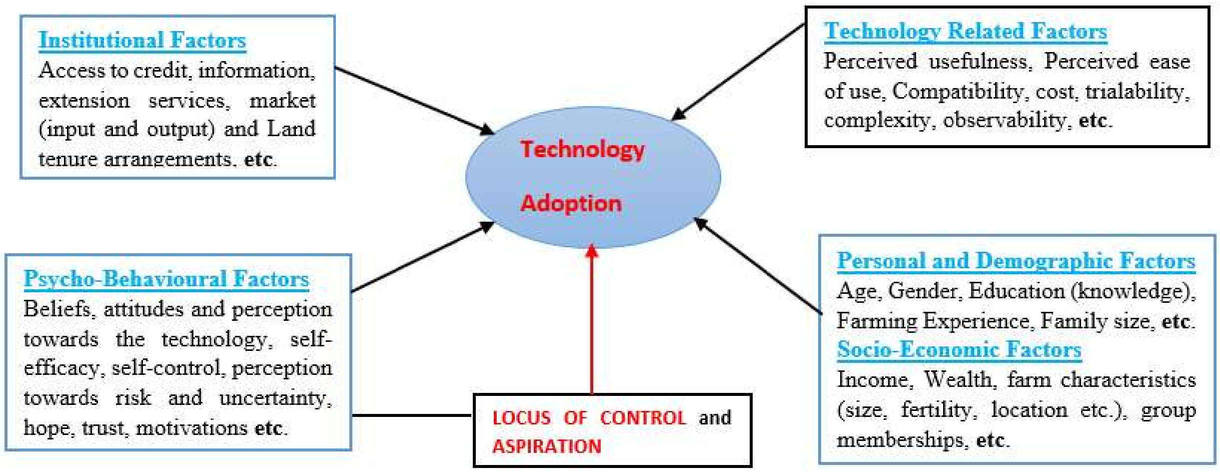

Figure 2.1: Factors affecting technology adoptions: from theoretical and empirical literature

CHAPTER THREE

RESEARCH METHEDOLOGY

In this section, we discuss the research methodology that we employ in this study. This includes data source and type, description of study area, description of data, measurement tools of interest variables, and finally, the specification of models and estimation strategies.

3.1. Data Source and Type

The data for this study is a cross sectional household level data. It was collected by the Social Sciences and Impact Assessment Unit (SSIAU) of International Center of Insect Physiology and Ecology (*icipe*) in December 2020.

3.2. Description of Study Area

The study area is the Jabi Tehnan, a district (woreda) in western Gojjam zone of the Amhara National Regional State of Ethiopia. Jabi Tehnan is found 397 km away from Addis Ababa. It is located in 36°40′E to 36°50′E longitude and 10°30′00″ N to 10°40′00″ N latitude while the altitude ranges from 1500 to 2300 meters above the sea levels (Asmare & Gure, 2019). The district is bordered on the east by Dega Damot district, on the southeast by Dembacha district, on the west by Bure town, on northwest by Sekella district, and on the north by Quarit district.

According to the agricultural office of the district, the land scape of Jabi-Tehnan, is mainly flat plain area which covers 65 % of the total land area. The remaining areas contain 15% mountainous, 15% undulating, and remaining 5% valley (Getahun, 2015). Agro-ecologically, majority of the area (88% of the district) is classified as Woyina Dega (subtropical or temperate zone) and the remaining 12% as kola (tropical zone); the annual rainfall in the district reaches up to 1,250 mm while the temperature of the district varies from average minimum of 14 °C to average maximum of 32 °C (Tafere et al., 2013).

Jabi-Tehnan district has 41 kebeles (two of which are urban kebeles) with total population of 277,590. The majority, or 94% of the population, i.e. 259,826 people, live in rural areas and primarily dependent on agriculture for its livelihood source while the remaining 6% accounting for about 17,724 people, live in urban areas (Tafere et al., 2013). The map of Jabi-Tehnan is given below in Figure 3.1.

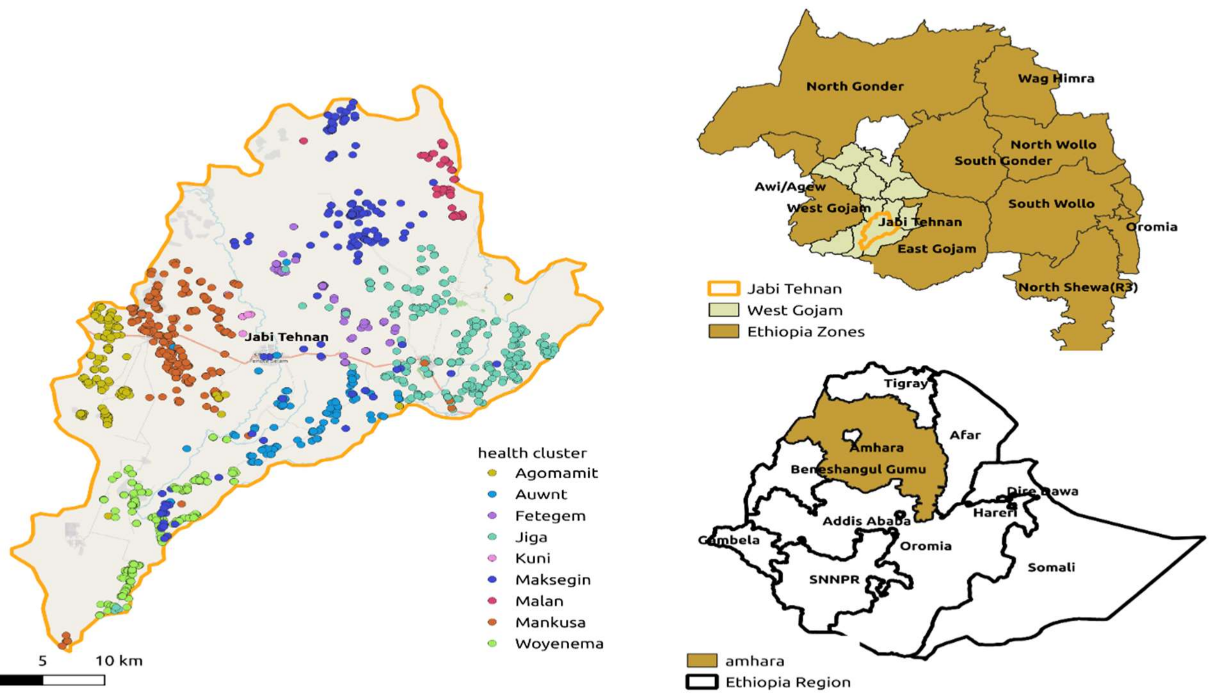

Figure 3.1: Map showing Jabi-Tehnan district in Amhara region Northwestern Ethiopia

Source: Asale et al., (2020)

Crop production is the main livelihood option in the district and the crops grown include: maize, finger millet, pepper, teff, wheat, faba beans, potato and barley, among others (Getahun, 2015). The district is known for its maize production (Getahun, 2015;Tafere et al., 2013).The farming community of Jabi Tehnan district, however, have multiple development constraints related to agricultural production (Tafere et al., 2013). Crop production in the district is highly challenged by the decline in soil fertility, the increasing price of fertilizer, and shortage of improved seed and crop pest problems in the selected intervention kebeles of Jabi-Tehnan (Tafere et al., 2013). This signifies that agricultural technology adoption in the areas might be helpful in minimizing the multiple development constraints.

3.3. Description of Data

The data covers 38 kebeles of the rural part of the district. On average, nearly 77 households were randomly selected from each of the 38 kebeles. The sample size of the study, which is the number of respondent individuals is 2,944. We prepared and used a structured questionnaire in collecting the data. The questionnaire includes information on personal and household characteristics, agricultural production (crop production and livestock ownership), technology adoptions or inputs usage (adoption and impact of PPT, house screening for malaria control, irrigation use, etc.), and factors affecting their decision on agricultural technologies.

The data was collected by trained enumerators, 18 enumerators with 3 supervisors. The enumerators and supervisors received a one-day training and have had a day piloting of the questionnaire before the actual data collection started. The training and the piloting helped us to ensure that enumerators and supervisors understand the questionnaire. The data is collected using the Computer-Assisted Personal Interviewing (CAPI) system designed using CSPro software. We asked the consent of individuals in the provision of information in advance and thus, data is collected based on the willingness of respondents.

3.4. Measurement Instruments

The main interest variables in this study are adoption of various technologies as outcome variables, and locus of control and aspiration as key explanatory variables. Therefore, in the following sections, we discuss the measurement of these variables.

3.4.1. Measuring Technology Adoption

Glover et al. (2019), Sumberg (2016), and Glover et al. (2016) stated that adoption cannot sufficiently be represented by dichotomous qualitative variables such as adopter and non-adopter since it often takes place by degree(extent and intensity). Instead, a more reflection of the adoption levels could be represented by continuous and discrete choices (Feder et al., 1985).

To measure technology adoption, we use three alternative measures: (1) A dummy measure, farmers taking the value 1, if adopted a technology under consideration and 0, otherwise; (2) A continuous measure, the total amount of input or inputs per harm size; and (3) A count or discrete measure, the number of technologies/inputs the farmers are using. The technologies/inputs we consider are irrigation, fertilizers, push pull technology (PPT), and pesticide.

3.4.2. Measuring Locus of Control

Locus of control is not directly measurable. Because it is a construct, defined as "a latent variable that can be defined in conceptual terms but cannot be directly measured or measured without error" (Sok et al., 2020, p. 6). We use both the Rotters' (1966) Internal- External (I-E) scale and Levenson's Likert format to elicit LOC.

Rotter's Internal-External LOC Scale: Binary Scale

To construct this scale, we ask respondents subjective questions designed for this purpose: two subjective questions related to internal LOC, stated in (1) below, and two questions related to external LOC stated in (2). Then, we let respondents choose between the two questions (which is forced choice format).

The questions are:

(A) Please tell me which of the two propositions you most agree with.

(1) 'Each person is primarily responsible for his/her success or failure in life'.

(2) 'One's success or failure in life is a matter of his/her destiny'.

(B) Please tell me which of the two propositions you most agree with.

(1) 'To be successful, above all one needs to work very hard'.

(2) 'To be successful, above all one needs to be lucky'.

Finally, we record their response as 1, if the respondent chooses the proposition stated in (1). i.e., she/he is assumed to have internal LOC, and 0, if they choose the proposition stated in (2). i. e., she/he is assumed to internal LOC.

Levenson's three scale (IPC scale): With Likert format

Levenson, (1973; and 1981) developed a three-scale measurement scale for LOC: Internal LOC scale (I), Chance LOC scale(C), and Powerful others LOC scale (P). In this method, Levenson (1981) differentiated the external LOC scale (in Rotter's scale) in to two scales: chance and powerful other scale. The rationale for this and explanation how it differs from Rotter's I-E scale is provided in Levenson (1973). Having internal LOC implies that individuals have stronger belief in their ability to influence events and outcomes relevant to their life. Chance LOC measures how much an individual beliefs that chance or fate influences the events and outcome related to his/her life. On the other, hand powerful others LOC scale signifies to what extent individuals believe that other powerful persons have influence on the event and outcomes related to them.

In applying this method, we ask respondent five questions related to Internal LOC scale, stated as (I) below, five question related to Chance LOC scale, stated as **(C)**, and five questions related to Powerful others LOC scale, stated as (P).

Some of the questions used to elicit IPC include:

> **(C)** To a great extent my life is controlled by accidental/chance happenings.
> **(P)** I feel like what happens in my life is mostly determined by powerful people.
> **(I)** I can mostly determine what will happen in my life.
> **(C)** Often, there is no chance of protecting my personal interests from bad luck happenings.
> **(P)** In order to have my plans work, I make sure that they fit in with the desires of people who have power over me.
> **(I)** When I get what I want, it is usually because I worked hard for it.

The respondents are provided a Likert format choices for their response. The Likert scale has six point, ranging from strongly disagree (-3), disagree (-2), slightly disagree (-1) to slightly agree (1) and agree (2), and strongly agree (3). So, for each questions of the total fifteen questions, the respondents have six options to choose among. Then, we record the responses for each question as values ranging from -3 to 6 as elaborated in Levenson (1981). Finally, we construct an index using factor analysis as used by Abay et al. (2017).

3.4.3. Measuring Aspiration

Aspiration is not also directly observable. To elicit and measure farmers' aspirations, we use a method proposed by Bernard & Taffesse (2014; 2012) and applied by Mekonnen & Gerber (2016). Individuals aspire for different things, and accordingly, they could have health aspirations, wealth/income aspirations, educational aspirations, and social status aspirations, among others. In general, individuals may aspire to a better life, to which the various aspiration contribute at various degrees (Bernard & Taffesse, 2014). To capture these dimensions, we construct the aspiration index using four dimensions of aspiration (income, asset, education, and social status aspiration). First, respondents are asked four questions to each of the four aspiration dimensions.

The two main questions are:

1) What is the level of (income, asset, education, and social status) that you have at present? (Current outcome level).
2) What is the level of (income, asset, education, and social status) that you would like to achieve? (Aspired outcome level).

However, not all life dimensions carry the same importance, and that this may vary along individuals' preferences (Bernard & Taffesse, 2014). Thus, to capture this, we compute aspiration weights for each of the four dimensions, which measures the relative importance of the four dimensions (categories) of aspiration to the individuals. In doing so, we provide the respondents 20 coins to allocate them among the four aspiration dimensions. No coin in category means the respondents do not attach any importance to it, and many coins in a category means they attach a significant importance to it. Then, we calculate the aspiration weight, w_i^n.

Finally, the aspiration index is given as:

$$ASP_i = \sum_{i=1}^{4} \left(\frac{A_i^n - \mu^n}{\sigma^n}\right) w_i^n \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(i)}$$

Where, ASP_i is aspiration index for individual i; A_i^n is the aspired level of outcome in terms of the four dimensions (n =4); w_i^n is the weight given to each of the four dimensions; μ^n and σ^n are the sample mean and the standard deviation of the aspired outcomes.

3.5. Model Specification

3.5.1. Theoretical framework

Assuming the farmers have a complete freedom to choose among existing alternative technologies, the decision to adopt largely depends on the farmers' perception of the benefits that she/he will gain once she/he adopts the technology against perceived costs and risks associated with the technologies (Justin et al., 2017). Dessart et al. (2019) mentioned farmers' perceptions of the benefits and costs associated with a specific agricultural practice are immediately related to the decision-making in question.

According to TAM of Davis (1986), individual's overall attitude toward using a given technology is a major determinant of whether or not the individual actually uses it. On the other hand, overall attitude toward using the given technology is determined by the perceived usefulness and ease of use.

Davis (1986) summarized his technology acceptance model using four relationships, and can be written in a simplified way as:

$$T_{use} = f(P_{use}, EOU, ATT, X_f) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

Where, T_{use} is the decision to use a technology, P_{use} refers to perceived usefulness of the technology, EOU refers to ease of use of the technology, ATT is the individuals' attitude towards using the technology, and X_f refers to the design features of the given technology.

In the function (1) above, individuals' decision whether to adopt or not a given technology as a function of the design features of the technology and ease of use of the technology. The design features are part of the category of the external variables in the constructs of the TPB (Davis, 1986). Thus, although this theory was mainly applicable to computer systems or technologies, however, it reveals that the actual use of any technology can depend on the characteristics of the technology under consideration.

On the other hand, according to the TPB, the decision to perform a given behaviour is a joint function of intention (which captures the motivational factors that influence a behavior) and perceived behavioural control (PBC). These two factors and finally the actual performance of the behaviour depend basically on three mains constructs which are BA, SN, and PBC. In TPB, Fishbein and Ajzen (1975), defined external variables as a composition of all variables not explicitly represented in their model. These external variables include demographic or personality characteristics of the actor, the nature of the behavior under consideration, characteristics of referents, and prior behavior, and persuasive communication and others.

Thus, considering whether to adopt or not a given technology as a behaviour, then according to the theory of planned behaviour (TPB), the decision to adopt a given technology is a function of the attitude (ATT) towards adopting the given technology, the subjective norm (SN), and the perceived behavioural control (PBC) while these three variables are affected by beliefs and external variables.

$$T_{use} = f(\mathrm{ATT}, \mathrm{SN}, \mathrm{PBC}, X_i) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

Where, X_i refers to all possible external factors including demographic (age, sex) and personality characteristics that can possibly affect directly the three constructs and then indirectly the behaviour (technology adoption) of individuals. Perceived behavioral control (PBC) is very important construct of theory of planned behaviour (Ajzen, 1991). It measures people's perception of the ease or difficulty of performing the behavior of interest and directly predicts behavioural outcomes. Ajzen (1991) stated that peoples' behavior is strongly influenced by their confidence in their ability to perform the behaviour that is by perceived behavioral control. Despite having difference in meaning and nature, thus, locus of control as perceived behavioural control and self-efficacy can have a direct impact on actual performance of a behaviour. LOC is a generalized belief of individuals about their influence on their life events. On the other hand, perceived behavioural control is individuals' belief of control they have towards performing a specific behaviour. So, apart from its own channel, LOC might correlate with perceived behavioural control and affect the specific behaviour under consideration (technology adoption).

Thus, combing equations (1) and (2) above, technology adoption decision becomes a function of the technology characteristics, locus of control, and other attributes of individuals.

$$T_{use} = f\left(\mathrm{LOC}, X_f, X_i\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

Where, LOC is measured individuals' locus of control, X_f refers to the vector of the technology related characteristics, and X_i refers to the vector of personal attributes of the decision maker (farmer) including demographic and socio-economic characteristics.

In Bernard et al. (2014) aspirations are defined as forward-looking goals or targets; and they are desire or ambition to achieve something. Relying on these definitions and from their review of literature in sociology, social psychology and economics, Bernard et al. (2014) identified three basic features of aspiration. The first is aspiration express goals or desired future end-states that are relevant to well-being. The second is aspirations evolve over time in response to life experience and circumstances. The third is aspirations are an important influence on behaviour or actions as they are goals. They motivate behaviour or provide motive power for action. Therefore, considering technology adoption as a behaviour or as an action (as it requires effort), aspiration will have influence on it.

Thus, taking above into account, the decision to adopt a given technology could further be expressed as a function of locus of control (LOC), aspiration (ASP), the characteristics of the technology itself (X_f), attributes of the individual such as demographic, socio-economic, personality, and other possible factors (X_i).

Thus, T_{use} becomes as:

$$T_{use} = f(\text{LOC}, \text{ASP}, X_f, X_i) \quad (4)$$

3.5.2. Empirical Model

There are two basic features of the outcome variable, technology adoption. First, as described in the earlier section, the general propensity to adopt a technology is not directly observed (not directly measurable). What we know or observe is whether an individual has currently adopted and uses a technology under consideration (a dummy measure). Thus, what we can do is to predict the unobserved farmers' propensity to adopt technologies given the observed dummy response variable. In short, about measurement, the outcome variable (technology adoption) can be expressed in three ways, as dummy variable, as ordered categorical variable, and as continuous variable.

Second, technology adoption is not a one-time decision. Because adoption is a process involving certain steps so it could be time dependent. Thus, as Besley & Case (1993) mentioned, this may indicate for a requirement of panel data, a combination of time series and cross sectional information for a better and comprehensive analysis and understanding of farmers' propensity to adopt technologies. However, as there is no previous information on the main interest variables (farmers' LOC and aspiration), the analysis depends only on a cross sectional data. Thus, considering this and the nature of the dependent variable, models for estimating the effect of LOC and aspiration on adoption decision and on intensity of adoption are specified as below.

i. Modelling technology adoption decision

In many studies, simple dichotomous variable approach is used for farmers' technology adoption decision (Udimal et al., 2017). The binary logit model is used when the outcome variable is dichotomous or takes the values 1 or 0 (Wooldridge, 2002 and Maddla, 1992).

Let y_i be farmers' adoption of a single input (irrigation, fertilizers (DAP, urea), pesticide, and PPT) which assumes a value 0, if a farmer does not currently use the technology, and 1 if the farmer adopts and uses the input. Given the possible explanatory variables of technology adoption, the binary logit model is given as:

$$P(y = 1|x) = f(x`\beta) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (5)$$

This implies that the probability that a farmer adopts a technology is a function of the explanatory variables, in vector X. Because in the logit model, the function F(.) follows a logistic distribution, it becomes,

$$\mathrm{P}\left(\mathrm{y} = \frac{1}{\mathrm{x}}\right) = \Lambda(\mathrm{x}\beta) = \frac{\exp(\mathrm{x}`\beta)}{1+\exp(\mathrm{x}`\beta)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (6)$$

The model in (6), is the binary logistic model used to estimate the effect of LOC and aspiration on the probability that farmers will adopt a given technology. To make the explanatory variables in a linear form, taking log of odds ratio, the model in (6) becomes,

$$ln\left(\frac{pi}{1-pi}\right) = \beta_0 + \beta_1 LOC_i + \beta_2 ASP_i + \beta_{\mathrm{k}}\boldsymbol{X} + \varepsilon_i \ldots\ldots\ldots\ldots\ldots\ldots (7)$$

Where, LOC_i and ASP_i are the locus of control and aspiration of household i; and X represents the vector of control variables; β_0, β_1, β_2, and β_{k} are parameters to be estimated; ε_i are classical error terms.

ii. Modelling intensity of adoption

Intensity of adoption of the technologies can be expressed in two ways, one as ordered discrete variable (the number of technologies adopted, count measure), and second as continuous variable (input used per farm size). In both cases, intensity of technology adoption is a limited variable in that its values are restricted to be in some ranges (Wooldridge, 2010).

In the first case, when the dependent variable assumes a discrete values (0, 1, 2, 3 and 4) we use an ordered logit model.

Let y_i* be the outcome variable (farmers' unobserved propensity to adopt agricultural technologies), then it is given as:

$$y_i^* = \beta_0 + \beta_1 LOC_i + \beta_2 ASP_i + \beta_k \boldsymbol{X} + \varepsilon_i \dots\dots\dots \quad (8)$$

Where, y_i^* is a latent variable, which is not directly observable; y_i be the observed ordered responses that assumes values 0, 1, 2, 3 and 4, which means 0, for non-adopters, 1 for adopters of only one input, 2 for adopters of two inputs, 3 for adopter of three inputs, and 4 for adopters of the four inputs under consideration; ε_i the error term**,** assumed to be unrelated with the covariates in vector X.

According to Long & Freese (2014) and Wooldridge (2010), the observed ordered variable y_i can be related with the unobserved propensity to adopt y_i^***,** as follow:

$$\Pr(y_i = J) = F(\alpha_J - x_i`\beta) - F(\alpha_{J-1} - x_i`\beta) \dots\dots\dots \quad (9)$$

Where, J is the number of ordered categories, β are vector of parameters to be estimated, α_j are the vectors of the thresholds or cut points to be estimated, and x_i are vector of all explanatory variables.

Specifically, assuming $\Lambda(.)$, the logistic distribution function in logit model, and given the five outcomes for the ordered response variable, the conditional probability of the observed technology adoptions can be computed as follow.

$$P(y_i = j|x_i) = \begin{cases} \Lambda(\alpha_1 - x_i`\beta) & \text{for } J = 0 \\ \Lambda(\alpha_2 - x_i`\beta) - \Lambda(\alpha_1 - x_i`\beta) & \text{for } J = 1 \\ \Lambda(\alpha_3 - x_i`\beta) - \Lambda(\alpha_2 - x_i`\beta) & \text{for } J = 2 \\ \Lambda(\alpha_3 - x_i`\beta) - \Lambda(\alpha_2 - x_i`\beta) & \text{for J} = 3 \\ 1 - \Lambda(\alpha_4 - x_i`\beta) & \text{for } J = 4 \end{cases} \dots\dots\dots \quad (10)$$

Thus, model (10) is the ordered logit model for technology adoption (measured as a count variable), where all variable are as defined above in (9).
Finally, in the second case, when the intensity of technology adoption is expressed as a continuous variable (input use), a linear regression model is used. Then, the model is given as:

$$Y_i = \beta_0 + \beta_1 LOC_i + \beta_2 ASP_i + \beta_2 \mathbf{X} + \varepsilon_i \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (11)$$

Where, Y_i is the intensity of technology adoption (taking values ≥ 0), which measures the extent of use of a given input per farm size, other variables are as defined in (7) and (8).

Regarding the estimation techniques precisely, three models as specified in (7), (10) and (11) are estimated. To estimate the binary logit model, which is the model for the two choices (to adopt or not a given technology), we use a maximum likelihood method. To estimate the ordered logistic regression model in (10), maximum likelihood method is used. On the other hand, an ordinary least square (OLS) is used in the estimation of the linear regression model in (11). These alternative specifications may help to compare and probe the robustness of the results.

CHAPTER FOUR

DATA ANALYSIS AND ESTIMATION RESULTS

In this chapter, we analyze and discuss the data using both descriptive and econometrics methods. In the descriptive analysis part, we discuss the demographic and socio-economic background of the sample households, the distribution of the data for the key interest variables (locus of control and aspiration) and the unconditional correlations between technology adoption, and locus of control and aspiration. In the econometric analysis part, we first discuss the goodness of fit of models and diagnostic tests, and we present the econometric results.

4.1 Descriptive Statistics

In this study, the sample households used for the analysis are 2,933 households. Initially, a total of 2,944 households were surveyed, however, in the data cleaning process, 11 observations were dropped because of missing information on relevant variables. We provide the summary statistics of all the variables in Table 4.1. The average age of the household heads in the sample is 48 years old. Many of the household heads, around 86.33 percent are male heads with only 13.67 percent being female heads. The average family size of the households is approximately five. i.e., on average, in each household there exists five members of the household/family. Regarding the educational status, 46.37 percent of the households' heads are illiterate, 49.61 percent of the households' heads have completed a primary school (grade 1 to eight), and only 4.02 percent of households' heads have completed secondary school and above. In this case, those households who can read and write either by attending formal education or informal education are considered as literates, thus, the number of illiterate people (46.37 percent) is high.

On economic related characteristics, the sample households have an average annual income and asset holding of 32, 598.807 birr and 20, 6052.93 birr, respectively. The farmers in the sample study have an average land holding (a land available for cropping and that is owned) of 1.06 hectare. This result confirms the previous statistics that most of the farmers (90 percent) in Ethiopia possess a farming land of size of one and less than 1 hectare (Louhichi et al., 2019). Maize is one of the most cultivated crop in the study area (Jabi-Tehnan). On average, the total land size cultivated for maize crop is 0.66 hectare, which is more than half of the average total land holding.

The statistics in Table 4.1 confirms that maize crop takes the largest share of cultivated crops in the district as stated in description of the study area.

Table 4.1: Definition and summary statistics of all variables

Variables	Mean	Standard deviations
Outcome variables		
Technology adoption		
Irrigation (1/0)	0.255	0.436
Push Pull Technology (1/0)	0.182	0.386
Fertilizer (1/0)	0.869	0.337
Pesticides (1/0)	0.615	0.487
Intensity of Technology Adoption		
Total DAP/NPS use in maize plot (kg)	144.941	124.643
DAP/NPS use in maize plots (kg/ha)	227.775	88.002
Total Urea use in maize plots (kg)	143.124	131.384
Urea used in maize plots (kg/ha)	221.661	87.724
Total Pesticides use (liter)	1.421	2.427
Pesticides use in maize plots (liter/ha)	0.669	1.32
Number of technologies/inputs used (Number)	1.922	0.905
Key independent variables		
Internal LOC(standardized index)	-0.001	1.001
External LOC(Standardized index)	-0.001	1.001
Aspiration (index)	0.017	0.604
Households' Characteristics		
Age of household head (Years)	47.969	12.684
Sex of household head (Male=1)	0.863	0.344
Family size (Number)	4.998	1.95
Annual income of household (birr)	32,598.807	26,671.335
Asset holdings of household (birr)	206,052.93	506,000.95
Illiterate (1/0)	0.464	0.499

Primary Schooling (1/0)	0.496	0.5
Schooling grade 9 and above (1/0)	0.04	0.197
Total land size owned and available for cropping (ha)	1.058	0.63
Number of maize plots cultivated (Number)	1.774	0.82
Total maize plot size cultivated (ha)	0.662	0.518
Maize plot size owned (ha)	0.42	0.339
Access to credit (1/0)	0.56	0.496
Access to extension service (1/0)	0.575	0.494
PPT information (1/0)	0.287	0.452
Distance to the main market (in walking minutes)	71.434	53.051
Cooperative membership (1/0)	0.636	0.481
Number of observations = 2, 933		

Source: Author's computation

As we stated in the methodology part, we measured technology adoption level in three alternative ways in this study. First, technology adoption as a dummy variable (1/0); second, as a continuous variable, which is expressed as the amount of input (kilogram or liter) used per hectare of cultivated land; and thirdly, as a count variable in which technology adoption level is measured by the number of inputs used by an individual (given some certain technologies/inputs). The first four rows in Table 4.1 show the summary of adoption variables used and the status of those technologies. The data shows strong variability across households.

Initially, there was information on seven agricultural technologies/inputs. From the data, we found that almost all households adopt and use improved seeds (98.98% adopter), fertilizers (DAP/NPS (99.25 %) and urea (99.26 %)) in maize plots. These variables have no reasonable variation in the sample in terms of adopter and non-adopter, we dropped them in the analysis. In contrast, though adoption status of fertilizers in other crops (other than maize) is also high, it shows a reasonable variation in the sample. DAP/NPS is adopted and used in other crops by 86.5 percent of the households while urea is used by 73.1 percent of the households. Therefore, 13.5 percent and 26.9 percent of the households in the sample are not adopting DAP/NPS and urea in other crops, respectively.

The higher adoption of improved seeds, fertilizers (DAP/NPS and urea) in maize crop plots could be for one reason because these agricultural inputs have long time been introduced. For instance, in Ethiopia in general, chemical fertilizers and improved seed have been introduced and highly promoted by government since 1960s (Bachewe et al., 2018; Taffesse & Tadesse, 2017). The other main reason is that the potential agricultural productivity of crops (mainly maize) in the district.

On the other hand, the adoption and use of inputs such as irrigation, push pull technology (PPT), and pesticide are very low. For instance, only 25.5 percent of the total households practice irrigation. Even though irrigation practice low, however, these value could be a good indicator of the progress made in irrigation practices in comparison with the past experiences. In the past, for instance in the year 2017/18 the total irrigated land at national level is estimated to be only 1.2 percent of the total crop areas (Louhichi et al., 2019). Pesticides are also adopted by many households in the district. While 61.5 percent of the households in the sample adopt pesticides, there is also a variation among adopters in terms of intensity of use.

The sample average usage of total DAP/NPS in all maize plots is 145 kg while the average DAP/NPS usage per hectare of maize plot is 227.76 kg. On the other hand, the average total use of urea is 143.12 kg while the average per hectare usage of urea is 221.66 kg which is nearly the same with DAP/NPS. In both fertilizers, the average per hectare usage is greater than the average total usages. This is because most households in the district hold a maize plot size of less than one hectare. However, the average use of DAP/NPS and urea on maize crops in the district are found to be higher than the recommended uses of respective fertilizers, which are 150 kg of DAP/NPS per hectare and 50 kg of urea per hectare (MoA, 2019).

Another indicator of the technology adoption we used is the number of technologies farmers adopted, which is a measure of the intensity of technology adoption. We considered four agricultural technologies (stated in Table 4.1) as a reasonable variation in adoption exists only in these inputs. The average number of technologies adopted by a household in the sample is 1.92, which means a farmer on average adopts and uses two out of the four given inputs. There are some households in the sample who adopted none of the inputs (5.7 percent of them) while only small number of households (3.6 percent) adopt all the inputs considered. Thus, there is also a variation in terms of the number of technologies adopted.

Locus of control and aspiration are the main independent variables of interest in this study. Their definition and the theoretical approaches on their measurement are discussed in chapters two and three, respectively. In this part, we discuss the distribution of the data on these key variables. One important concern in empirical issues is that the reliability and validity of measurement of the LOC. The factor loading of these items is Figure 4.1.

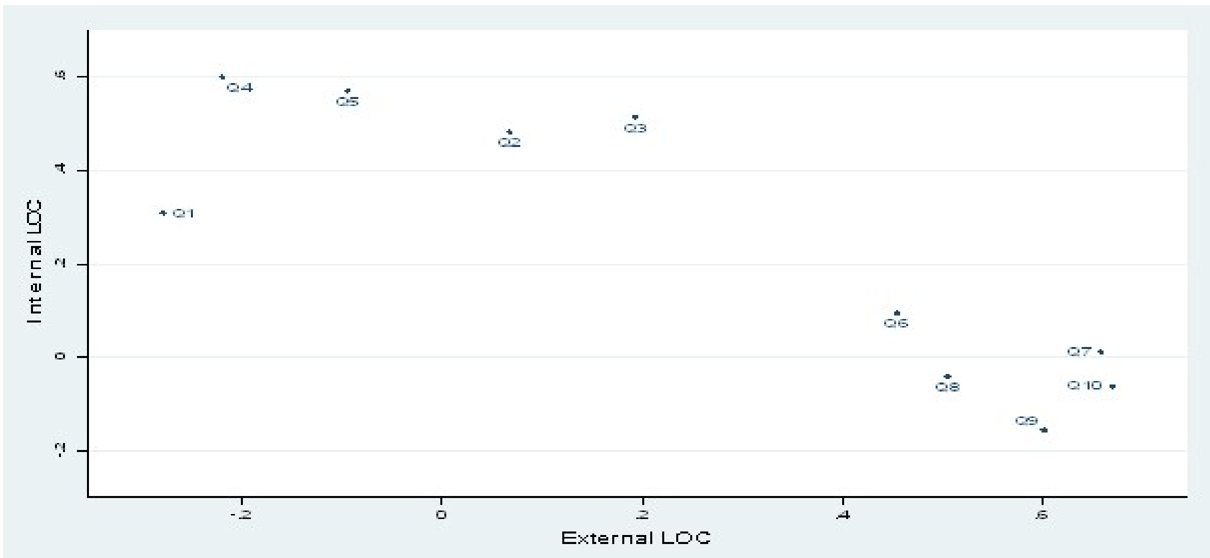

Figure 4.1: Factor loadings from Rotter's (1966) internal-external LOC items

Figure 4.1 depicts the loadings of the ten items designed to elicit LOC by Rotter (1966). The plot clearly indicates that the ten items can be classified into two factors, where questions Q1 to Q5 belong to internal LOC, and questions Q6 to Q10 belong to external LOC.

To measure the reliability or internal consistency of the items in the Likert scale, we use the Cronbach's alpha. The Cronbach's alpha also indicates the items are internally consistent to measure the Levenson's (1981) three scales of LOC (see Table A1. in the appendix). The distributions of LOC are provided in Fig 4.2.

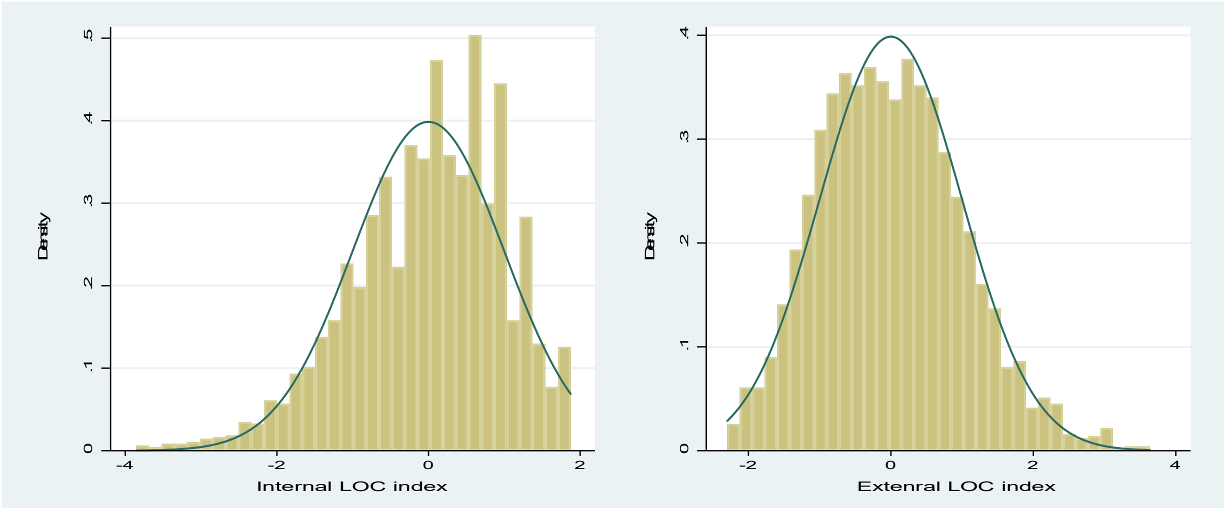

Figure 4.2: Distribution of farmers' internal and external locus of control indexes

The index for aspiration is constructed from the data on farmers aspiration towards four selected outcomes (income, asset, education, social status) using the formula and procedures proposed by Bernard & Taffesse (2014). The distribution the aspiration index is provided in Fig. 4.3.

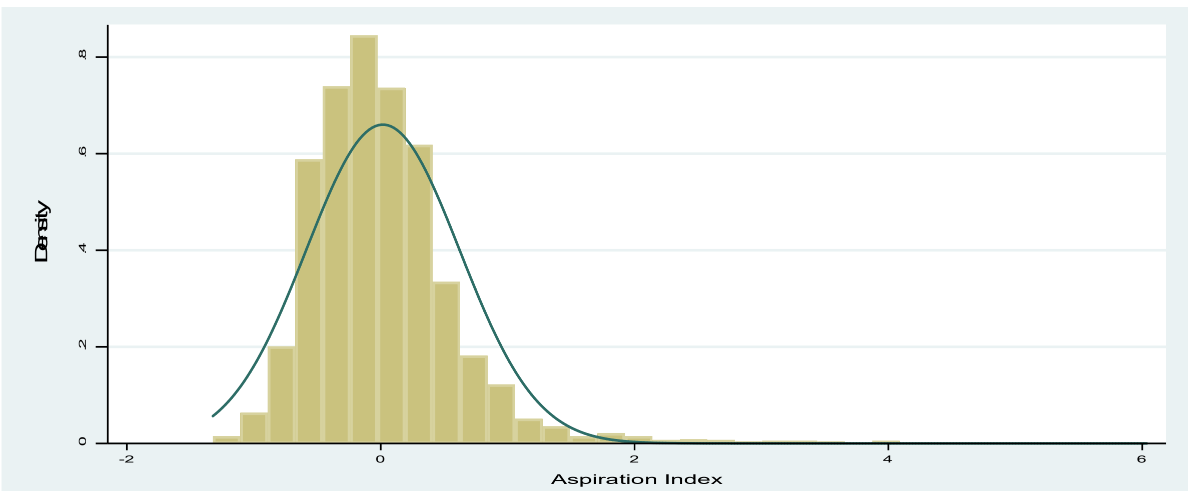

Figure 4.3: Distribution of farmers' aggregate aspiration index

4.1.1. Unconditional Correlation between Agricultural Technology Adoption, and LOC and Aspiration

In this subsection, we show the correlation between the outcome variables, and LOC and aspiration. First, we provided the unconditional correlation between LOC (as measured in indexes, internal LOC index and external LOC index) and technology adoptions using the mean values of internal and external LOC levels and results are given in Table 4.2 and Table 4.3. Then, we have also provided the correlation result when LOC is measured as dummy (as external LOC and internal LOC) in Table 4.5. On the other hand, as aspiration is expressed only as a continuous measure, we made unconditional correlation analysis using its mean value. This helps at least to understand who adopters are and who non-adopters are.

The unconditional correlation results between technology adoption, and LOC and aspiration provide an interesting results. Results in Table 4.4 indicate that the mean value of the internal LOC for households adopting irrigation is higher than the mean value of the non-adopter households. The same for PPT, the mean values of the internal LOC for households adopting PPT is higher than the mean values of internal LOC for non-adopter households. This implies, those households adopting a given technology are associated with having higher internal LOC while these households who are non-adopters are associated with having less internal LOC.

In all the technologies we considered, households who are adopters have higher mean value of internal LOC than households who are non-adopters. More importantly, while the mean value of the internal LOC for non-adopters is negative, the mean value of the internal LOC for adopters is positive. This has important implication. Because, internal LOC is a standardized measure, having negative mean values of internal LOC for non-adopters implies that they have internal LOC less than even the sample average internal LOC. On the other hand, having a positive average value of internal LOC for adopters implies that they have an internal LOC greater than the average of internal LOC in the sample.

Table 4.2: Two-way cross tabulation between internal LOC and technology adoption

		Internal LOC level(index)	
		Mean	Standard deviation
Irrigation (1/0)	Adopters	0.151	1.021
	Non-adopters	-0.053	0.989
PPT (1/0)	Adopters	0.105	0.986
	Non-adopters	-0.024	1.003
Pesticide (1/0)	Adopters	0.081	0.935
	Non-adopters	-0.134	1.085
Fertilizer (1/0)	Adopters	0.037	0.98
	Non-adopters	-0.251	1.099

Source: Author’s computation

Results in Table 4.3 show the unconditional correlation between technology adoption and external LOC. These results are identical but opposite interpretations. In this case, the mean value of the external LOC for adopters is less than the mean value of the external LOC for non-adopters. Simply, non-adopters have higher mean value of external LOC than adopters. The results are consistent in all the technologies we considered. Besides, the mean value of external LOC for adopters is negative and the mean value of external LOC for non-adopters is positive. This implies non-adopters have higher internal LOC than the sample average and adopters have less external LOC than the sample average.

Table 4.3: Two-way cross tabulation of external LOC and technology adoption

		External LOC level(index)	
		Mean	Standard Deviation
	Adopters	-0.207	1.018
Irrigation (1/0)	Non-adopters	0.070	0.985
	Adopters	-0.145	1.057
PPT (1/0)	Non-adopters	0.032	0.985
	Adopters	-0.052	0.971
Pesticide(1/0)	Non-adopters	0.083	1.042
	Adopters	-0.011	0.981
Fertilizer (1/0)	Non-adopters	0.066	1.130

Source: Author's computations

Table 4.4 shows the unconditional correlations between technology adoption and aspiration level. The results show that adopters of agricultural technologies have higher mean value of aspiration level than non-adopters. The relationships are same and consistent in all the technologies we considered. This might indicate that those who are adopting agricultural technologies are those who have better aspiration levels.

Table 4.4: Two-way cross tabulation of aspiration level on technology adoption

		Aspiration Level(index)	
		Mean	Standard deviation
	Adopters	0.176	0.684
Irrigation (1/0)	Non-adopters	-0.037	0.565
	Adopters	0.16	0.662
PPT (1/0)	Non-adopters	-0.014	0.568
	Adopters	0.065	0.623
Pesticide (1/0)	Non-adopters	-0.56	0.566

	Adopters	0.042	0.602
Fertilizer (1/0)	Non-adopters	-0.148	0.6

Source: Author's computations

We also provide the results of the cross tabulation of technology adoption and LOC, when LOC as measured as a dummy measure. Table 4.5 confirm the existence of significant correlation between LOC and adoption of technology adoption relying on the values of Pearson's chi2 probability, which shows a significant difference between the correlation of internal LOC and external LOC with adopters and non-adopter of technologies. Specifically, 85.29 percent of adopters of irrigation have internal LOC while 79.7 percent of households with external LOC are non-adopters of irrigation. Similarly, 87.28 percent of adopters of PPT have internal LOC, while 87.45 of households with external LOC are non-adopter of PPT. We have same kind of relationships from the correlations between LOC and farmers' adoption status of for fertilizer and pesticides.

Table 4.5: Two-way cross tabulation between technology adoption and LOC

Technology Adoption		Internal-External LOC scale (1/0))		
		External LOC	Internal LOC	Total
	Non-adopter	432	1753	2185
Irrigation (1/0)	Adopter	110	638	748
	Total	542	2391	2933
		Pearson chi2 (1)= 9.4906		Pr = 0.002
	Non-adopter	474	1924	2398
PPT (1/0)	Adopter	68	467	535
	Total	542	2391	2933
		Pearson chi2 (1)=14.4570		Pr = 0.000
	Non-adopter	250	878	1128
pesticide (1/0)	Adopter	292	1513	1805
	Total	542	2391	2933
		Pearson chi2 (1)=16.5108		Pr = 0.000
	Non-adopter	99	285	384
Fertilizer (1/0)	Adopter	443	2106	2549
	Total	542	2391	2933
		Pearson chi2 (1)=15.6382		Pr = 0.000

Source: Author's computation

Beside to the existing differences in the decision to adopt or not (being adopter and non-adopter) among households given certain technologies, differences exist in terms of the total amount of input used and/or amount of input used per hectare of a farm size for crops.

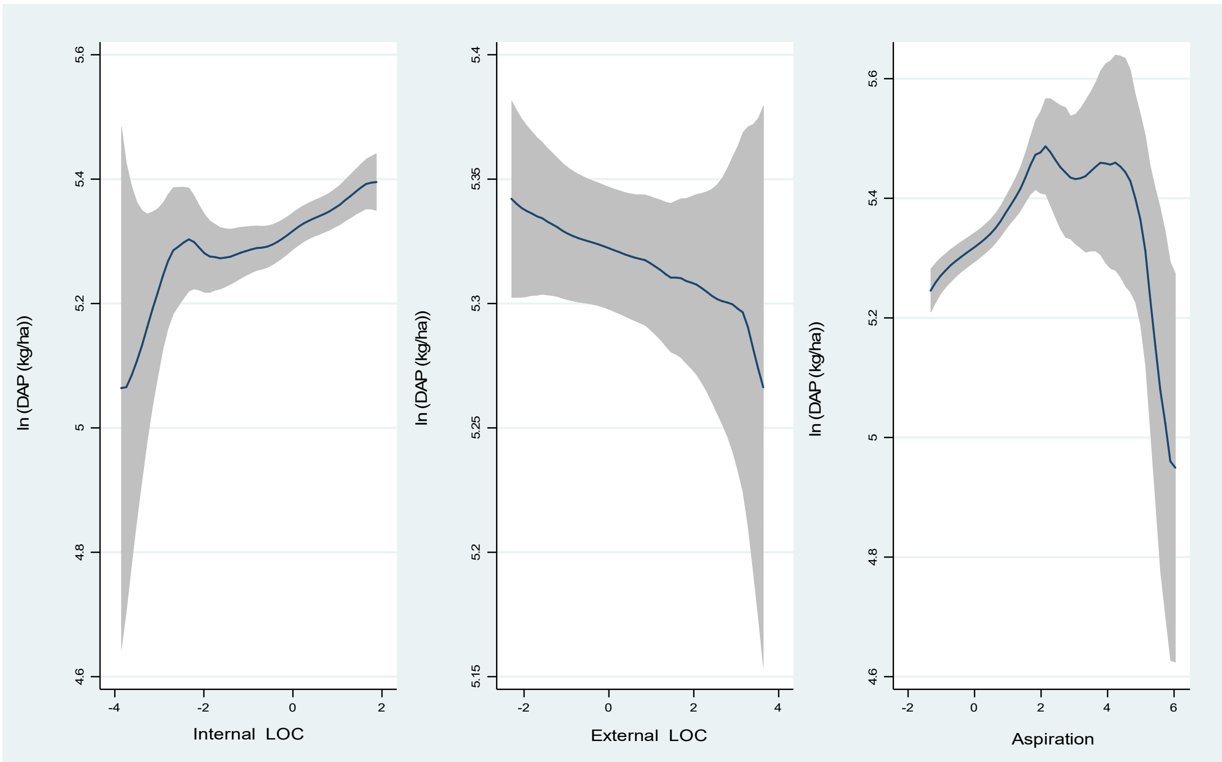

Figure 4.3a: Nonparametric regression of DAP/NPS (kg/ha) on internal LOC, external LOC and aspiration

The same association with above are also observed in the data for the relationship between the amount of urea use in maize plots, and LOC and aspiration. While there exist a difference in recommended amount of DAP/NPS and urea per hectare of maize crops, the households are using almost the same amount of DAP/NPS and urea per hectare of maize crops. As for DAP/NPS while households with high internal LOC and moderate aspiration are associated with high use of urea in maize plots, in contrast households with high external LOC are associated with low use of urea in their maize plots

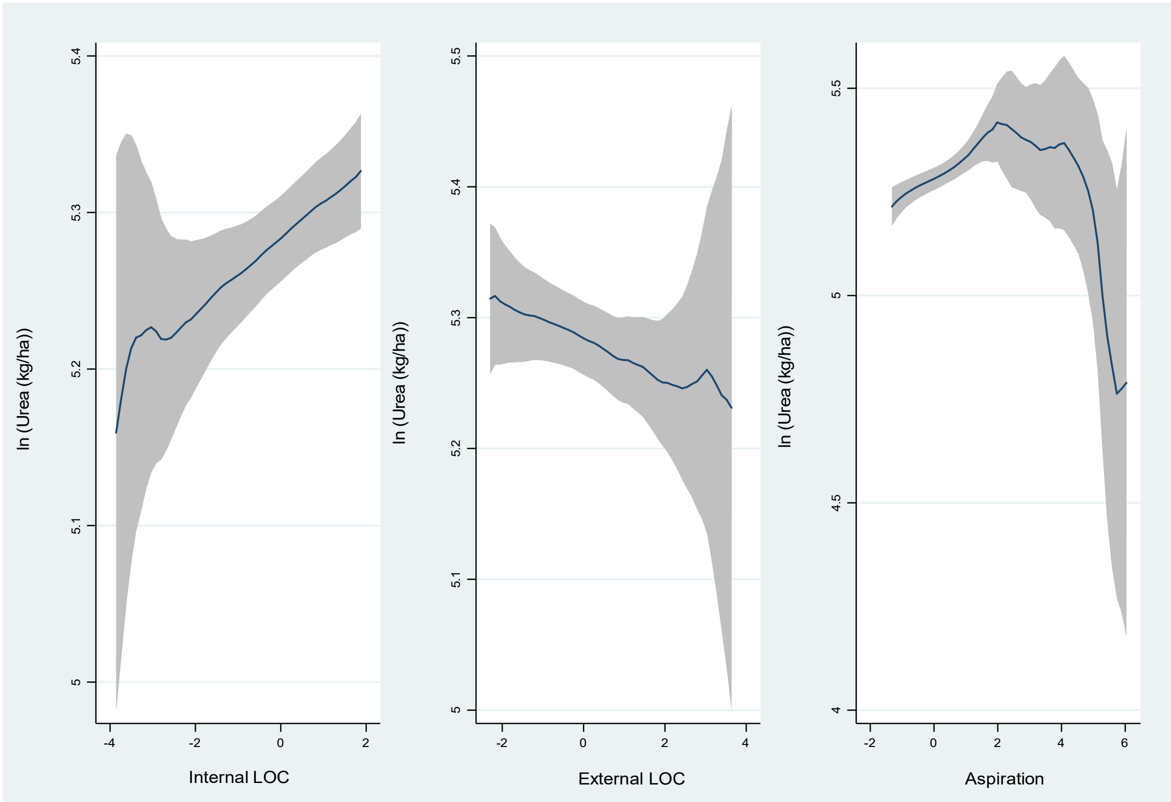

Figure 4.3b: Nonparametric regression of Urea (kg/ha) on internal LOC, external LOC and aspiration

Thus, from both the cross tabulations and the figures above, we understand that there exists an association between technology adoption, and LOC and aspiration of farming households for which we confirmed the same results in the econometrics analysis.

4.2 Estimations of the Econometrics Models

In the econometrics analysis, we estimate and discuss three models: binary logistic model, ordered logistic model and ordinary least square (OLS) model. While the binary logistic model is the main model used for the analysis of the effect of locus of control and aspiration on technology adoption decision, the other two models are used as an alternative analysis. We first discuss the goodness of fit of these models and diagnostic tests.

4.2.1 Models' Goodness of fit and diagnostic Tests

In this thesis, we use binary logistic regression model for estimating the effect of LOC and aspiration on technology adoption decision. However, as a robust exercises, we use alternative specifications, ordered logistic regression and multiple linear regression for modeling intensity of adoption. One of the serious issues in econometric estimations is the problem of endogeneity that may arise for many causes. Mekonnen & Gerber (2016) stated the endogenous nature of aspiration, but it is also difficult to find good instruments. Besides, Abay et al. (2017) noted the possible occurrences of endogeneity problems with LOC. We suspect that endogeneity problem could arise both with LOC and aspiration. Because of the absence of good instruments, we have used alternative specifications. We found consistent associations between LOC and aspiration with technology adoption. Besides, as used and suggested by Abay et al. (2017), we also examined the effect of LOC and aspiration on the willingness to adopt PPT given full information on it. This method might mitigate some problems of endogeneity and confounding factors as in this case we are dealing with hypothetical or a decision on future action, willingness to adopt PPT. In all our results, our discussions are based on the association or correlations between LOC and aspiration with technology adoption. We do not give causation interpretation to the estimated coefficients.

The other common problem particularly in cross sectional data is heteroscedasticity problem. As a mitigation, in all our regressions we used a robust standard errors in which we clustered the standard errors at household-level.

On the goodness of fit of models, there is no perfect or single measure of goodness of fit in binary choice models, rather in most cases what we do is we compare models using some criteria such as information selection criteria, pseudo R^2, and Hosmer Lemeshew statistics and we prefer the one with the better value based on the decision criteria in each test statistics. For instance, Long & Freese (2014) stated that pseudo-R^2 can be used as rough measure of the models' adequacy while they also mentioned that we cannot be certain of the optimality of the model selected using this criteria. Given this, in all our models we noted that the pseudo-R^2 is improved when we consider all the available covariates and when we control for the Kebele level dummies. For this reason, our all discussions are based on the estimation results in which we considered key covariates and we control the Kebele dummies. The other goodness of fit measure is using the Hosmer and Lemeshew statistics, which is used to assess the overall fit of the model. We used this test after fitting all the binary logistic models and the result indicate goodness of fit of the models (see Table 4B, appendix).

4.2.2 Technology Adoption Decision: Binary Logit Model

We estimated the logistic regression models as specified in the methodology part using maximum likelihood method and the results are provided in tables Table 4.6. The results in Table 4.6 show the effect of LOC and aspiration on adoption decision of agricultural technologies: fertilizers, push pull technology, irrigation, and pesticides. The full results with Kebele fixed effects are provided in Table 1B in the appendix.

From Table 4.6, we infer that internal LOC is statistically significant and positively associated with adoption of all the agricultural technologies: fertilizer, irrigation, pesticides, and PPT. The higher the households' internal LOC, the higher the probability of adopting these agricultural technologies. In contrast, external LOC is found to be statistically significant and negatively associated with adoption of irrigation and willingness to adopt PPT while it is statistically insignificant in the case of fertilizer and pesticides. Therefore, households who believe that they have control over events pertaining to their life are associated with high willingness to adopt PPT while households believing that event related to their life are controlled by external factors have less willingness to adopt PPT. Besides, aspiration is also found to be statistically significant and positively associated with adoption of irrigation, pesticides, and PPT while insignificant in the case of fertilizer adoption. When we make the interpretation, it is important to note that having higher internal LOC implies indirectly having low external LOC and vice versa.

Apart from above discussion, one important finding is that when households are provided full information of a given technology, their propensity to adopt the technology increase as expected. Before information on PPT is provided, previously only 18.24 percent of households were adopting PPT while 81.76 percent of households were non-adopters. However, after provision of information on PPT, 76.67 percent of households are found to be willing to adopt PPT only because full information is provided.

Table 4.6: Logistic regression of LOC and aspiration on technology adoption

Variables	(1) Fertilizer (1/0)	(2) Irrigation (1/0)	(3) Pesticides (1/0)	(4) PPT (1/0)	(5) PPT adoption willingness (1/0)
Internal LOC	0.1724**	0.0929*	0.1474***	0.1102*	0.1263**
	(0.07)	(0.0556)	(0.0447)	(0.0573)	(0.0528)
External LOC	0.0989	-0.1166**	-0.062	-0.0748	-0.1659***
	(0.0726)	(0.0582)	(0.0469)	(0.0602)	(0.0539)
Aspiration	0.2806	0.2347**	0.1846**	0.1562*	0.0719
	(0.1855)	(0.0963)	(0.0889)	(0.092)	(0.1186)
Age (Years)	-0.023***	0.0023	-0.0107***	-0.013***	-0.0186***
	(0.006)	(0.0047)	(0.0038)	(0.0048)	(0.0042)
Sex (Male=1)	0.8459***	-0.2513	0.5755***	1.143***	0.6533***
	(0.1863)	(0.182)	(0.1332)	(0.2791)	(0.1355)
Household size (Number)	0.1606***	0.0386	0.0322	0.1585***	0.1626***
	(0.0415)	(0.0308)	(0.0248)	(0.0285)	(0.0295)
Land size (ha, log)	0.8266***	0.4896***	0.1865**	-0.0485	-0.0061
	(0.1284)	(0.0989)	(0.0789)	(0.0967)	(0.0067)
Access to credit (1/0)	0.4576***	0.1515	0.4699***	-0.13	0.3163***
	(0.1417)	(0.1146)	(0.0942)	(0.1146)	(0.1095)
Access to extension service (1/0)	0.7885***	0.4385***	0.6931***	0.9745***	0.7995***
	(0.1446)	(0.1173)	(0.0923)	(0.1246)	(0.1067)
Distance to market (in walking minutes)	-0.0008	0.0008	0.0002	-0.0021	-0.0048***
	(0.0016)	(0.0015)	(0.0011)	(0.0015)	(0.0013)
Number of plots (Number)	0.2842***	-0.0316	0.1374**	0.0145	0.0381

	(0.105)	(0.0709)	(0.0601)	(0.0047)	(0.0461)
Cooperative membership (1/0)	-0.0241	-0.0254	-0.1232	0.2455	0.2584**
	(0.1474)	(0.1254)	(0.0983)	(0.123)	(0.11)
Education dummy (1/0)	0.337**	0.0524	0.2037**		
	(0.1562)	(0.1147)	(0.0916)		
Primary School (1/0)				0.4373***	0.1909*
				(0.1163)	(0.1106)
Schooling grade 9 and above (1/0)				-0.15	-0.0695
				(0.283)	(0.2713)
PPT information (1/0)				0.5831***	0.1392
				(0.1118)	(0.1189)
Kebele fixed effects	Yes	Yes	Yes	Yes	Yes
Constant	1.3078**	-2.472***	-0.6392*	-3.833***	0.0002
	(0.6025)	(0.5154)	(0.3579)	(0.4771)	(0.3918)
Observations	2,933	2,933	2,933	2,933	2,933
Pseudo R^2	0.2925	0.2994	0.1344	0.1348	0.1719

Source: Author's computation

Note: *LOC stands for Locus of Control. LOC (both internal and external) and aspiration are measured as continuous variable (indexes). In all regressions, standard errors are adjusted for 2,993 clusters using household's id. Asterisks: *, ** and *** indicate statistical significance of coefficients at 10%, 5% and 1%, respectively.*

The sign of the coefficient in the logit regression output are also the sign of the marginal effect of the respective explanatory variables (Cameron & Trivedi, 2009). Therefore, despite the difference in the magnitude of marginal effects, the sign or direction of the relationships are directly interpreted from the sign of the coefficient for all respective independent variables. In Table 4.7, we present the Average Marginal effect (AMEs). The values are the average marginal effects of a one standard deviation (SD) change in the explanatory variables on the probability of the outcome variables. For instance, one standard deviation increase in internal LOC of households is associated with 0.012 or 1.2 percent increase in the probability of adopting irrigation practice. The other coefficients are interpreted in a similar fashion. This results are very close with the findings of Abay et al., (2017) in which they found 1.5-2 percent increment in probability of adopting chemical fertilizers for a standard deviation increase in internal LOC, and 1-1.4 percent reduction in probability of adopting chemical fertilizers for a standard deviation increase in external LOC. We also report the odds ratio and the marginal effects on the odds ratio of technology adoption for optional interpretations. The results are provided in Table 1B.2 and Table 1B.3 in the appendix. The coefficient are used in interpreting the direction of effect of the independent variables.

Table 4.7: Average marginal effects (AMEs) of LOC and Aspiration on technology adoption

Constructs		Pr(Irrigation)	Pr(PPT)	Pr(Fertilizer)	Pr(Pesticides)
Internal LOC	SD	0.012	0.015	0.014	0.029
	p-value	0.097	0.060	0.010	0.001
External LOC	SD	-0.015	-0.010	0.008	-0.012
	p-value	0.041	0.205	0.163	0.118
Aspiration	SD	0.018	0.013	0.014	0.022
	p-value	0.016	0.096	0.112	0.035

Source: Author's computation

Note: *Marginal changes on the probability of technology adoption are reported for a standard deviation (SD) change in LOC and aspiration.*

Overall, regardless of the method of interpretations (using coefficients, odds ratio, marginal effects) we use, the results tell us that higher internal LOC and higher aspiration levels are associated with higher propensity to adopt or use certain agricultural technologies including irrigation, push pull technology, fertilizers, and pesticides. In contrast, though not in all cases, households having external LOC are less likely to adopt agricultural technologies.

4.2.3 Intensity of Technology Adoption

We express intensity of adoption in two ways: 1) as continuous measure that is the amount of input used, for instance amount of dap/urea used, and 2) as a count measure, expressed in terms of the number of agricultural inputs a farming household adopts and uses.

4.2.3.1 Adoption measured as continuous variable: Multiple Linear Regression Model

Taffesse & Tadesse (2017) stated that the effects of LOC are more significant on farmers' decision whether to adopt or not a certain agricultural technology rather than decisions on the intensity of adoption once the adoption decision is made. However, as discussed in the descriptive part reasonable differences also exist in terms of intensity of adoption for which LOC and aspiration. Therefore, it is helpful to explore these observable differences among farmers in terms of intensity of adoption.

The results in Table 4.8 confirm the results from the descriptive part in which we graphically showed that internal LOC and aspiration to be positively associated with total use of DAP/NPS and Urea in maize plots. Internal LOC and aspiration level have a consistent significant in the intensity of use of DAP/NPS, urea and pesticides. In contrast, external LOC is found to be insignificant in most cases. Nevertheless, the sign of relationship is negative in two of the three technologies.

Specifically, those farming households who have high internal LOC that is those who perceive that life outcomes can be sufficiently influenced or controlled, are more likely to use more of the inputs, DAP/NPS, urea, and pesticides. Besides, households with high aspiration level are also associated with high use of these inputs. These result of OLS estimation of the multiple regression model support the previous results of the binary logistic regressions.

Table 4.8: OLS estimates of the effects of Locus of control, Aspiration on Intensity of Adoption

Variables	DAP (kg)	Urea (kg)	Pesticides (kg)
Internal LOC	0.024**	0.029**	0.037***
	(0.012)	(0.013)	(0.011)
External LOC	0.001	-0.002	-0.022**
	(0.016)	(0.017)	(0.011)
Aspiration	0.06***	0.05***	0.034*
	(0.018)	(0.019)	(0.019)
Age (Years)	-0.004***	-0.005***	-0.002***
	(0.001)	(0.001)	(0.001)
Sex (Male=1)	0.129**	0.136**	0.107***

Variables	DAP (kg)	Urea (kg)	Pesticides (kg)
	(0.052)	(0.055)	(0.031)
Household size (Number)	0.03***	0.036***	0.021***
	(0.007)	(0.007)	(0.006)
Education (1/0)	-0.008	-0.008	0.048**
	(0.023)	(0.025)	(0.022)
Access to credit (1/0)	0.041*	0.06**	0.08***
	(0.024)	(0.025)	(0.023)
Access to extension service (1/0)	0.15***	0.148***	0.107***
	(0.027)	(0.028)	(0.022)
Distance to market (in walking minutes)	0.002	0.0001	0.002
	(0.003)	(0.003)	(0.003)
Number of plots (Number)	0.053***	0.045***	0.039***
	(0.012)	(0.013)	(0.014)
Cooperative membership (1/0)	0.071**	0.04	-0.015
	(0.028)	(0.029)	(0.023)
Maize plot size (ha, log)	0.687***	0.661***	
	(0.042)	(0.042)	
Owned maize plot (ha, log)	0.216***	0.191***	
	(0.068)	(0.071)	
Land size (ha, log)			0.065***
			(0.019)
Kebele fixed effects	Yes	Yes	Yes
Constant	4.781***	4.801***	0.227**
	(0.121)	(0.118)	(0.091)
Observations	2933	2933	2933
R-squared	0.511	0.49	0.239

Source: Author's computation

Note: *All dependent variables are in log form. In all the regressions, standard errors are adjusted for 2,993 clusters using household's id. Asterisks: *, ** and *** indicate statistical significance of coefficients at 10%, 5% and 1%, respectively.*

The coefficients in Table 4.8 are not directly interpreted as the dependent variables are in log forms as in the logistic regression models. For simplicity of interpretation, we report the average marginal effects in table 4.9 below. Given results in Table 4.9, a one standard deviation increases in farming households' internal LOC is associated with 2.4 percent increase in use of DAP/NPS in maize plots. Similarly, a one standard deviation increase in the aspiration level of farming households' is associated with 3.7 percent increase in use of DAP/NPS in maize plots.

The same ways for urea, a one standard deviation increase in farming households' internal LOC and aspiration level are associated with 2.9 percent and 3 percent increase in consumption of urea in maize plots, respectively. A one standard deviation increase in internal LOC and aspiration of households' is associated with 3.7 percent and 2.1 percent increase in consumption of pesticides in crop plots, respectively. All the values in Table 4.11 are interpreted the same way.

Table 4.9: Average marginal effects of LOC and aspiration on intensity of adoption

		DAP (kg)	Urea (kg)	Pesticides (liter)
	SD	0.024	0.029	0.037
Internal LOC	p-value	0.048	0.025	0.001
	SD	0.001	-0.002	-0.022
External LOC	p-value	0.938	0.919	0.044
	SD	0.037	0.030	0.021
Aspiration	p-value	0.001	0.010	0.072

Source: Author's computation

Note: *Average marginal changes are reported for a standard deviation (SD) change in the explanatory variables.*

4.2.3.2 Adoption measured as count variable: Ordered Logit Models

Given the count measure for technology adoption, the adoption status of households' ranges from no adoption at all (non-adopters) to adopting all the stated technologies. Thus, the outcome variable assumes a values 0, 1, 2, 3, and 4. We estimated the ordered logistic model and results are reported in Table 4.10 below. The easy way for interpretation of results from the estimation of ordered logistic models is to estimate the AMEs of explanatory variables on the probability of the outcome. Table 4.11 are results of AME computed from the estimation of the ordered logistic regression, in which the outcome takes five values (0, 1, 2, 3, and 4).

Table 4.10: Estimation results of the ordered logistic regression models

Variables	Number of Technologies Adopted
Internal LOC	0.174***
	(0.038)
External LOC	-0.059
	(0.044)
Aspiration	0.249***
	(0.08)
Age (Years)	-0.013***
	(0.003)
Sex (Male=1)	0.628***
	(0.129)
Household Size (Number)	0.108***
	(0.021)
Education (1/0)	0.295***
	(0.079)
Land size (ha, log)	0.38***
	(0.069)
Access to credit (1/0)	0.362***
	(0.079)
Access to extension service (1/0)	0.993***
	(0.082)
Distance to market (in walking minutes)	0.001
	(0.001)
Number of plots(Number)	0.186***
	(0.049)

Variables	Number of Technologies Adopted
Cooperative membership (1/0)	0.066
	(0.082)
Kebele fixed effects	Yes
/cut1	-1.28***
	(0.333)
/cut2	1.032***
	(0.331)
/cut3	3.486***
	(0.337)
/cut4	5.838***
	(0.349)
Observations	2933
Pseudo R^2	0.114

Source: Author's computation

Note: *In all the regressions, standard errors are adjusted for 2,993 clusters using household's id. Asterisks: *, ** and *** indicate statistical significance of coefficients at 10%, 5% and 1%, respectively.*

From results in Table 4.11 internal LOC has have a negative marginal effects for the first two categories while it has a positive marginal effects on the last two categories, column (4) and (5). On the other hand, external LOC has a positive relationship with the first three categories while negatively related with the last two categories, but it is statistically insignificant. The positive coefficient of external LOC is exactly opposite to the effect of internal LOC. Aspiration is statistically significant and negatively related with the first two categories while statistically significant and positively related with the last three categories, column (1), (2) and (3).

These results have an interesting interpretations. The -0.008 indicates, on average, a one standard deviation increase in internal LOC of households reduces the probability of identifying in category one, as a non-adopter by 0.8 percent, and reduces the probability of identifying in category two, as adopter of one technology by 2.1 percent. On the other hand, it increases the probability of identifying the household in the fourth category, as adopter of three technologies by 2.1 percent, and increases the probability of identifying the household in the fifth category, as adopter of four technologies by 0.6 percent. This implies, having internal LOC is associated with adoption of more number of technologies.

The same way, a one standard deviation increase in aspiration level of farming households reduces the probability of being in the first category, as non-adopter by 0.7 percent while reduce the probability of being in the second category, as adopter of just one technology by 1.8 percent. On the other hand, it increases the probability of being in the third category, as adopter of two technologies by 0.1 percent, increases the probability of being in the fourth category, as adopter of three technologies by 1.8 percent, increases the probability of being in the last category, as adopter of four technologies by 0.6 percent. This implies having higher aspiration level is associated with adoption of more number of technologies.

Summing up, having higher internal LOC and higher aspiration level are associated with adoption of more number of technologies while having lower internal and lower aspiration level are associated with adoption of lower number of technologies.

Table 4.11: Average marginal effects of LOC and Aspiration on intensity of adoption

		(1)	(2)	(3)	(4)	(5)
Constructs		Non-adopter	One adopters	Two adopters	Three adopters	Four adopters
	SD	-0.008	-0.021	0.001	0.021	0.006
Internal LOC	p-value	0.000	0.000	0.142	0.000	0000
	SD	0.003	0.007	-0.001	-0.007	-0.002
External LOC	p-value	0.158	0.148	0.231	0.144	0.140
	SD	-0.007	-0.018	0.001	0.018	0.006
Aspiration	p-value	0.000	0.000	0.072	0.000	0.001

Source: Author’s computation

Note: *Average marginal changes are given for a standard deviation (SD) change in explanatory variables.*

CHAPTER FIVE

CONCLUSIONS AND POLICY IMPLICATIONS

In Ethiopia, the national development policies and plans recognize the importance of increasing agricultural productivity and its transformation to accelerate the overall development, and to ascertain food security and poverty reduction. To achieve agricultural productivity and its objectives, adoption of agricultural technologies is a key strategy of the government.

In this study, we examined the effect of farming households' locus of control and aspiration on their technology adoption decisions and intensity of adoption. Traditionally, it is believed that farmers' external constraints mostly related with economic, institutional, and market related factors influence farmers' adoption of agricultural technologies. Besides the external constraints, psycho-behavioral aspects related to decision makers found to be correlated with farmers' adoption decisions and intensity of adoption. The purpose of this thesis was to quantify the effects of locus of control and aspiration, which are key indicators of pyscho-behavioral factors, on technology adoption in Northwest Ethiopia. We have used econometric methods using a cross-sectional survey data collected in December 2020.

We find that farming households who believe that they have control or influence on events pertaining to their life (having internal locus of control) to be associated with higher propensity to adopt certain agricultural technologies including irrigation, fertilizer, push pull technology and pesticides. Besides, households who have a better aspiration to a better life outcomes (in terms of education, income, asset, and social status) are associated with a higher propensity to adopt agricultural technologies including irrigation practices, fertilizers, pesticides, and push pull technologies.

In contrast, farmers who believe that their actions, decisions (including whether to adopt or not agricultural technologies) are controlled or influenced by external factors (having external locus of control) are associated with less propensity to adopt agricultural technologies. While the sign of effect for external locus of control on adoption is negative and consistent in all cases, it is found to be statistically insignificant in most cases. We found same results on the effect of locus of control and aspiration on intensity of adoption. The results imply even between adopters, those farmers' who have internal locus of control and high aspiration level are associated with adoption of more number of technologies and more use of inputs.

Our results suggest that interventions that enhances farming households' psychological and behavioral characteristics can play a role in the promotion of agricultural technologies. Therefore, we believe that effectively using the extension system for improving farmers' psychological capital (internal locus of control and aspiration) will play part in promoting the adoption of agricultural technologies. Provision of credit for the specific purpose of adoption of agricultural technologies, market access for both inputs and outputs, and access to information (particularly for new agricultural technologies) will enhance the promotion of agricultural technologies. Finally, we suggest further studies to be undertake on same topic relying on large sample sizes and on panel or longitudinal data sets for considering the dynamic process of adoption and to consider the issues of endogeneity. Analyzing important factors that contribute to improved farming households' psychological characteristics will be another research work.

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Appendix:

Table A: Descriptive statistical tables and Figures

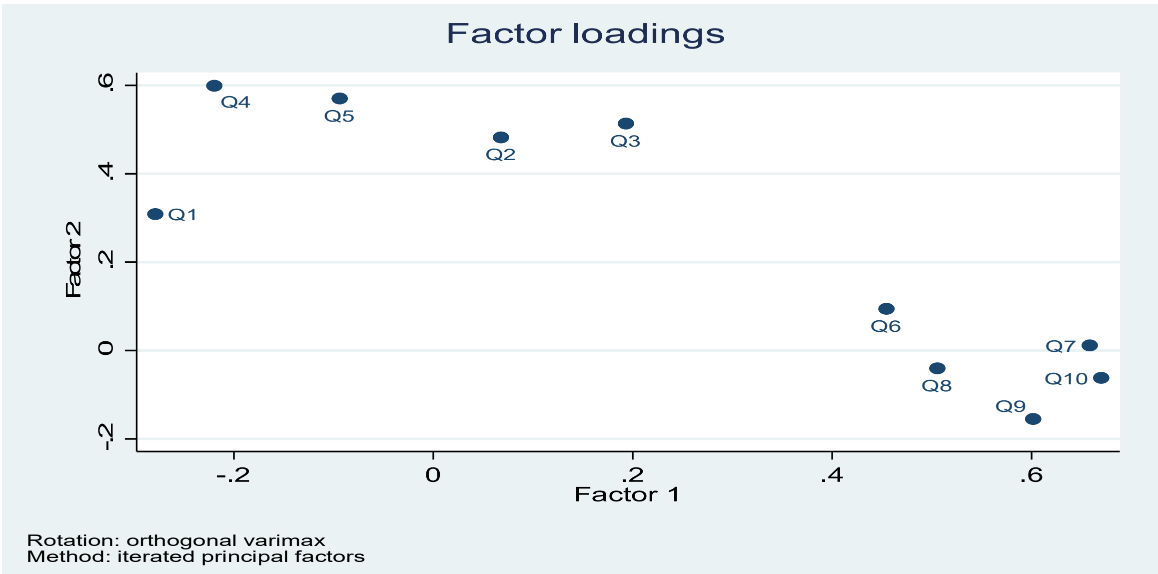

Figure 4.1: Factor loadings from the Rotter's (1966) LOC items

```
. alpha IS1-IS5

Test scale = mean(unstandardized items)

Average interitem covariance:     .5785024
Number of items in the scale:            5
Scale reliability coefficient:      0.5997

. alpha CS1-CS5

Test scale = mean(unstandardized items)

Average interitem covariance:     .8563572
Number of items in the scale:            5
Scale reliability coefficient:      0.6290

. alpha PS1-PS5

Test scale = mean(unstandardized items)

Average interitem covariance:      1.08701
Number of items in the scale:            5
Scale reliability coefficient:      0.7174
```

Table 1A: Cronbach's Alpha for LOC items

. tab loc1 irrigation, chi

Internal-External LOC scale(1/0))	If irrigation is used in at least one plot: No	Yes	Total
External LOC	432	110	542
Internal LOC	1,753	638	2,391
Total	2,185	748	2,933

Pearson chi2(1) = 9.4906 Pr = 0.002

. tab loc1 ppt, chi

Internal-External LOC scale(1/0))	Push Pull Technology adoption status: Non Adopt	Adopter	Total
External LOC	474	68	542
Internal LOC	1,924	467	2,391
Total	2,398	535	2,933

Pearson chi2(1) = 14.4570 Pr = 0.000

. tab loc1 fertilizer_other_d, chi

Internal-External LOC scale(1/0))	Adoption status of Fertilizer in all other crop plots: Non Adopt	Adopter	Total
External LOC	99	443	542
Internal LOC	285	2,106	2,391
Total	384	2,549	2,933

Pearson chi2(1) = 15.6382 Pr = 0.000

. tab loc1 insecticide_d, chi

Internal-External LOC scale(1/0))	Adoption status of Insecticides in all crop plots: Non Adopt	Adopter	Total
External LOC	250	292	542
Internal LOC	878	1,513	2,391
Total	1,128	1,805	2,933

Pearson chi2(1) = 16.5108 Pr = 0.000

. tab loc1 ppt_adoption_willingness, chi

Internal-External LOC scale(1/0))	Willingness to adopt push pull technology, given information on it: No	yes	Total
External LOC	208	334	542
Internal LOC	476	1,915	2,391
Total	684	2,249	2,933

Pearson chi2(1) = 84.2760 Pr = 0.000

Table 2A: Unconditional correlations between technology adoption, and LOC and aspiration

Figure 1A1: Nonparametric regression of LOC and Aspiration on technology Adoption

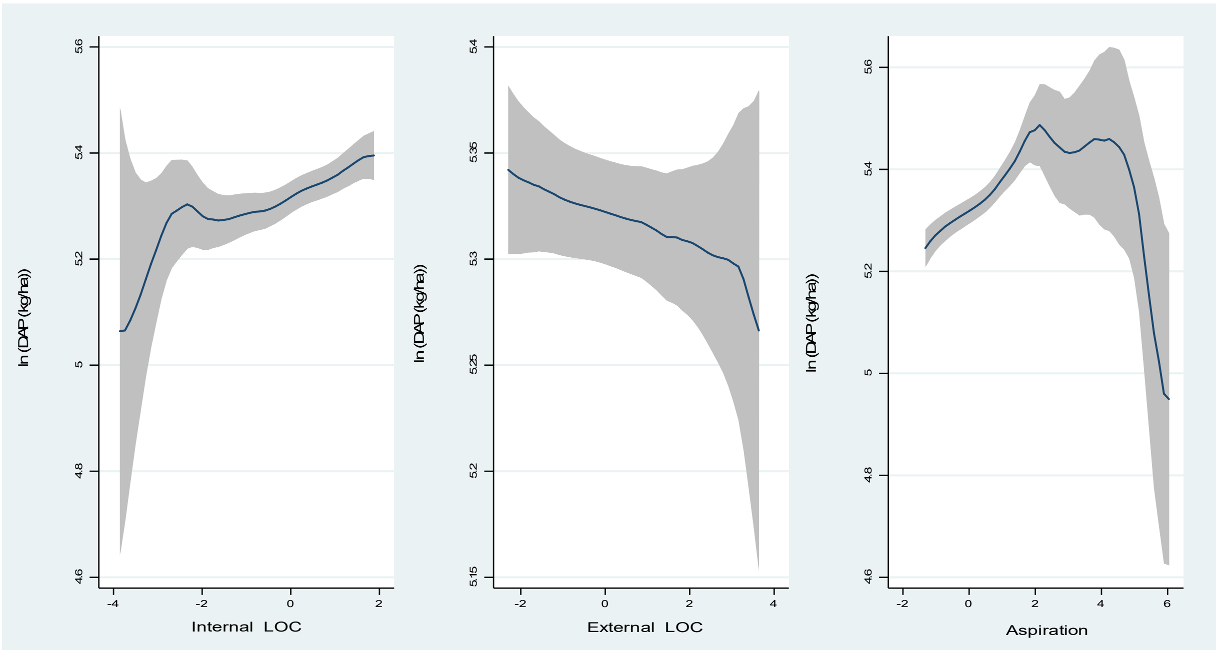

Figure 1A1: Nonparametric regression of LOC and Aspiration on intensity of adoption (DAP/ha)

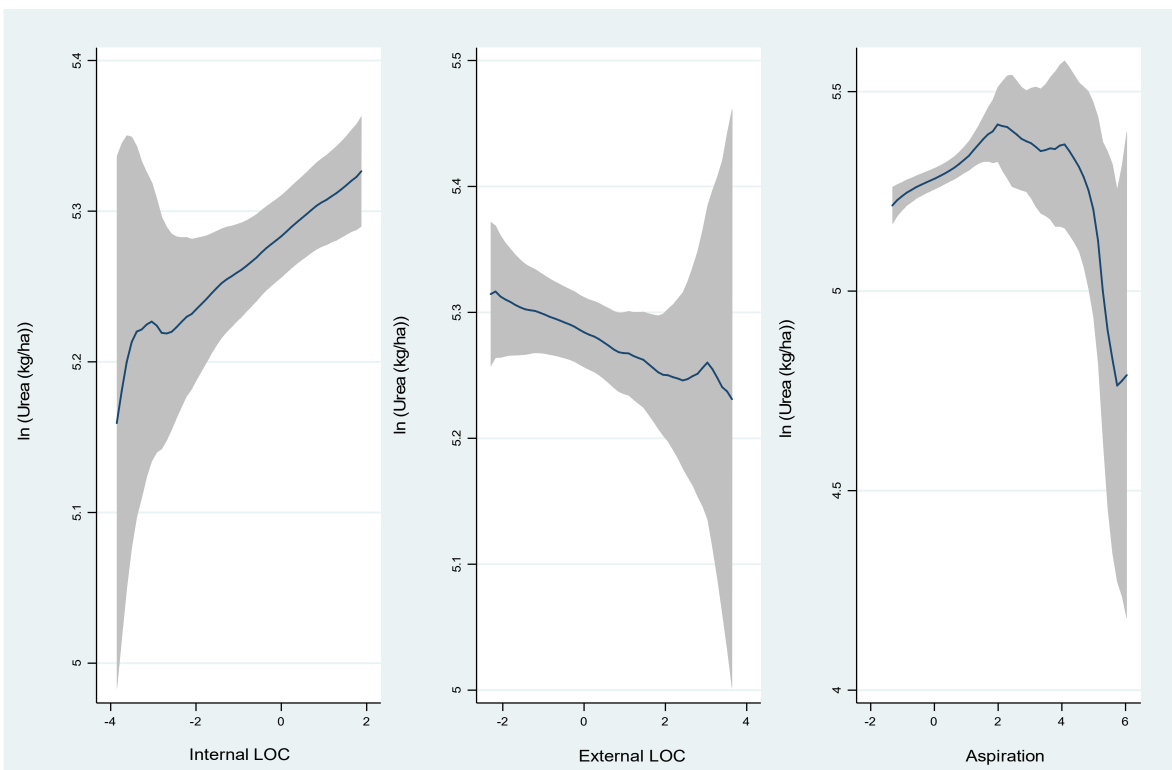

Figure 1A2: Nonparametric regression of LOC and Aspiration on intensity of adoption (Urea/ha)

TABLE B: Econometric Model Estimation Results

TABLE 1B: Estimation results of binary logistic regressions of LOC and aspiration on technology adoption

Explanatory Variables	(1) Fertilizer	(2) Pesticides	(3) Irrigation	(4) PPT	(5) PPT Adoption willingness
Internal LOC	0.172**	0.147***	0.093*	0.11*	0.126**
	(0.07)	(.0045)	(0.056)	(0.057)	(0.053)
External LOC	0.099	-0.062	-0.117**	-0.075	-0.166***
	(0.073)	(0.047)	(0.058)	(0.06)	(0.054)
Aspiration	0.281	0.185**	0.235**	0.156*	0.072
	(0.186)	(0.089)	(0.096)	(0.092)	(0.119)
Age (Years)	-0.023***	-0.011***	0.0002	-0.013***	-0.019***
	(0.006)	(0.004)	(0.005)	(0.005)	(0.004)
Sex (Male=1)	0.846***	0.575***	-0.251	1.143***	0.653***
	(0.186)	(0.133)	(0.182)	(0.279)	(0.135)
Household size (Number)	0.161***	0.032	0.039	0.159***	0.163***
	(0.041)	(0.025)	(0.031)	(0.029)	(0.029)
Education (1/0)	0.337**	0.204**	0.052		
	(0.156)	(0.092)	(0.115)		
Land size (ha, log)	0.827***	0.186**	0.49***	-0.048	0.798***
	(0.128)	(0.079)	(0.099)	(0.097)	(0.12)
Access to credit (1/0)	0.458***	0.47***	0.152	-0.13	0.316***
	(0.142)	(0.094)	(0.115)	(0.115)	(0.11)
Access to extension service (1/0)	0.788***	0.693***	0.439***	0.974***	0.8***
	(0.145)	(0.092)	(0.117)	(0.125)	(0.107)
Distance to market (Walking minutes)	-0.001	0.001	0.001	-0.002	-0.005***
	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
Number of plots (Number)	0.284***	0.137**	-0.032	0.015	0.038
	(0.105)	(0.06)	(0.071)	(0.005)	(0.046)
Cooperative membership (1/0)	-0.024	-0.123	-0.025	0.245	0.258**
	(0.147)	(0.098)	(0.125)	(0.123)	(0.11)
Illiterate (Base variable)					
Primary schooling				0.437***	0.191*

(1/0)					
				(0.116)	(0.111)
Schooling grade 9 and above(1/0)				-0.15	-0.069
5gna (base kebele)					
Abaseme	-0.194	-0.423	4.259***	0.483	-0.935**
	(0.629)	(0.369)	(0.539)	(0.463)	(0.439)
Agumamit (1/0)	-0.019	0.248	2.079***	0.58	-0.301
	(0.729)	(0.417)	(0.468)	(0.471)	(0.524)
Arbawash (1/0)	-0.115	0.086	0.397	-0.235	-0.589
	(0.603)	(0.334)	(0.481)	(0.454)	(0.403)
Awunt (1/0)	-0.89	-0.335	-15.844***	-0.476	-0.051
	(0.606)	(0.34)	(0.404)	(0.473)	(0.49)
Berekegn (1/0)	0.382	0.378	-1.635**	0.707	-0.393
	(0.621)	(0.35)	(0.821)	(0.433)	(0.392)
Dingra (1/0)	0.338	1.316***	-1.787*	0.376	-1.096***
	(0.674)	(0.424)	(1.072)	(0.446)	(0.423)
Dumeri (1/0)	-0.702	-0.582	1.011*	0.306	0.61
	(0.638)	(0.404)	(0.525)	(0.497)	(0.559)
Frat (1/0)	-0.648	0.806**	-1.119**	-0.107	-1.049***
	(0.571)	(0.327)	(0.516)	(0.389)	(0.366)
Guay (1/0)	-0.893*	0.099	2.141***	-0.077	-0.536
	(0.536)	(0.321)	(0.413)	(0.414)	(0.406)
Hodanshe (1/0)	13.471***	-0.924**	1.468***	0.189	-0.196
	(0.514)	(0.394)	(0.476)	(0.47)	(0.567)
Jiga (1/0)	-1.04*	-0.763**	1.931***	0.413	-1.283***
	(0.59)	(0.34)	(0.437)	(0.429)	(0.412)
Mana (1/0)	0.795	-0.556	1.312***	1.201***	-0.203
	(0.664)	(0.341)	(.442)	(0.413)	(0.451)
Mankusa (1/0)	-0.698	-1.065***	2.082***	-0.096	-0.405
	(0.521)	(0.306)	(0.404)	(0.398)	(0.377)
Mebesh (1/0)	14.49***	-0.569	0.15	1.227**	0.428
	(0.6)	(0.435)	(0.731)	(0.551)	(0.73)
Mender (1/0)	1.246	1.237**	0.252	-0.206	0.156
	(1.27)	(0.489)	(0.536)	(0.501)	(0.575)
Mircha (1/0)	-0.526	-0.154	-2.495**	-0.756	-1.084***
	(.614)	(.341)	(1.074)	(.479)	(0.417)
Rados (1/0)	1.471*	-0.177	-0.052	0.441	0.033
	(0.764)	(0.326)	(0.5)	(0.411)	(0.396)
Shimebed (1/0)	-0.859	0.193	-0.603	0.577	-1.248***
	(0.608)	(0.377)	(0.645)	(0.467)	(0.45)
Wonge (1/0)	-0.13	-0.696**	-0.22	0.216	-1.135***
	(0.631)	(0.326)	(0.487)	(0.414)	(0.39)
Yeraber (1/0)	-0.233	-0.14	1.48***	0.191	-0.026

	(0.698)	(0.385)	(0.477)	(0.502)	(0.572)
Yesheret (1/0)	-0.356	0.349	1.28***	-1.045	-0.913**
	(.669)	(.387)	(0.473)	(0.685)	(0.421)
Zaba (1/0)	-0.66	0.021	2.567***	-0.174	0.083
	(0.593)	(0.347)	(0.441)	(0.425)	(0.468)
Malan Lijit (1/0)	-1.144**	-0.072	-0.203	0.864**	-0.899**
	(0.551)	(0.345)	(0.534)	(0.423)	(0.419)
Segodet Mekerecha (1/0)	-1.533**	0.307	-1.362	0.395	0.3
	(0.656)	(0.416)	(1.103)	(0.562)	(0.592)
Bugi (1/0)	-1.299**	-0.84**	1.578***	-0.173	-1.122**
	(0.626)	(0.394)	(0.489)	(0.534)	(0.465)
Arbaytu Ensesa (1/0)	-0.792	-0.325	3.612***	0.075	-1.437***
	(0.636)	(0.388)	(0.514)	(0.489)	(0.456)
Azmer (1/0)	2.122**	0.95***	-0.319	-0.591	0.447
	(0.827)	(0.338)	(0.512)	(0.464)	(0.401)
Agbi (1/0)	-0.923*	0.924***	1.943***	-0.038	-0.883**
	(0.515)	(0.337)	(0.419)	(0.421)	(0.379)
Atat Ashti (1/0)	0.093	1.055**	0.321	0.479	0.006
	(0.777)	(0.45)	(0.56)	(0.482)	(0.559)
Ergb (1/0)	-3.228***	1.912***	-1.675**	-0.39	0.056
	(0.512)	(0.357)	(0.7)	(0.429)	(0.368)
Kuni Sankesta (1/0)	-0.196	0.06	0.088	0.005	-0.024
	(0.557)	(0.32)	(0.465)	(0.402)	(0.401)
Woynema (1/0)	-.937*	1.043***	2.781***	0.098	-0.581
	(0.542)	(0.333)	(0.423)	(0.429)	(0.407)
Waga (1/0)	.802	-.735**	.843*	.647	-0.379
	(0.669)	(0.329)	(0.457)	(0.415)	(0.403)
Zengebel Bedega (1/0)	0.349	0.145	-0.797	0.763*	0.006
	(0.645)	(0.338)	(.627)	(0.423)	(0.441)
Jamat Enkokema (1/0)	-0.546	-0.493	0.202	0.538	-1.317***
	(0.728)	(0.361)	(0.517)	(0.454)	(0.433)
Gorefa (1/0)	-1.124*	-.197	2.924***	0.644	-1.061**
	(0.593)	(0.38)	(0.483)	(0.457)	(0.445)
Fetegem (1/0)	0.526	0.4	-1.556	-0.923	-0.394
	(0.663)	(0.368)	(1.068)	(0.686)	(0.461)

Constant	1.308**	-.639*	-2.472***	-3.833***	0.00
	(0.602)	(0.358)	(0.515)	(0.477)	(0.392)
Observations	2933	2933	2933	2933	2933
Pseudo R^2	0.293	0.134	0.299	0.135	0.172

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

TABLE 1B.1: AMEs of LOC and Aspiration on probability of technology Adoption

```
. mchange internal_LOC external_LOC asp_in

logit: Changes in Pr(y) | Number of obs =

Expression: Pr(irrigation), predict(pr)

             |   Change   p-value
-------------+-------------------
internal LOC |
          +1 |    0.012     0.097
         +SD |    0.012     0.097
    Marginal |    0.012     0.094
external LOC |
          +1 |   -0.015     0.041
         +SD |   -0.015     0.041
    Marginal |   -0.015     0.044
asp index    |
          +1 |    0.031     0.017
         +SD |    0.018     0.016
    Marginal |    0.030     0.014

Average predictions

             |       No       Yes
-------------+-------------------
  Pr(y|base) |    0.745     0.255
```

```
. mchange internal_LOC external_LOC asp_index

logit: Changes in Pr(y) | Number of obs = 2933

Expression: Pr(ppt), predict(pr)

             |   Change   p-value
-------------+-------------------
internal LOC |
          +1 |    0.015     0.060
         +SD |    0.015     0.060
    Marginal |    0.014     0.054
external LOC |
          +1 |   -0.010     0.205
         +SD |   -0.010     0.205
    Marginal |   -0.010     0.214
asp index    |
          +1 |    0.021     0.101
         +SD |    0.013     0.096
    Marginal |    0.020     0.089

Average predictions

             | Non Ado~r   Adopter
-------------+-------------------
  Pr(y|base) |    0.818     0.182
```

```
. mchange internal_LOC external_LOC asp_index

logit: Changes in Pr(y) | Number of obs = 2864

Expression: Pr(fertilizer_other_d), predict(pr)

             |    Change   p-value
-------------+--------------------
internal LOC |
          +1 |     0.014     0.010
         +SD |     0.014     0.010
    Marginal |     0.014     0.013
external LOC |
          +1 |     0.008     0.163
         +SD |     0.008     0.163
    Marginal |     0.008     0.173
asp index    |
          +1 |     0.022     0.102
         +SD |     0.014     0.112
    Marginal |     0.023     0.128

Average predictions

             |  Non Ado~r   Adopter
-------------+--------------------
  Pr(y|base) |     0.134     0.866
```

```
. mchange internal_LOC external_LOC asp_index

logit: Changes in Pr(y) | Number of obs = 2933

Expression: Pr(insecticide_d), predict(pr)

             |    Change   p-value
-------------+--------------------
internal LOC |
          +1 |     0.029     0.001
         +SD |     0.029     0.001
    Marginal |     0.029     0.001
external LOC |
          +1 |    -0.012     0.188
         +SD |    -0.012     0.188
    Marginal |    -0.012     0.186
asp index    |
          +1 |     0.036     0.034
         +SD |     0.022     0.035
    Marginal |     0.036     0.037

Average predictions

             |  Non Ado~r   Adopter
-------------+--------------------
  Pr(y|base) |     0.385     0.615
```

```
. mchange internal_LOC external_LOC asp_index

logit: Changes in Pr(y) | Number of obs = 2933

Expression: Pr(ppt_adoption_willingness), predict(pr)

             |    Change   p-value
-------------+--------------------
internal LOC |
          +1 |     0.018     0.014
         +SD |     0.018     0.014
    Marginal |     0.018     0.016
external LOC |
          +1 |    -0.025     0.003
         +SD |    -0.025     0.003
    Marginal |    -0.024     0.002
asp index    |
          +1 |     0.010     0.538
         +SD |     0.006     0.540
    Marginal |     0.010     0.544

Average predictions

             |        No       yes
-------------+--------------------
  Pr(y|base) |     0.233     0.767
```

TABLE 1B.2: Odds ratio of the logistic regression of LOC and aspiration on technology adoption

	(1)	(2)	(3)	(4)	(5)
Constructs	Irrigation (1/0)	PPT (1/0)	Pesticides (1/0)	Fertilizer (1/0)	PPT adoption Willingness (1/0)
Internal LOC	1.097*	1.117*	1.159***	1.188**	1.135**

	(0.061)	(0.064)	(0.052)	(0.083)	(0.06)
External LOC	0.89**	0.928	0.94	1.104	0.847***
	(0.052)	(0.056)	(0.044)	(0.08)	(0.046)
Aspiration	1.265**	1.169*	1.203**	1.324	1.075
	(0.122)	(0.108)	(0.107)	(0.246)	(.127)
Observations	2856	2933	2933	2864	2933
Pseudo R^2	0.29	0.135	0.134	0.286	0.172

Standard errors are in parentheses

**** p<.01, ** p<.05, * p<.1*

TABLE 1B.3: Percentage change in odds of technology adoption for % change in Standard Deviations (SD) of LOC and Aspiration

For Irrigation

```
. listcoef, help percent

logit (N=2933): Percentage change in odds

  Odds of: Yes vs No
```

	b	z	P>|z|	%	%StdX	SDofX
internal_LOC	0.0929	1.670	0.095	9.7	9.7	1.001
external_LOC	-0.1166	-2.003	0.045	-11.0	-11.0	1.001
asp_index	0.2347	2.438	0.015	26.5	15.2	0.604

For Push Pull Technology

```
. listcoef, help percent

logit (N=2933): Percentage change in odds

  Odds of: Adopter vs Non Adopter
```

	b	z	P>|z|	%	%StdX	SDofX
internal_LOC	0.1102	1.924	0.054	11.7	11.7	1.001
external_LOC	-0.0748	-1.242	0.214	-7.2	-7.2	1.001
asp_index	0.1562	1.698	0.089	16.9	9.9	0.604

For Pesticides

```
. listcoef, help percent

logit (N=2933): Percentage change in odds

  Odds of: Adopter vs Non Adopter
```

	b	z	P>|z|	%	%StdX	SDofX
internal_LOC	0.1474	3.298	0.001	15.9	15.9	1.001
external_LOC	-0.0620	-1.320	0.187	-6.0	-6.0	1.001
asp_index	0.1846	2.075	0.038	20.3	11.8	0.604

<u>For Fertilizer</u>

```
. listcoef, help percent

logit (N=2933): Percentage change in odds

  Odds of: Adopter vs Non Adopter
```

	b	z	P>|z|	%	%StdX	SDofX
internal_LOC	0.1724	2.463	0.014	18.8	18.8	1.001
external_LOC	0.0989	1.363	0.173	10.4	10.4	1.001
asp_index	0.2806	1.513	0.130	32.4	18.5	0.604

<u>For PPT adoption Willingness</u>

```
. listcoef, help percent

logit (N=2933): Percentage change in odds

  Odds of: yes vs No
```

	b	z	P>|z|	%	%StdX	SDofX
internal_LOC	0.1263	2.393	0.017	13.5	13.5	1.001
external_LOC	-0.1659	-3.076	0.002	-15.3	-15.3	1.001
asp_index	0.0719	0.607	0.544	7.5	4.4	0.604

TABLE 2B: OLS estimation of multiple linear regress of technology adoption

	(1)	(2)	(3)	(4)	(5)
Explanatory variables	ln(DAP (kg))	ln(Urea(kg))	ln(Pesticides (liter))	ln(DAP(kg/ ha)	ln(Urea(kg/h a))
Internal LOC	0.024**	0.029**	0.037***	0.025*	0.029**
	(0.012)	(0.013)	(0.011)	(0.013)	(0.014)
External LOC	0.001	-0.002	-0.022**	0.002	-0.003
	(.016)	(.017)	(0.011)	(0.018)	(0.018)
Aspiration	0.06***	0.05***	0.034*	.063***	0.052**
	(0.018)	(0.019)	(0.019)	(0.02)	(0.021)
Age (Years)	-0.004***	-0.005***	-0.002***	-0.005***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Sex (Male=1)	0.129**	0.136**	0.107***	0.139**	0.15**
	(0.052)	(0.055)	(0.031)	(0.058)	(0.063)
Household size (Number)	0.03***	0.036***	0.021***	0.033***	0.039***
	(0.007)	(0.007)	(0.006)	(0.008)	(0.007)
Education (1/0)	-0.008	-0.008	0.048**	-0.008	-0.009
	(0.023)	(0.025)	(0.022)	(0.025)	(0.027)
Maize plot size (ha, log)	0.687***	0.661***		-0.313***	-0.335***
	(0.042)	(0.042)		(0.045)	(0.046)
Owned maize plot size (ha, log)	0.216***	0.191***		0.24***	0.211***
Land size (ha, log)			0.065***		
			(0.019)		
	(0.068)	(0.071)		(0.071)	(0.074)
Access to credit (1/0)	0.041*	0.06**	0.08***	0.048*	0.07**
	(0.024)	(0.025)	(0.023)	(0.027)	(0.028)
Access to extension service (1/0)	0.15***	0.148***	0.107***	0.163***	0.16***
	(0.027)	(0.028)	(0.022)	(0.03)	(0.031)
Distance to market (in walking minutes)	-0.001	0.001	0.001	-0.002	-0.005***
	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
Number of plots (number)	0.053***	0.045***	0.039***	0.057***	0.052***
	(0.012)	(0.013)	(0.014)	(0.013)	(0.014)
Cooperative membership (1/0)	0.071**	0.04	-0.015	0.075**	0.044
	(0.028)	(0.029)	(0.023)	(0.031)	(0.032)

5gna (base kebele)

Abaseme	0.06	0.002	-0.175**	0.058	-0.001
	(0.1)	(0.1)	(0.081)	(0.106)	(0.107)
Agumamit (1/0)	0.23*	0.068	-0.039	0.22	0.054
	(0.136)	(0.135)	(0.095)	(0.144)	(0.143)
Arbawash (1/0)	-0.037	-0.027	-0.07	-0.036	-0.025
	(0.046)	(0.052)	(0.082)	(0.047)	(0.053)
Awunt (1/0)	-0.057	-.05	.035	-.069	-0.065
	(0.083)	(0.086)	(0.093)	(0.091)	(0.095)
Berekegn (1/0)	-0.08	-.098	.174*	-.089	-0.107
	(0.07)	(0.073)	(0.092)	(0.079)	(0.082)
Dingra (1/0)	-0.152	-0.211**	0.186**	-0.161	-0.219**
	(.095)	(0.098)	(.094)	(0.101)	(0.105)
Dumeri (1/0)	-0.176*	-0.228**	-0.093	-0.204	-0.255**
	(0.102)	(0.102)	(0.121)	(0.127)	(0.127)
Frat (1/0)	0.029	0.069	0.57***	0.025	0.05
	(0.072)	(0.076)	(0.085)	(0.073)	(0.083)
Guay (1/0)	0.057	0.003	-0.005	0.05	-.006
	(0.071)	(0.072)	(0.083)	(0.074)	(0.076)
Hodanshe (1/0)	0.094	-0.202	-0.131	0.087	-0.209
	(0.071)	(0.14)	(0.106)	(0.072)	(0.136)
Jiga (1/0)	-0.073	-0.228**	-0.153*	-0.094	-0.268**
	(0.077)	(0.096)	(0.087)	(.093)	(0.119)
Mana (1/0)	0.224***	0.018	-0.254***	0.221**	-0.003
	(0.082)	(0.094)	(0.076)	(0.086)	(0.105)
Mankusa (1/0)	-0.024	-0.383***	-0.251***	-0.041	-0.409***
	(0.099)	(0.106)	(0.077)	(0.106)	(0.115)
Mebesh (1/0)	0.053	0.06	-0.077	0.055	0.061
	(0.062)	(0.065)	(0.1)	(0.064)	(0.067)
Mender (1/0)	0.104	-0.136	0.246**	0.099	-0.147
	(0.069)	(0.116)	(0.103)	(0.07)	(0.12)
Mircha (1/0)	0.043	-0.09	-0.014	0.034	-0.103
	(0.077)	(0.078)	(0.085)	(0.082)	(.083)
Rados (1/0)	-0.14**	-0.19***	0.004	-0.164**	-0.213***
	(0.066)	(0.069)	(0.089)	(0.077)	(0.079)
Shimebed (1/0)	-0.008	-0.136	0.012	-0.035	-0.164
	(0.108)	(0.105)	(.092)	(0.129)	(0.127)
Wonge (1/0)	-0.082*	-0.152***	-0.15*	-0.083*	-0.154***
	(0.048)	(0.052)	(0.085)	(0.049)	(0.053)
Yeraber (1/0)	-0.294***	-0.328***	-0.036	-0.307***	-0.344***
	(0.102)	(0.106)	(0.095)	(0.109)	(0.112)
Yesheret (1/0)	0.019	-0.066	0.068	0.022	-0.064
	(0.054)	(0.067)	(0.09)	(0.056)	(0.068)
Zaba (1/0)	0.175***	0.019	-0.192**	0.172***	0.014
	(0.056)	(0.062)	(0.085)	(0.057)	(0.063)

Malan Lijit (1/0)	-0.47***	-0.336***	0.088	-0.529***	-0.358***
	(0.105)	(0.081)	(0.096)	(0.132)	(0.095)
Segodet Mekerecha (1/0)	-0.188***	-0.075	0.021	-0.187**	-0.073
	(0.072)	(0.068)	(0.099)	(0.073)	(0.069)
Bugi (1/0)	-0.253***	-0.256***	-0.136	-0.258***	-0.265***
	(0.076)	(0.075)	(0.105)	(0.079)	(0.078)
Arbaytu Ensesa (1/0)	-0.019	0.011	0.056	-0.023	0.003
	(0.102)	(0.106)	(0.106)	(0.109)	(0.112)
Azmer (1/0)	-0.169***	-0.282***	0.174**	-0.173***	-0.285***
	(0.052)	(0.056)	(0.085)	(0.054)	(0.058)
Agbi (1/0)	-0.095	-0.151	-0.052	-0.106	-0.174
	(0.093)	(0.102)	(0.075)	(0.099)	(0.113)
Atat Ashti (1/0)	-0.151**	-0.096	0.353***	-0.154**	-0.102
	(0.063)	(0.064)	(.113)	(0.064)	(0.066)
Ergb (1/0)	0.211***	0.317***	0.695***	0.213***	0.313***
	(0.055)	(0.061)	(0.084)	(0.057)	(0.064)
Kuni Sankesta (1/0)	-0.009	0.013	-0.07	-0.014	0.008
	(0.069)	(0.072)	(0.078)	(0.072)	(0.075)
Woynema (1/0)	0.232***	0.311***	.438***	0.238***	0.314***
	(0.055)	(0.059)	(0.09)	(0.057)	(0.061)
Waga (1/0)	0.031	-0.076	-0.133	0.034	-0.09
	(0.046)	(0.067)	(0.083)	(0.047)	(0.08)
Zengebel Bedega (1/0)	-0.163***	-0.174***	-0.02	-0.167***	-0.178***
	(0.053)	(0.058)	(0.084)	(0.054)	(0.059)
Jamat Enkokema (1/0)	-0.04	-0.247**	-0.114	-0.049	-0.258**
	(0.097)	(0.096)	(0.089)	(0.104)	(0.103)
Gorefa (1/0)	0.084	0.046	0.081	0.081	0.041
	(0.096)	(0.097)	(0.109)	(0.103)	(0.104)
Fetegem (1/0)	0.129***	0.003	0.098	0.136***	0.007
	(0.047)	(0.058)	(0.092)	(0.048)	(0.059)
_cons	4.781***	4.801***	0.227**	4.747***	4.77***
	(0.121)	(0.118)	(0.091)	(0.132)	(0.129)
Observations	2933	2933	2933	2933	2933
R-squared	0.511	0.49	0.239	0.127	0.114

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

TABLE 2B.1: Average Marginal Effects from OLS estimation of MLR

For DAP/NPS

```
. mchange $x3 asp_index, amount(sd) brief

regress: Changes in xb | Number of obs = 2933

Expression: Linear prediction, predict()
```

	Change	p-value
internal LOC		
+SD	0.024	0.048
external LOC		
+SD	0.001	0.938
asp index		
+SD	0.037	0.001

<u>For UREA</u>

```
. mchange $x3 asp_index, amount(sd) brief

regress: Changes in xb | Number of obs = 2933

Expression: Linear prediction, predict()
```

	Change	p-value
internal LOC		
+SD	0.029	0.025
external LOC		
+SD	-0.002	0.919
asp index		
+SD	0.030	0.010

<u>For Pesticides</u>

```
. mchange $x3 asp_index, amount(sd) brief

regress: Changes in xb | Number of obs = 2933

Expression: Linear prediction, predict()
```

	Change	p-value
internal LOC		
+SD	0.037	0.001
external LOC		
+SD	-0.022	0.044
asp index		
+SD	0.021	0.072

<u>For DAP/NPS per hectare</u>

```
. mchange $x3 asp_index, amount(sd) brief

regress: Changes in xb | Number of obs = 2933

Expression: Linear prediction, predict()
```

	Change	p-value
internal LOC		
+SD	0.025	0.057
external LOC		
+SD	0.002	0.902
asp index		
+SD	0.038	0.001

<u>For Urea per hectare</u>

```
. mchange $x3 asp_index, amount(sd) brief

regress: Changes in xb | Number of obs = 2933

Expression: Linear prediction, predict()

             |     Change    p-value
-------------+----------------------
internal LOC |
         +SD |      0.029      0.035
external LOC |
         +SD |     -0.003      0.876
asp index    |
         +SD |      0.031      0.014
```

TABLE 3B: Estimation results of the ordered logistic regression models

Explanatory variables	Number of technology adopted	Adoption Status
Internal LOC	0.174***	0.156***
	(0.038)	(0.039)
External LOC	-0.059	-0.042
	(0.044)	(0.043)
Aspiration	0.249***	0.229***
	(0.08)	(0.079)
Age(Years)	-0.013***	-0.01***
	(0.003)	(0.003)
Sex(Male=1)	0.628***	0.562***
	(0.129)	(0.13)
Household Size(Number)	0.108***	0.106***
	(0.021)	(0.022)
Educ_dummy(1/0)	0.295***	0.304***
	(0.079)	(0.08)
ln(land Size(ha))	0.38***	0.322***
	(0.069)	(0.069)
Access to credit(1/0)	0.362***	0.32***
	(0.079)	(0.081)
Access to extension service(1/0)	0.993***	0.947***
	(0.082)	(0.083)
Distance to market(in walking minutes)	0.00	-0.001
	(0.001)	(0.001)
Number of plots (Number)	0.186***	0.154***
	(0.049)	(0.052)
Cooperative Membership(1/0)	0.066	0.062
	(0.082)	(0.085)
5gna (base kebele)		

Abaseme	1.882***	1.917***
	(0.331)	(0.358)
Agumamit (1/0)	1.31***	1.222***
	(0.404)	(0.373)
Arbawash (1/0)	0.081	0.058
	(0.321)	(0.322)
Awunt (1/0)	-0.771***	-0.791**
	(0.298)	(0.326)
Berekegn (1/0)	0.324	0.4
	(0.318)	(0.324)
Dingra (1/0)	0.749**	0.787**
	(0.315)	(0.319)
Dumeri (1/0)	-0.077	-0.105
	(0.427)	(0.428)
Frat (1/0)	0.131	0.171
	(0.27)	(0.277)
Guay (1/0)	0.885***	0.78**
	(0.326)	(0.319)
Hodanshe (1/0)	0.263	0.236
	(0.378)	(0.399)
Jiga (1/0)	0.541	0.544
	(0.357)	(0.372)
Mana (1/0)	0.837**	0.771**
	(0.37)	(0.363)
Mankusa (1/0)	0.331	0.364
	(0.302)	(0.299)
Mebesh (1/0)	0.355	0.091
	(0.398)	(0.453)
Mender (1/0)	0.53	0.477
	(0.349)	(0.337)
Mircha (1/0)	-.648**	-0.603*
	(0.303)	(0.316)
Rados (1/0)	0.191	0.069
	(0.301)	(0.318)
Shimebed (1/0)	0.097	0.17
	(0.358)	(0.351)
Wonge (1/0)	-0.441	-0.496
	(0.3)	(0.321)
Yeraber (1/0)	0.689*	0.804**
	(0.409)	(0.405)
Yesheret (1/0)	0.375	0.416
	(0.378)	(0.37)
Zaba (1/0)	1.212***	1.135***
	(0.343)	(0.346)
Malan Lijit (1/0)	-0.061	0.193

	(0.393)	(0.387)
Segodet Mekerecha (1/0)	-0.169	-0.163
	(0.404)	(0.397)
Bugi (1/0)	-0.082	0.138
	(0.48)	(0.445)
Arbaytu Ensesa (1/0)	1.494***	1.533***
	(0.345)	(0.363)
Azmer (1/0)	0.568**	0.538*
	(0.277)	(0.288)
Agbi (1/0)	1.063***	1.029***
	(0.321)	(0.326)
Atat Ashti (1/0)	0.741*	0.753**
	(0.397)	(0.369)
Ergb (1/0)	-0.671**	-0.942***
	(0.267)	(0.295)
Kuni Sankesta (1/0)	0.101	0.063
	(0.288)	(0.297)
Woynema (1/0)	1.691***	1.715***
	(0.307)	(0.316)
Waga (1/0)	0.243	0.092
	(0.283)	(0.301)
Zengebel Bedega (1/0)	0.34	0.333
	(0.305)	(0.316)
Jamat Enkokema (1/0)	-0.121	-0.165
	(0.329)	(0.356)
Gorefa (1/0)	1.322***	1.318***
	(0.39)	(0.385)
Fetegem (1/0)	0.191	0.144
	(0.311)	(0.324)
/cut1	-1.28***	0.932***
	(0.333)	(0.341)
/cut2	1.032***	3.383***
	(0.331)	(0.348)
/cut3	3.486***	
	(0.337)	
/cut4	5.838***	
	(0.349)	
Observations	2933	2933
Pseudo R^2	0.114	0.126

*Standard errors are in parentheses   *** p<.01, ** p<.05, * p<.1*

Table 3B.1: Average Marginal Effects from ordered logit model estimations

```
. mchange $x3 asp_index, amount(sd) brief

ologit: Changes in Pr(y) | Number of obs = 2933

Expression: Pr(number_of_tech_adopted), predict(outcome())
```

	0	1	2	3	4
internal LOC					
+SD	-0.008	-0.021	0.001	0.021	0.006
p-value	0.000	0.000	0.148	0.000	0.000
external LOC					
+SD	0.003	0.007	-0.001	-0.007	-0.002
p-value	0.195	0.185	0.272	0.180	0.175
asp index					
+SD	-0.007	-0.018	0.001	0.018	0.006
p-value	0.001	0.002	0.078	0.002	0.005

TABLE 4B: Hosmer- Lemeshew goodness of fit measure statistics

```
Logistic model for irrigation, goodness-of-fit test

       number of observations =      2933
 number of covariate patterns =      2933
           Pearson chi2(2882) =      2926.61
                  Prob > chi2 =         0.2765

Logistic model for ppt, goodness-of-fit test

       number of observations =      2933
 number of covariate patterns =      2933
           Pearson chi2(2882) =      2812.47
                  Prob > chi2 =         0.8198

Logistic model for fertilizer other d, goodness-of-fit test

       number of observations =      2933
 number of covariate patterns =      2933
           Pearson chi2(2882) =      2846.65
                  Prob > chi2 =         0.6768

Logistic model for pesticide d, goodness-of-fit test

       number of observations =      2933
 number of covariate patterns =      2933
           Pearson chi2(2882) =      2955.68
                  Prob > chi2 =         0.1658
```

End!