

UNIVERSITY FOR DEVELOPMENT STUDIES

**CREDIT ACCESS, IMPROVED TECHNOLOGY ADOPTION AND
TECHNICAL EFFICIENCY OF MAIZE FARMERS IN THE UPPER EAST
REGION, GHANA**

EMMANUEL MANBEY TAMPOLING

2019



UNIVERSITY FOR DEVELOPMENT STUDIES

**CREDIT ACCESS, IMPROVED TECHNOLOGY ADOPTION AND
TECHNICAL EFFICIENCY OF MAIZE FARMERS IN THE UPPER EAST
REGION, GHANA**

BY

EMMANUEL MANBEY TAMPOLING

(BSc. Agriculture Technology)

(UDS/MEC/0079/16)

**THESIS SUBMITTED TO THE DEPARTMENT OF AGRICULTURAL AND
RESOURCE ECONOMICS, FACULTY OF AGRIBUSINESS AND
COMMUNICATION SCIENCES IN PARTIAL FULFILLMENT OF THE
REQUIREMENTS FOR THE AWARD OF MASTER OF PHILOSOPHY
DEGREE IN AGRICULTURAL ECONOMICS**

FEBRUARY, 2019



DECLARATION

I hereby declare that this thesis/dissertation is the result of my own original work and that no part of it has been presented for another degree in this University or elsewhere:

Emmanuel Manbey Tampoling
(Student) (Signature) (Date)

Supervisors'

We hereby declare that the preparation and presentation of the thesis was supervised in accordance with the guidelines on supervision of thesis laid down by the University for Development Studies.

Sylvester Nsobire Ayambila (PhD)
(Main Supervisor) (Signature) (Date)

Mr. Dennis Sedem Ehiakpor
(Co-Supervisor) (Signature) (Date)

Joseph Agebase Awuni (PhD)
(Head of Department) (Signature) (Date)



ABSTRACT

Increasing the adoption of improved technologies through the provision of adequate credit is necessary to resolve the problem of low crop productivity due to the constant decline of soil fertility and climate change impact on agriculture. The study examines access to credit, adoption of improved technologies and adoption effect on maize technical efficiency of 240 farmers in the Upper East Region, Ghana. A multi-stage sampling approach was used to select the farmers. Face-to-face interviews were carried out to collect primary data using semi-structured questionnaires. Using the multivariate probit model, the results found that row-line technology (*RLT*), legume-maize intercropping technology (*LMIT*) and soil/stone bunding technology (*SBT*) are adopted together by farmers. Adoption of improved maize technologies was significantly affected by sex, age, education, farm size, farm location, distance to local input-shop, extension contacts, FBO membership and access to training on improved farming methods. The results of Poisson regression with endogenous treatment showed that farmers who accessed credit were more likely to increase the adoption of improved technologies. The stochastic frontier production estimation results showed that adoption of more improved technologies, farm size, inorganic fertilizer and seeds were associated with higher maize output. Adopting more improved technologies on the other hand reduces technical efficiency of maize farmers. The mean maize technical efficiency was 0.75, which meant that 25% of maize output was lost due to technical inefficiency. High cost of improved technologies was ranked as the most serious constraint facing farmers in the adoption of improved technologies in maize production. The study suggests the provision of credit facilities to farmers to increase the adoption of improved technologies. Moreover, policies should be targeted at the factors that affect maize production and technical efficiency of farmers.



ACKNOWLEDGEMENTS

All Glory and honour be to the Almighty God for giving me life, good health, wisdom and knowledge to go through these years of hard work and sleepless nights.

I humbly want to thank my supervisor, Dr. Sylvester Nsobire Ayambila and co-supervisor Mr. Dennis S. Ehiakpor in the Agribusiness Management and Finance and Agricultural and Resource Economics Departments respectively of the Faculty of Agribusiness and Communication Sciences, for taken time off their busy schedules to thoroughly guide me through the work. Without them this work would not have been a success.

My profound gratitude also goes to the entire board of the USAID Feed the Future Agriculture Technology Transfer (ATT) Exceptional Scholars' Grant for the funding which enabled me to carry out this research.

To the Head of Department (HOD) of the Agricultural and Resource Economics and all the lecturers in the department, I say thank you all for your support.

I also remain indebted to Mr. Mensah Tawiah Cobbinah for his immense contributions to the success of this work. I remain thankful to Mr. Ziba Daniel for his unflinching support in diverse ways concerning this work. I am also indebted to Mr. and Mrs. Aaron Aduna for their encouragement, spiritual and moral support which greatly helped me throughout this work.

My outmost thanks also go to my wonderful wife Kugre Patricia and my children; Louyin, Yinpangzuome and Nawuntebigtam for the love and prayer support given me during this work. Last but not the least, I do sincerely remain grateful to my siblings for their support in many ways which also led to the successful completion of the work.



DEDICATION

This work is dedicated to my late parents (Mr. and Mrs. Tampoling Engme), my wife (Patricia Kugre) and children (Louyin, Yinpangzuome and Nawuntebigtam).



TABLE OF CONTENTS

DECLARATION	i
ABSTRACT.....	ii
ACKNOWLEDGEMENTS	iii
DEDICATION	iv
TABLE OF CONTENTS.....	v
LIST OF TABLES.....	ix
LIST OF FIGURES	x
LIST OF ACRONYMS	xi
CHAPTER ONE	1
INTRODUCTION	1
1.0 Background	1
1.1 Problem Statement.....	4
1.3 Research Objectives	6
1.4 Justification of the Study.....	7
1.5 Structure of Thesis	8
CHAPTER TWO	9
LITERATURE REVIEW	9
2.0 Chapter Outline	9
2.1 Overview of Agriculture and Maize Production in Ghana	9
2.2 Definition and Concept of Agricultural Technology Adoption	11
2.3 Adoption Concept	12
2.3.1 Improved seed technology (IST) adoption	16
2.3.2 Inorganic fertilizer technology (IFT) adoption.....	17
2.3.3 Intercropping technology (IT) adoption	18





2.3.4 Row-line planting adoption	20
2.3.5 Soil/stone bunding technology adoption	21
2.4 Theoretical Framework for Farm Technology Adoption	22
2.5 Adoption Studies	29
2.6 Determinants of Farm Technology Adoption	30
2.6.1 Farmer Characteristics	30
2.6.2 Farm-specific Factors	31
2.6.3 Institutional and Communication Factors.....	32
2.7 Access to Credit and Farmers' Adoption of Improved Technologies.....	33
2.8 Effect of Adoption of Technologies on Farm Output	34
2.8.1 Definition and Concept of Production and Efficiency	34
2.8.2 Determinants of Technical Efficiency	37
CHAPTER THREE	39
RESEARCH METHODOLOGY.....	39
3.0 Chapter Outline	39
3.1 Study area.....	39
3.2 Research Design.....	40
3.3 Target Population and Sampling Techniques.....	41
3.4 Data Collection Methods.....	41
3.5 Data Analysis	42
3.6 Conceptual Framework	42
3.7 Theoretical framework	44
3.7.1 Binary probit model analysis of factors influencing access to credit by farmers	46
3.7.2 The Multivariate Probit Model	49
3.7.3 Poisson Regression with Endogenous Treatment.....	51



3.7.4 The Stochastic Frontier Approach.....	56
3.7.5 Analysis of farmers’ constraints in technology adoption in maize production	59
CHAPTER FOUR.....	61
RESULTS AND DISCUSSION	61
4.0 Chapter Outline	61
4.1 Descriptive Statistics of Farmer Characteristics	61
4.2 Farm-specific characteristics.....	65
4.3 Institutional Factors.....	67
4.4 Adoption of Improved Maize Technologies	71
4.5.1 Factors Affecting the Access to Credit.....	73
4.4.2 Factors Influencing the Adoption of Improved Maize Technologies.....	75
4.5 Effect of Access to Credit on Improved Maize Technology Intensity-Poisson Regression with Endogenous Treatment.....	85
4.5.1 Factors Affecting the Intensity of Adoption of Improved Maize Technologies.....	86
4.6 Improved Technology Adoption and Output of Maize Farmers.....	89
4.6.1 Stochastic frontier results	90
4.6.2 Determinants of Technical Inefficiency	93
4.6.3 Distribution of Technical Efficiency	95
4.7 Ranking of Constraints Facing Farmers in the Adoption of Improved Technologies in Maize Production.....	96
CHAPTER FIVE	97
SUMMARY, CONCLUSIONS AND RECOMMENDATIONS.....	97
5.0 Chapter Outline	97
5.1 Summary	97
5.2 Conclusions	99

5.3 Recommendations	100
REFERENCES	101
Appendix I: Research Questionnaire	122



LIST OF TABLES

Table 3. 1: Description of Variables used in the MVP model	51
Table 3. 2: Description of variables in the standard Poisson model.....	53
Table 3. 3: Description of variables in the standard probit model.....	55
Table 3. 4: Description of variables in the stochastic frontier model	57
Table 3. 5: Description of variables in the technical inefficiency model	59
Table 4. 1: Summary Statistics of Demographic Characteristics of Respondents.....	64
Table 4. 2: Summary Statistics of Farm-specific Characteristics of Respondents	66
Table 4. 3: Summary Statistics of Institutional Factors	69
Table 4. 4: Farmer Adoption of Improved Maize Technologies	72
Table 4. 5: Factors Influencing Access to Credit Using the Binary Probit Model	75
Table 4. 6: Maximum likelihood estimation results of factors influencing the adoption of five (5) improved technologies	84
Table 4. 7: Poisson Regression Results showing the Factors Influencing Adoption Intensity, Including Access to Credit.....	89
Table 4. 8: Results of hypothesis test.....	90
Table 4. 9: Hypothesis tests showing the appropriate inclusion of the adoption in the stochastic frontier production function.	91
Table 4. 10: Maximum Likelihood Estimates of Stochastic Frontier Estimation.....	92
Table 4. 11: Maximum Likelihood Estimation Results of Technical Inefficiency.....	94
Table 4. 12: Ranking of Constraints in Improved Technology Adoption	96



LIST OF FIGURES

Figure 2. 1: Adopter Categorization on the Basis of Innovativeness	15
Figure 3. 1: Map of Upper East Region.....	40
Figure 3. 2: Conceptual framework of factors influencing adoption.....	44
Figure 4. 1: Results of Maize Output of Farmers	67
Figure 4. 2: Efficiency scores of maize farmers	95



LIST OF ACRONYMS

ATC	Agricultural Technology Centre
FAO	Food and Agricultural Organisation
FBO	Farmer Based Organisation
GDP	Gross Domestic Product
GSS	Ghana Statistical Service
HYVs	High Yielding Varieties
IFDC	International Fertilizer Development Centre
IFT	Inorganic Fertilizer Technology
IMF	International Monetary Fund
IMVs	Improved Maize Varieties
IMVT	Improved Maize Varieties Technology
IPTs	Improved Production Technologies
ISSER	Institute of Statistical Social and Economic Research
LMIT	Legume- Maize Inter-Cropped Technology
LPM	Linear Probability Model
LR	Likelihood Ratio
MoFA	Ministry of Food and Agriculture
Mt	Metric tonnes
MVN	Multivariate Normal
MVP	Multivariate Probit
NGOs	Non-governmental Organisations
NPK	Nitrogen Phosphorus Potassium



OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary Least Squares
PBL	Project-Based Learning
PHC	Population and Housing Census
RPT	Row Planting Technology
SARI	Savannah Agricultural Research Institute
SBT	Stone/soil Bunding Technology
SFA	Stochastic Frontier Analysis
SFP	Stochastic Frontier Production
SSA	Sub-Saharan Africa
TE	Technical Efficiency
UN	United Nations
USAID	United States Agency for International Development



CHAPTER ONE

INTRODUCTION

1.1 Background

Agriculture is demonstrated to be the path to prosperity and the achievement of most of the sustainable development goals, especially ending hunger and poverty by 2030 (Nhemachena *et al.*, 2018). The sector plays an important role in nations' economic growth, enhancing their food security, as well as poverty reduction and rural development. As such, agriculture remains Africa's surest bet for growing inclusive economies and creating decent jobs mainly for the youth. Africa has about 51 million farms of which 80% (or 41 million) are smaller than 2 ha in size (Lowder *et al.*, 2016).

The sub-Saharan Africa population is projected to increase from 814 million people in 2010 to 1.7 billion by 2050, increasing its share of the global population from 12% to 18% (UN, 2011). This will increase the demand for food tremendously and will make the goal of halving hunger even more challenging and this is expected to be severe especially in sub-Saharan Africa as the population size is estimated to double and the high economic growth rates of the last decade may continue in the near future (Africa, 2011; Ministry of Foreign Affairs, 2011c; World Bank, 2011). Given these conditions, the resulting food demand in sub-Saharan Africa is expected to increase by a factor of four to five, by 2050 (OECD/PBL, 2012). The increase in food demand is projected to be achieved by



increasing agricultural production through expansion of agricultural land and improved agricultural productivity.

Ghana's agriculture though has declined to about 20% in terms of its contribution to GDP in recent years; it still remains a major part of the country economy in the area of food production and offers employment to about 45% of the country's teaming labour force (Okudzeto *et al.*, 2014). Ministry of Food and Agriculture (MoFA) indicated that agriculture remains key to the entire economic growth and development in Ghana and it is expected to lead the growth and structural transformation of the economy and optimize the benefits of accelerated growth (MoFA, 2015). In 2014 for instance, agriculture (value added) represented 22% of GDP, with services at 50%, and industry at 28% (World Bank, 2015). While in terms of employment, agriculture, service and industries engaged about 45%, 41% and 14% of the labour force respectively (MoFA, 2016). According to FAO (2015), notwithstanding the huge size and contributions of the agricultural sector to the nation's economy, Ghana is still a net importer of some key agricultural products, such as cereals, sugar and poultry. In 2015, Ghana imported a total of 113,037Mt (to the value of \$ 26.84 million) of maize (MoFA, 2016).

Maize is the most important cereal crop in Ghana. It is grown in all the agro-ecological zones in the country. According to MoFA (2016), about 880,000 hectares of land was committed to maize production in 2015 in Ghana. Maize cropping systems and production technologies are different among the various agro-ecological zones where a significant amount of the crop is cultivated (Morris *et al.*, 2003). Average grain yields of





maize are correspondingly modest, averaging less than 2Mt/ha. Total annual maize production between 2013 and 2015 was estimated to be about 1.7 million Mt on the average experiencing an average shortfall in domestic maize production of about 2% between 2010 and 2012 (MoFA, 2016). The government of Ghana and Non-Governmental Organisations continue to formulate and implement agricultural policies, aimed at increasing production of the key staple food crops in order to meet the country's increasing demand and to improve food security.

In developing countries like Ghana, most farmers have to accept low yields as they are probably unable to consider the use of improved production methods as most of them operate at the subsistence levels. In areas where improved maize varieties have been widely adopted, genetic yield gains are inhibited by the use of poor management practices. Use of fertilizers and other crop management practices remain limited. Soil nutrient depletion and degradation poses fundamental challenges to Ghana's rain-fed maize production system and its sustainability. The problem of disease and pest control among other different production practices is acute on the small-scale and resource-poor systems under which maize is typically cultivated (Ofori & Baffour, 2006).

Production of the crop is currently dominated by smallholder farmers who rely on rain-fed conditions with limited use of improved seeds, fertilizer, mechanisation, post-harvest facilities and climate information. As a result, average yields are well below attainable levels and post-harvest losses are high (Jayne *et al.*, 2010). Investors in commercial farming have the opportunity to increase yields per hectare in maize by the use of



improved production technologies in order to capitalize on the large and growing demand for this critical staple crop in developing countries such as Ghana (Jayne *et al.*, 2010). However, majority of farmers depend on traditional methods of production which has decreased the level of maize productivity. According to Muzari *et al.* (2012) over 70% of maize production in the developing countries is from smallholders who use traditional methods of production.

By virtue of improved input to output relationships, new technology raises output and reduces average cost of production which in turn results in substantial gains in farm income (Challa, 2013). Adopters of improved technologies increase their productions, leading to improved socio-economic development. On the other hand, non-adopters find it difficult to maintain their marginal livelihood with socio-economic stagnation leading to deprivation (Jain *et al.*, 2009). Improved technologies adoption is believed to be a major factor in the success of the Green Revolution experienced by Asian countries (Ravallion & Chen, 2004). Understanding credit access and production technologies adoption by maize farmers and other stakeholders in the production process is key to enhancing food security in Ghana and in particular the Upper East Region.

1.2 Problem Statement

Increasing the adoption of improved production technologies to enhance agricultural productivity especially maize is important due to the constant decline of soil fertility and climate change (Rosegrant *et al.*, 2009). Also, to meet the growing demand for maize due to population growth and the rapid expansion of the biofuel industry, growth in



productivity is important (MoFA, 2016). But actual yield of maize still remains far below potential yields in Ghana. This has partly been attributed to low adoption of improved technologies such as improved crop varieties and fertilizers as well as use of inappropriate pest control measures (Suri, 2011; Muzari *et al.*, 2012).

The areas of technology development and promotion for crops are mostly new varieties and management regimes, soil fertility management, weed and pest management, irrigation and water management (Loevinsohn *et al.*, 2012). However, in developing countries including Ghana, the available agricultural infrastructures and facilities such as irrigation, input and product markets, credit as well as extension services to facilitate higher adoption tend to be developed poorly (Muzari *et al.*, 2012). Also, farmers find it difficult combining specific technologies to improve yields due to poor knowledge and lack of training as well as access to credit to purchase improved inputs (Muzari *et al.*, 2012). These challenges together with other socio-economic and management factors of farmers affect technical efficiency. In general, farmers make trade-offs or combine improved technologies as potential strategies to minimise cost and increase production. However, the resulting effect of adopting one or more technologies on output and technical efficiency of farmers is less exploited, especially in the Upper East Region. Therefore, any steps taken to increase agricultural productivity especially in maize is critical in order to meet expected rising demand and as such, it is instructive to examine the determinants of credit access and improved technology adoption as well as technical efficiency in maize production in the Upper East Region. These forgoing problems lead the study to formulate the following research questions:



1. What are the determinants of access to credit by maize farmers in the Upper East Region?
2. What are the factors influencing adoption of improved technologies in maize production in the Upper East Region?
3. What is the effect of access to credit on the intensity of adoption of the improved technologies in maize production among farmers in the Upper East Region?
4. What is the effect of adoption of improved production technologies on technical efficiency of farmers in the Upper East Region?
5. What constraints do farmers face in the adoption of improved technologies in maize production?

1.3 Research Objectives

The main objective of the study is to examine credit accessibility, adoption of improved technologies and technical efficiency of maize farmers in the Upper East Region of Ghana.

Specifically, the study seeks to;

1. explore the determinants of access to credit by farmers in the Upper East Region.
2. identify the factors influencing adoption of improved technologies in maize production in the Upper East Region.
3. estimate the effect of access to credit on the intensity of adoption of the improved technologies among farmers in maize production in the area.
4. determine the effect of adoption of improved production technologies on maize output in the Upper East Region.

5. identify and rank the constraints facing farmers in the adoption of improved technologies in maize production.

1.4 Justification of the Study

Maize is a very important staple crop in the Ghanaian household and bulk of it produced goes into food consumption and it is arguably the most important food security crop. The ability of maize farmers to improve yield levels and achieve sustainable production is a major concern. Considering that farmers in Ghana grow and consume maize substantially, any technology that succeeds in increasing the productivity of resources devoted to maize production will bring about a lot of benefits to the vast majority of the rural population.

To increase agricultural productivity through all stakeholders' efforts, the possible factors that influence adoption of improved technologies need to be understood. The result of this research will provide relevant information to government agencies, extension workers, cooperative unions, development partners/NGOs in formulating policies and coordinating their implementation to address the gaps identified so as to offer appropriate response to the needs of the farmer in the Upper East Region. Farmers will also benefit from the findings of the study by knowing the appropriate combinations of improved technologies that produce maximum output in maize. This study will also add to the stock of knowledge or literature on credit access, improved technologies adoption and farm productivity.



1.5 Structure of Thesis

This study is structured into five (5) chapters.

Chapter 1 presents the introduction which gives a background to the study. The introduction also contains the problem statement, research questions and its corresponding objectives and the justification of the study. The foregoing section (structure of thesis) is also included in this chapter. Chapter 2 reviews literature on pertinent studies on adoption of improved technology and efficiency as well as access to credit. Chapter 3 contains the materials and methods employed in the collection and analysis of data. Chapter 4 is the presentation of results generated from the data collected from the field. It also contains the discussions of the results in comparison with past studies. Chapter 5 presents the summary, conclusions and recommendations of the study.



CHAPTER TWO

LITERATURE REVIEW

2.0 Chapter Outline

This chapter reviews literature related to the key concepts of the study such as adoption of farm technologies and its determinants, effect of access to credit on farm technology adoption and the effect of farm technology adoption on agricultural productivity. The chapter also examines the theoretical and conceptual frameworks for analysing adoption decisions of farmers.

2.1 Overview of Agriculture and Maize Production in Ghana

Agriculture is crucial to the livelihood of many people and Ghana's economy, though its share of GDP has decreased in recent years, it continues to be vital to economic growth and rural development. In 2016, agriculture contributed about 18.3% to GDP and 29% to foreign exchange (GSS, 2017, ISSER, 2017). The sector employs 51.5% of the Ghanaian active labour force. While low levels of mechanisation and the effects of drought and climate change among other factors are threatening to slow growth in the sector. The government's commitment to investing in technologies and establishing new policies such as planting for food and jobs and fertilizer subsidies to support the sector are in the right direction.

The agricultural sector in Ghana is dominated by smallholder farmers who form the majority (80%) of the crop producers and account for over 90% of the total output





(Wood, 2013; MoFA, 2016). Nevertheless, farming population comprises predominantly of resource-poor farmers, cultivating on marginal plots of land with rudimentary farming system, low capitalization and declining productivity resulting from bad weather conditions, poor technology application and low credit access which is the core among the constraints. Consequently, these smallholders are trapped within subsistence agriculture, and hence adoption of improve technologies is vital for agricultural commercilisation and higher productivity.

Maize is one of the three grains (including wheat and rice) that account for more than 50% of the world's production of cereals (Awika, 2011). MoFA (2016) noted that maize is the most important cereal crop with the highest production and consumption in Ghana. Maize serves as highest source of food security for Ghanaians and it is produced in all agro-ecological zones. Maize is the highest producing and consuming crop in Ghana (USAID, 2014). Maize is produced predominantly by smallholder resource poor farmers under rain-fed conditions (Savannah Agricultural Research Institute (SARI, 1996).

According to FAO (2005), maize yields are far below achievable levels, and this is as a result of low utilisation of farm inputs and technologies. Maize yield has been estimated to about 481 kg/acre in Upper East Region (Amanor-Boadu *et al.*, 2015). Lack of access to credit is one of the contributing factors to the low productivity in the region (Anang *et al.*, 2015). The effect of access to credit on farmers' adoption of improved technologies is expected to be enormous.

2.2 Definition and Concept of Agricultural Technology Adoption

Advocates of agricultural growth admit that increasing productivity in agriculture in a sustainable manner requires developing and diffusing new technologies. New and improved technologies are often required to upgrade agricultural commodities for markets that demand high quality standards (Eaton & Shepherd, 2001). Technologies exist in different forms and serves varying purposes. At the farm level, a technology may be developed to amend soil conditions (e.g., ploughs, fertilizers), plant/sow (planters), weed, protect crop quality, and or harvest (e.g., combined harvesters). Loevinsohn *et al.* (2013) have explained that technologies are means and or methods used in producing goods and services efficiently, which include methods of organisation and physical technique. A technology can be new and specific to a particular place or group of farmers, or represents a modified version of what was already in use. The purpose of a technology is to change a given production process at undesirable state to a more advanced and desirable state.

Technology has been described as a knowledge that permits some tasks to be accomplished more easily, which also include the services rendered to manufacture the product (Lavison, 2013). Bonabana-Wabbi (2002) noted that technology helps to save time and labour by enabling the farmer to do work more easily and cost-effectively to achieve the highest possible results. According to Donkoh (2006), a technology represents the current state of knowledge of how resources are combined efficiently to achieve desirable output, solve problems, fulfil needs or satisfy wants. From the

perspective of the producer, technology is itself a product of utility and may serve one or more purposes. Technology is understood by farmers in different ways; it can be considered as how to cultivate a crop successfully or the kind of crop varieties and fertilizers suitable for the soil or innovations introduced by scientists (Chi & Yamada, 2002).

2.3 Adoption Concept

Rogers & Shoemaker (1971) cited in Yigezu *et al.* (2015) stressed that adoption is “a decision to make full use of a new idea as the best course of action available”. The term adoption has been defined as a dynamic process of integrating a new technology into existing practice and is usually preceded by a period of ‘trying’ and some degree of adaptation (Loevinsohn *et al.*, 2013). In other words, adoption can be explained as the extent to which new innovations and technologies is used (Donkoh & Awuni, 2011) or the decision to accept a technology (Bonabana-Wabbi, 2002). In addition, Dankwa (2001) explained adoption as the acceptance and use of technology for one season or more.

As outlined by Feder *et al.* (1985), the adoption process first exposes the farmer to the technology (also known as knowledge transfer stage) by specifying its potentials. At this early stage, the farmer may have low interest in the technology due to limited knowledge about it but with time, farmer tends to learn more about the technology and eventually tend to appreciate it, and then adopt. This is why Feder *et al.* (1985) state that adoption is



a mental process an individual pass from first hearing about an innovation to final utilisation of it.

The adoption concept has also been compared with diffusion. However, according to Donkoh and Awuni (2011), the two concepts differ in terms of the time frame and population within which they operate. Donkoh *et al.* (2006) citing Feder *et al.* (1985) therefore explained that adoption occurs when an individual or a household makes use of an innovation and diffusion as when the use of a technology or innovation is spread within a particular location. Earlier, Rogers (1983) conceptualised five steps through which an adoption decision must pass through before a technology is finally adopted as: awareness, interest, evaluation, acceptance, trial and then finally adoption. Adoption can also be described from two perspectives: (1) rate of adoption and (2) intensity of adoption as indicated by Bonabana-Wabbi (2002). The former is defined as the relative speed with which farmers adopt an innovation and has as one of its pillars, the element of 'time' whereas the latter refers to the level of use of a given technology in any time period (Bonabana-Wabbi, 2002).

Adoption is a complex phenomenon because it varies with the technology being adopted. In an adoption study by Doss (2003), a farmer was categorized as an adopter of improved seed if he/she was using seeds that had been recycled for several generations from hybrid ancestors. In other studies, adoption was identified with following the extension service recommendations of using only new certified seed (Bisanda *et al.*, 1998; Ouma *et al.*,



2002). Chi & Yamada (2002) argue that it is common to see farmers preferring one technology to the other.

Adoption of agricultural technologies can be grouped into two broad levels: aggregate and individual (farm-level) adoption (Feder *et al.*, 1985). The aggregate technology adoption is the process of the spread of a new technology within a region whereas the individual technology adoption is the extent to which a new technology is employed in long-run equilibrium, when information about the products and its potentials has spread widely among farmers. The individual adoption is measured at the farmer level while the aggregate adoption is measured over the whole population at hand.

Rogers (2010) categorised adoption into five categories: innovators, early adopters, early majority, late majority and laggards. He explained the adoption categories as falling into a range of percentages. For instance, he placed innovators as forming the 2.5% of a group that adopt a new idea. The next 13.5% to adopt an innovation are defined as early adopters. The next 34% of the adopters to the left-side of the mean are called the early majority. The 34% of the group to the right of the mean are the late majority, and the last 16.0% are considered laggards (see Figure 2.1).



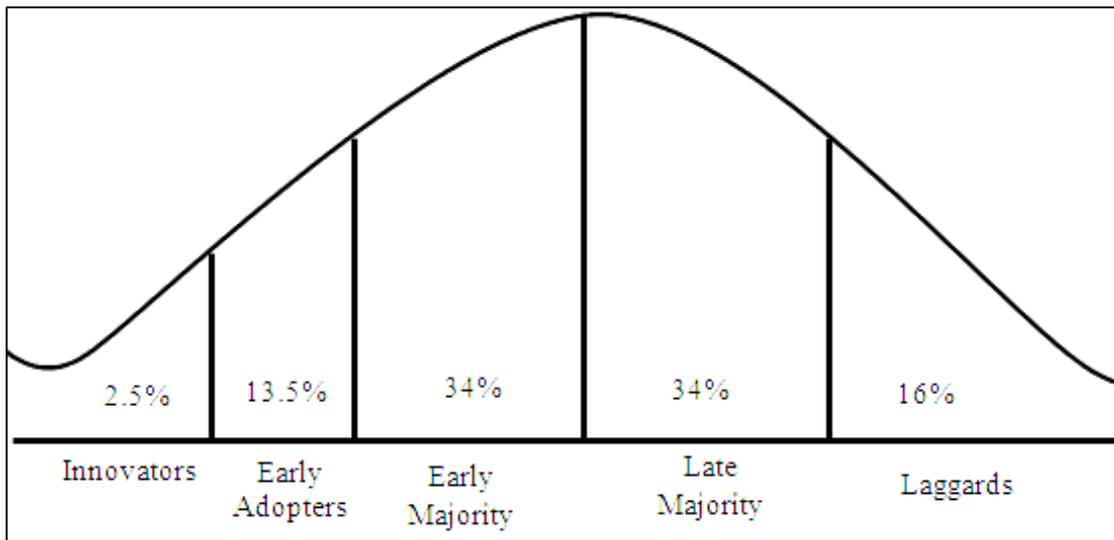


Figure 2. 1: Adopter Categorization on the Basis of Innovativeness

Source: Rogers (1962)

In the figure demonstrated above, the innovators, also referred to as risk-takers are those who are willing to experience new ideas (Rogers, 2003). He further added that innovators are the gatekeepers bringing the innovation in from outside of the system. The early adopters on the other hand, are more limited within the boundaries of the social system. As noted by Rogers (2003), early majority could be described as leaders or role models toward innovation because they put their stamp of approval on a new idea by adopting it. The early majority usually take more time than it takes innovators and early adopters to adopt a technology (Rogers & Shoemaker, 1971). Also, the late majority occupies one-third of all members of the social system who wait until most of their peers adopt the innovation. Rogers (2003) stated that laggards have the traditional view and they are more doubtful about innovations and change agents than the late majority. As the most



localized group of the social system, their interpersonal networks mainly consist of other members of the social system from the same category.

2.3.1 Improved seed technology (IST) adoption

The development of improved (or high-yielding) crop variety begun during the early 1960s and their widespread adoption by farmers in Asia and in Latin America marked the beginning of what is known as the ‘Green Revolution’. Improved crop variety is a product of crop breeding or engineering programmes. Improved seed variety is important for increasing crop productivity and farmer’s income and rural poverty alleviation (Bruins, 2009; Alene *et al.*, 2009; Krishna & Qaim, 2008). In Ghana, maize varieties have been developed by research institutions.

The adoption of improved crop varieties is of particular interest to researchers. For instance, Danso-Abbeam *et al.* (2017) carried out a study to identify the determinants of adoption of improved maize variety (IMV) among farmers in the Northern Region of Ghana. Using a multinomial logit, their study revealed that age of the household head, household size, level of experience, farm workshop attendance, the number of years in formal education, access to agricultural credit, membership of a farmer-based organisation, availability of labour and extension contacts influence the adoption of IMV. In northern Tanzania, Nkonya *et al.* (1997) investigated the determinants of adoption of improved seed variety and chemical fertilizer by maize farmers. Using a bootstrapped simultaneous equation Tobit model, they showed that the adoption of improved maize



seed was positively affected by nitrogen use per hectare, farm size, education of farmers, and visits by extension agents.

2.3.2 Inorganic fertilizer technology (IFT) adoption

Low and declining soil fertility is a major cause of low crop productivity in sub-Saharan Africa. The use of more external nutrients such as chemical and organic fertilizers have been suggested to enable farmers achieves potential yields. Research indicates that between 1980 and 2004, SSA lost about 4.4 million tonnes of nitrogen, 0.5 million tonnes of phosphorus and 3 million tonnes of potassium and this cost the continent about \$4 billion worth of soil nutrients a year (IFDC, 2006). Fertilizer has the ability to restore certain depleted nutrients in the soil thereby meeting specific nutritional needs of crops as well as minimising potential environmental hazards of continuous cropping (Verma & Sharma, 2007). Research shows that about 50% increase in global food production can be achieved through fertilizer application (Olson, 1970).

In spite of the numerous benefit of fertilizer in replenishing soil nutrients, adoption is low in SSA compared to the rest of the world. For instance, the World Bank (2012) estimates that fertilizer application in SSA was about 10.5kg/ha compared to South Asia, Latin America, and the Caribbean which apply about 176 kg/ha, 92.2 kg/ha, and 79.5 kg/ha respectively. To improve farmers' access to fertilizer, the government of Ghana instituted the fertilizer subsidy programme in 2008 to increase food security and rural incomes (Yawson *et al.*, 2010). The programme basically covered four types of inorganic fertilizer: Urea, Sulphate of ammonia, NPK, 15:15:15 and NPK 23:10:15. Fertilizer





adoption has been found to increase with farm size (Nkonya *et al.*, 1997). In another study, Emmanuel *et al.* (2016) examined the impact of agricultural extension service on adoption of chemical fertilizer. They revealed that access to extension services significantly promotes adoption of chemical fertilizer.

2.3.3 Intercropping technology (IT) adoption

Intercropping is one of the ancient practices that increase diversity in agriculture. In modern agriculture, intercropping is one of the sustainable agricultural intensification systems because it improves ecological balance (Mousavi & Eskandari, 2011). Intercropping is one of the measures suggested to reduce environmental and economic risks (Min *et al.*, 2017). Intercropping is used to mean a multiple cropping system that two or more crops planted in a field during a growing season (Mousavi & Eskandari, 2011). The combination of crops could include: (1) annual plants with annual plants intercrop; (2) annual plants with perennial plants intercrop; and (3) perennial plants with perennial plants intercrop (Eskandari *et al.*, 2009; Ghanbari-Bonjar & Lee, 2003). Intercropping has been found to ensure more utilisation of resources, increase the quantity and quality of products and reduce crop damage by pests, diseases and weeds (Mousavi & Eskandari, 2011).

Adopting intercropping is more likely to increase crop productivity because the use of plants of leguminosae family improve soil fertility through biological nitrogen fixation. Odhiambo & Ariga (2001) analysed maize and beans intercrops in different ratios of seed and found that production increased due to reduced competition between species



compared with competition within species. This is because intercropping enables the judicious utilization of time and space to increase total crop output per unit area (Hossen, 2016). Min *et al.* (2017) concluded that intercropping is an important source of income for farmers, especially in low-income household.

There are various types of intercropping: (1) row-intercropping, (2) mixed- intercropping, (3) strip-intercropping and (4) relay intercropping (Vandermeer, 1992; Ofori & Stern, 1987). Row intercropping refers to the cultivation of one crop simultaneously with another on the same piece of land at a particular time where at least one crop is planted in regular rows. Also, mixed cropping refers to the growing of at least two crops simultaneously on the same piece of at a particular time with no distinct row arrangement. Strip-intercropping on the other hand occurs when the farmers grow one crop simultaneously with another in the same piece of land at a particular time in different strips wide enough to permit independent cultivation but narrow enough for the crops to interact ergonomically while relay intercropping refers the cultivation of at least one crop simultaneously during part of the life cycle of each.

Min *et al.* (2017) examined the adoption of intercropping among smallholder rubber farmers in Xishuangbanna, China. They found that Intercropping adoption is affected by ethnicity, household wealth and family labour. Rajasekharan & Veeraputhran (2002) examined the factors influencing farmers' adoption of intercropping in three regions of Kerala using the Tobit model. Their results demonstrated that availability of family labour, the type of intercrops and perception of profitability of intercropping were found



significant in explaining the adoption behaviour in all three regions. Hossen (2016) conducted a study to analyse adoption of intercropping with jackfruit by the farmers of Bhaluka Upazilla under Mymensingh District, Bangladesh. Using correlation analysis, the author revealed that among education, farm size, income from jackfruit and intercrop, Cosmopolitanism and innovativeness showed significant relationships with their adoption of intercropping with jackfruit.

2.3.4 Row-line planting adoption

The broadcasting method has long been practiced as a traditional way of planting seeds by most farmers using a high seed rate of between 20-50 kg per hectare (ATC, 2013). However, this practice has been found to reduce yield because the unequal distribution of seeds causes increased competitions for nutrients and water, and also makes weeding and other crop protection measures very difficult (Fufa *et al.*, 2011). Vandercasteelen *et al.* (2014) on the other hand noted that row-line planting reduces seed rate to 2.5 and 3.0 kg per hectare. This ensures optimal absorption of plant nutrients for higher growth. Row-line planting also improves weeding efficiency. However, this method also involves extra labour (Mentire & Gecho, 2017).

From the literature, adoption of row line planting has been analysed by several researchers. In Ethiopia, Mentire & Gecho (2017) conducted a study to examine the factors affecting adoption of wheat row planting technology in the Sodo Zuriya Woreda, Wolaita Zone, Southern Ethiopia. They found that sex of household head, educational status, household size in adult equivalent, oxen ownership, and participation in

agricultural training and demonstrations were the significant factors affecting the adoption of wheat row planting technology.

Tafese (2016) studied the determinants of adoption and intensity of adoption of row planting using a survey data of 300 farming households in Wolaita zone, Ethiopia. They revealed that educational status of household head, farming experience, farm size, annual off-farm income, distance to nearest market and training on row planting significantly influenced adoption and level of adoption of row planting.

2.3.5 Soil/stone bunding technology adoption

Stone/soil bunding technology (SBT) is a line of stones implemented on the contour slopes of a field (Maiga, 2005). According to the author, the bund line height ranges between 20cm and 30cm and is designed to reduce runoff. SBT is a land and water management techniques. There are two types of stone bunds: bunds made by lining up one big rock at a time and those made by overlapping 3 small rocks (a furrow is dug and two rocks are placed underneath and one above). This method helps to control soil erosion and allows water to seep into the soil, providing better crop yields (Wolka & Negash, 2014; Traore *et al.* (2017).

The adoption of SBT is increasing among farmers in northern Ghana in recent years (Nkegbe & Shankar, 2014). A number of studies have explored the determinants of adoption of SBT (Amsalu & Graaff, 2007; Maiga, 2005). In Ethiopia, Amsalu & De Graaff (2007) age of farmers, farm size, perceptions on technology profitability, slope, livestock size and soil fertility are important determinants of adoption of SBT. Maiga



(2005) analysed the determinants of adoption of stone bunding and found farm size and off-farm income as important determinants of adoption of stone bunding technology.

2.4 Theoretical Framework for Farm Technology Adoption

Adoption decisions of farmers are usually studied in the framework of utility-maximisation theory. The theory states that a farmer will adopt a technology only if the net utility associated with adoption is greater than the utility from adopting alternative technologies. In other words, a farmer will adopt if the expected returns from adopting a technology exceed the cost of its adoption and vice versa. From the microeconomic theory of utility, we can assume that farmers maximise their utility function subject to some constraints (Asfaw *et al.*, 2012). Following McFadden (1974), the utility function of the farmer adopting a technology can be treated as a random variable because it is unknown to the researcher.

If we denote U_j as the utility function of farmer i who adopts a technology and U_k as the utility function when the farmer does not adopt a technology, then the farmer will choose to adopt a new technology if the utility gained from adopting is greater than the utility from not adopting only if the change in utility between adopting improved farm technologies and not adopting the technology ΔU is greater or equal to 0. Mathematically, this can be represented as:

$$\Delta U = U_j \geq U_k \quad (2.1)$$



where

$$\Delta U_j = \alpha X_j + e_j \quad (2.2)$$

and

$$\Delta U_k = \alpha X_k + e_k \quad (2.3)$$

From Equations (2.2 and 2.3), we realise that the utility function regarding farmers' adoption has two components; the deterministic component and the stochastic component known as the random component. The deterministic component is exogenous and is made up of explanatory variables and a set of linearly related parameters while the random component may result from missing data/variables (omitted variable), measurement errors and misspecification of the utility function. In order that we can explain farmers' decisions, the probabilistic model is often used in the estimation process. Following Verbeek (2004), the probability of choosing j technology over k technology is given by:

$$\begin{aligned} \Pr(j | C) &= \Pr\{(\alpha X_{ij} + e_{ij}) \geq (\alpha X_{ik} + e_{ik})\} \\ &= \Pr\{(\alpha X_{ij} - \alpha X_{ik}) \geq (e_{ik} - e_{ij})\} \quad \forall j \neq k \in C \end{aligned} \quad (2.4)$$





Adoption can either be a discrete variate with binary or fractional response outcomes, or continuous in nature (Challa, 2013). A probabilistic estimation approach is usually applied in a context where the adoption variable is discrete while a continuous variable approach is used in a context where the adoption variable continuous (Doss, 2003). In the case where the adoption variable is dichotomous such as adopt or not adopt, yes or no, access to credit or no access, binary dependent variables such as logit and probit models have been employed.

In the case where some values on adoption are missing, Tobit and Heckman models among others have been used in literature to measure adoption of agricultural technologies. The discrete choice models are usually grounded in the framework of random utility theory. For such dependent variables, the basic assumption of normality as pertained to the OLS is violated and hence, the computed probabilities based on the OLS approach may fall outside 0 and 1 (Greene, 2003). This is one major limitation of the linear probability model (LPM).

The advantage the LPM has over the binary probit and logit models is linearity easiness and simplicity in its calculation of the explanatory variables, which the estimated coefficients can be interpreted as marginal effects (Pindyck & Rubinfeld, 1981; Amemiya, 1981; Gujarati, 2009), it normally produces constant marginal effects (Capps & Kramer, 1985; Maddala, 1983). The probit and logit models are able to overcome the defect of the LPM by using a link function that effectively transforms the regression

model so that predicted values fall within the zero-one interval (Maddala, 1983; Wooldridge, 2002; Brooks, 2008).

The probit and logit models only differ in their link functions. While the probit model operates with the assumption that the error terms are normally distributed, the logit model assumes the logistic distribution. Apart from their distribution, the two models are quite similar and make it very difficult to select one over the other as they all produce almost the same results. On a lighter note, a researcher would choose the logit model over the probit model due to its simplicity in computing and interpreting the logistic distribution (Maddala, 1983).

One approach in modelling binary response variables using the probit or logit models as specified by Goldberger (1964), Maddala (1983), Gujarati (2009) and Greene (2003) is to begin with the specification of an underlying latent (unobservable) response variable D_i^* which is specified as linear function consisting of a deterministic component and an error term:

$$D_i^* = \beta X_i' + \varepsilon_i \quad (2.5)$$



where; D_i^* is the latent (unobserved) dependent variable, $\beta X_i'$ is the deterministic component which consist of unknown parameters (β) and observable explanatory variables (X_i) and ε_i is the error term.

where the observed dummy variable (D_i) defined as:

$$D_i = \begin{cases} 1 & \text{if } D_i^* > 0 \text{ (Adopted)} \\ 0 & \text{if } D_i^* \leq 0 \text{ (Non-adopted)} \end{cases} \quad (2.6)$$

And the probability of observing the outcome of interest can be written as:

$$\Pr(D_i = 1) = \Pr(\varepsilon_i > -\beta X_i') = 1 - F(-\beta X_i') \quad (2.7)$$

where; $F(\bullet)$ is the cumulative distribution function of ε_i , and the likelihood function for calculating the probabilities for the observed value is then defined and in the case of the logit model, the functional form of ε is the logistic, which is specified by the equation below:

$$F(-\beta X_i') = \frac{e^{-\beta X_i'}}{1 + e^{-\beta X_i'}} \quad (2.8)$$



and in the probit model, the functional form of ε_i is the standard normal distribution which is specified as:

$$F(-\beta X_i') = \int_{-\infty}^{-\phi'x_i/\sigma} \frac{1}{(2\pi)^{1/2}} \exp\left(-\frac{t^2}{2}\right) dt \quad (2.9)$$

Furthermore, where the adoption variable consists of multiple correlated binary decision outcomes, the multivariate binary regression model should be employed (Chib & Greenberg, 1998). For instance, in the case of this study, adoption include the application of one or more of the following improved maize technologies; improved seed, inorganic fertilizer, maize-legume intercropping, row-line planting and stone bunding. This type of categorical choice modelling is different from the multinomial regression models because the multivariate probit or logit models do not obey the assumption of the independence of irrelevant alternatives (Greene 2003).

The general specification of the multivariate probit/logit models according to Capellari and Jenkins (2003) is given by:

$$Y_{ij}^* = W_{ij}'\alpha + \omega_{ij}, \quad Y_{ij} = 1 \text{ if } Y_{ij}^* > 0 \text{ and } 0 \text{ otherwise}$$

(2.10)

with variance-covariance matrix of:



$$\Sigma \approx N \left[\begin{pmatrix} 1 & & & \\ \rho_{12} & 1 & & \\ \dots & \dots & \dots & \dots \\ \rho_{1M} & \rho_{2M} & \rho_{3M} & 1 \end{pmatrix} \right] \quad (2.11)$$

The specification of the multivariate probit model stems from the fact that an improved crop technology is usually a bundle of innovations rather than a single technical or managerial intervention (Mwabul *et al.*, 2006). Owusu (2016) however, argued that farmers must adopt the entire package of the components in a technology if an agricultural technology consists of perfectly complementary components in order to improve crop yields.

In a study to model farmers' adoption decisions of multiple crop technologies in Ethiopia, Yigezu *et al.* (2015) used the multivariate probit model to analyse farmers' decisions to adopt at least one of the crop technologies. Other economists have also measured the rate of adoption of a technology (Akino & Hayami, 1975; Maiangwa *et al.*, 2010). According to Akino & Hayami (1975), the intensity of adoption can be calculated as the ratio of total land area under which the crop is cultivated with the application of the said technology, to the total land area under which the crop in question is cultivated. This can be expressed as a proportion variable (Herdt & Capule, 1983; Maiangwa *et al.*, 2010) and estimated using the fractional or beta regression (Wooldridge, 2002) or classified into ordered categories (such as full, partial or no adopters) and estimated using the ordered regression model.





From this study, the decision of a farmer to adopt improved technologies is in two-folds; first is the binary decision to adopt the technology and second is the decision that leads him to adopt a number of the technologies. The latter notion is what is referred to as count decision. In this case, the Poisson or negative binomial regression models can be used.

2.5 Adoption Studies

A lot of adoption studies have been conducted in the past decades in the field of agriculture (Ruttan, 1977; Feder *et al.*, 1985; Kutoet *al.*, 2000; Alene *et al.*, 2000; Tesfaye & Alemu, 2001; Donkoh, 2006; Donkoh & Awuni, 2011). Yigezu *et al.* (2015) noted that the first studies on technology adoption were carried out during the decade following the introduction of high yielding varieties (HYVs) in the mid-1960s (by Ruttan, 1977; Feder *et al.*, 1985).

Mmbando & Baiyegunhi (2016) examined factors influencing adoption of improved maize varieties (IMVs) in Hai District, Tanzania using the logistic regression model. In Kenya, Ouma & De-Groote (2011) examined the determinants of improved maize seed and fertilizer adoption using the Heckman two-stage model. In Ghana, studies on adoption of improved farm technologies include Wiredu *et al.*, 2015; Mal *et al.*, 2013; Yirga & Hassan, 2013). Owusu (2016) employed the logit model to analyse the factors influencing adoption of improved maize technologies in the Kwahu Afram Plains North District of Ghana.



2.6 Determinants of Farm Technology Adoption

This section reviews some factors that influence farmers' adoption decisions regarding agricultural technologies. The factors influencing agricultural technology adoption have been grouped into the following major factors; demographic and socio-economic characteristics, personality variables, communication factors among others (Rogers & Shoemaker, 1971). Other researchers (Kebede *et al.*, 1990) have broadly classified the factors that influence adoption of technologies into Social, Economic and physical factors. McNamara *et al.* (1991) also noted that the factors influencing adoption can be grouped into farmer characteristics, farm structure, institutional characteristics and managerial structure while Wu & Babcock (1998) classified them under human capital, production, policy and natural resource characteristics.

2.6.1 Farmer Characteristics

Demographic and socio-economic factors such as age, gender, household size, education among others have featured predominantly in past studies. Studies such as Agbamu (1993) and Anyaegbulam *et al.* (1995) find negative influence of household size on farmers' adoption behaviour. The finding of Martey *et al.* (2013) shows that age is an important factor that increases farmers' adoption of inorganic fertilizer technology. This could be that young adults are more dynamic and innovative in terms of technology adoption and will be more likely to adopt improved technologies as argued by Enete & Igbokwe (2009). Furthermore, Nmadu *et al.* (2015) established significant relationship between age, education, farming experience, social status and farmers' adoption.



Another study by Danso-Abbeam *et al.* (2017) in Ghana shows that age of the household head, household size, level of experience and the number of years in formal education were the significant demographic and socio-economic factors influencing farmers' adoption of improved maize variety. In Mozambique, Uaiene *et al.*, (2009) have also found that education of farmer positively influences adoption behaviours.

Decision-making is a key process in traditional households due to individuals' control and access to resources, which tends to favour males. In the study by Sodjinou *et al.* (2015), gender was found to have significant and positive effect on adoption. Buyinda & Wumbede (2008) showed that education of farmers positively influences adoption of farm technologies. In South Western Nigeria, Afolami *et al.* (2015) revealed that adoption of improved cassava varieties was significantly affected by farming experience and farming as a major occupation. Also, Sodjinou *et al.*, 2015 found a negative link between age and farmers' adoption decisions whereas Ghimire & Huang (2016) found a positive relationship between age and farmers' adoption. Awotide *et al.* (2016) and Simtowe *et al.* (2016) argued that younger farmers are less risk-averse to adopting new technologies than the aged.

2.6.2 Farm-specific Factors

Bonabana-Wabbi (2002) has attested that farm size is the most important factor influencing the adoption of agricultural technologies. Onyeneke (2017) observed that farm size had a positive and significant influence on the likelihood of adopting agrochemicals and inorganic fertilizer whereas Martey *et al.* (2013) revealed that farm



size reduces the adoption of inorganic fertilizer technology arguing that small-scale farmers often face financial constraint in purchasing costly inputs. Furthermore, Payne *et al.*, (2003) found a positive correlation between the probability to adopt improved maize technologies and farm size while Gockowski & Ndoumbe (2004) found a negative relationship between farm size and farmers' adoption of farm technologies. Nkonya *et al.* (1997) revealed that farm size tends to reduce the adoption of improved technologies, particularly fertilizer whereas Uaiene *et al.* (2009) found that farmers with larger farms were more likely to adopt an improved technology compared with those with small farmers.

2.6.3 Institutional and Communication Factors

Danso-Abbeam *et al.* (2017) in Ghana found that farm workshop attendance, membership of a farmer-based organisation, availability of labour and extension contacts influence the adoption of improved maize variety. In Tanzania, Mmbando & Baiyegunhi (2016) revealed that education, access to credit facilities, access to off-farm income, access to extension services, membership of farmer groups/association and participation in on-farm trials/demonstrations were significantly related to farmers' adoption of improved maize variety. In Ghana, Abdul-Hanan *et al.* (2014) attested that distance to an input store reduces the adoption of the input. Ouma & De-Groote (2011) examined the determinants of improved maize seed and fertilizer adoption in Kenya using the Heckman two-stage model and found that access to hired labour, education of household head and number of extension contacts significantly influenced farmers' adoption of farm technologies. In Nigeria, Awotide *et al.* (2016) studied agricultural technology adoption and found

income from rice production, membership in a farmer based organisation, distance to the nearest sources of seed and level of training were significant predictors of farmers' adoption.

2.7 Access to Credit and Farmers' Adoption of Improved Technologies

Access to credit is an important factor in farmers' production because it determines the accessibility of farm inputs when own income is low or missing. Njogu *et al.* (2017) argued that credit is the single most important variable for enhancing production and productivity and also a reliable route for increasing the adoption of improved technologies. Adeyeye *et al.* (2016) noted that credit is a temporary substitute for personal savings, which catalyses the process of agricultural production and productivity. This is because the adoption of improved technologies to increase productivity is relatively expensive and small-holder farmers cannot afford to self-finance it. As a result, the use of agricultural technologies is very low. Also, Okwoche *et al.* (1998) have found that access to credit positively influence farmers' adoption of improved technologies. Similarly, Obisesan *et al.* (2016) found a significant and positive link between access to credit and adoption of improved cassava production technology. Also, Ouma & De-Groote (2011) attested that access to credit and farmers' adoption of farm technologies are significantly and positively related. Uaiene (2009) attested that technology adoption is associated with access to credit. Mmbando & Baiyegunhi (2016) and Danso-Abbeam *et al.* (2017) revealed significant relationship between access to credit and farmers' adoption of improved maize varieties. Nmadu *et al.* (2015) established a positive significant effect of access to credit on farmers' agricultural technology adoption.





2.8 Effect of Adoption of Technologies on Farm Output

When an economy produces goods and services at least cost so as to maximize production levels, that economy is said to be productively efficient. Amare *et al.* (2012) examined the effect of agricultural technology adoption on yields. They found that adoption of agricultural technology had a positive and significant influence on yield. In addition, Bruce (2015) analysed the adoption of improved rice varieties on farmers' output using the treatment effect model and found that adoption of the improved rice varieties significantly increased farmers' outputs. Studies such as Diagne & Demont (2007) have also examined the effect of agricultural technology adoption on yields and found a significant and positive influence of adoption of agricultural technology on yield.

2.8.1 Definition and Concept of Production and Efficiency

In the estimation of farm productivity, the Stochastic Frontier Analysis (SFA) has widely been used to estimate the relationship between input and output of the farm households in the sample. In addition, SFA can help us to estimate farm productivity by accounting for both inefficiency and white noise in the data. The SFA has two components; the production function and the inefficiency equation. Thus, according to Coelli (1995), the SFA is preferred for assessing efficiency because it deals with stochastic noise and permits statistical test of hypothesis pertaining to production structure and degree of inefficiency.

Efficiency on the other hand has been defined as the effective use of variable resources for the sole purpose of profit maximization, given that the best production technology is



made available (Kebede, 2001) or the efficient combination of resources (inputs) to produce any given amount of output at least cost (Forsund *et al.*, 1980). Technical efficiency has been defined as the effectiveness with which a given set of input is used to produce an output (Leibenstein, 1966).

In the SFA, the first equation is the production function which shows the relationship between the traditional inputs such as land, labour, fertilizer and seeds while the second equation include the socio-economic and demographic factors, plot-level characteristics, environmental factors and non-physical factors on technical inefficiency. The output equation is given by:

$$Q = f(X^s, \beta) \exp(\varepsilon) \quad (2.12)$$

where, Q represents output, X^s represents the conventional inputs, β is a vector of unknown parameters to be estimated, and ε is a random disturbance. Equation (2.12) can take the following forms; quadratic functional forms, the linear functional forms and the Cobb-Douglas and transcendental functional forms. The SFA comprises a production function of usual regression type with a composite disturbance term equal to the sum of two error components. This is represented as:

$$\varepsilon_i = v_i - u_i \quad (2.13)$$



where v_i is symmetric, identically and independently distributed error term representing random variation in output due to random exogenous, measurement errors, omitted explanatory variables, and a statistical noise beyond the control of the producing unit. u_i on the other hand, is a nonnegative error term representing the stochastic shortfall associated with farm-specific factors which leads to the farm not attaining maximum efficiency of production; is the technical inefficiency of the farm and ranges between zero and one.

The technical inefficiency (u_i) can be specified as:

$$u_i = Z'\delta_i \quad (2.14)$$

where Z = vector of explanatory variables associated with the technical inefficiency effects which could include socioeconomic and farm management characteristics and δ = vector of unknown parameters to be estimated. This may follow a half-normal, truncated normal, exponential or gamma.

The technical efficiency (TE) can be calculated as:

$$TE_i = \frac{q_i}{q_i^*} = \frac{f(X_i'\beta)\exp(V_i - U_i)}{f(X_i'\beta)\exp(V_i)} = \exp(-U_i) \quad (2.15)$$

where q_i = observed value of maize output and q_i^* = frontier value of maize output. This expression shows the difference between the actual output and the potential output.

If $U_i = 0$, then $q_i = q_i^*$ implying that the production lies on the frontier, and hence, technically efficient and the farm obtains its maximum potential output given the level of inputs. However, if $U_i > 0$, production lies below the frontier and the farm is technically inefficient.

2.8.2 Determinants of Technical Efficiency

From Equation (2.15), technical efficiency of maize farmers can be defined as the ratio of actual output of maize to the optimal output, provided the production of maize is naturally random. Technical inefficiency on the other hand, can be defined as the opposite of technical efficiency (thus, 1-TE). Several factors such as socio-demographic and economic, farm-specific, environmental factors and institutional characteristics have been found to influence technical inefficiency of farmers (Chirwa, 2007). Essilfie *et al.* (2011) using the stochastic frontier to estimate farm level technical inefficiency among small-scale maize farmers revealed that age of farmers and formal education reduces inefficiencies while household size and off-farm income increases inefficiencies.

Abdul-Hanan & Abdul-Rahman (2017) investigated the technical efficiency of maize farmers in Ghana. Their analysis revealed that gender, age, farm size, education and access to extension reduce technical inefficiency while membership in association increases technical inefficiency in maize production. Furthermore, Kuwornu *et al.* (2013)



estimated technical inefficiency for maize farmers in the Eastern Region of Ghana. They found that extension visit, FBO membership, frequency of meeting by members of FBOs, formal training in maize farming, cash and in-kind credits are the major determinants of the farmers' technical efficiency level.

In most recent studies, efforts have been made to examine the technical efficiency levels in cocoa production. For instance, Dzene (2010) examined the determinants of technical efficiency of cocoa farmers in Ghana from 2001 to 2006. It was discovered that all (socioeconomic factors and non-labour inputs) except household size and intensive use of insecticides significantly impacted on technical efficiency. Other factors like fertilizer intensity and quality of farm maintenance also had positive effect and significantly influenced technical efficiency. In a study by Bempomaa & Acquah (2014) to determine the factors influencing technical efficiency of maize production in Ghana, sex of farmer, age and off-farm work activities were found to have a significant effect on technical inefficiencies in production.



CHAPTER THREE

RESEARCH METHODOLOGY

3.0 Chapter Outline

This chapter contains the materials and methods used in the collection and analysis of data. It also presents the background of the study area.

3.1 Study area

The study was conducted in Upper East Region, which is located in the north-eastern corner of the country. The region lies between longitude 00 and 10 West and latitudes 10° 30' N and 11°N. It shares boundaries with Burkina Faso to the north, the Republic of Togo to the east, Sissala East District in Upper West Region to the west and West Mamprusi District in Northern Region to the south. The land is relatively flat with a few hills to the East and Southeast. The total land area of the region is about 8,842 sq km, which translates into 2.7 percent of the total land area of the country. The research however, was carried out specifically in three districts of the region namely, Kassena-Nankana West, Bawku West and Talensi. These districts also form part of the major maize production areas in the region. They also share many common characteristics of being largely rural in nature with majority of their respective populations depending on subsistence agriculture as their main source of livelihood. The districts share similar vegetation and climatic conditions which are common to the Northern Savannah Zones of Ghana mainly made up of the Northern, Upper West and Upper East regions with climate in the region characterized by one rainy season from May/June to September/October.



The mean annual rainfall during this period is between 800 mm and 1100 mm. There is a long spell of dry season from November to mid-February, characterized by cold, dry and dusty harmattan winds. Temperatures during this period can be as low as 14 degrees centigrade at night, but can go to more than 35 degrees centigrade during the daytime.



Figure 3. 1: Map of Upper East Region

3.2 Research Design

This study employed mainly quantitative research design. The study was cross-sectional, involving the use of face-to-face interviews and semi-structured questionnaires to collect primary data in a survey. A multi-stage sampling approach was employed to select the





respondents. Both descriptive analysis (frequencies, percentages, means and standard deviations) and econometric techniques (Probit model; Multivariate probit model; Poisson regression with endogenous treatment and the stochastic frontier model) were employed to analyse the research objectives.

3.3 Target Population and Sampling Techniques

All maize farmers in the Upper East Region of Ghana were eligible for the study. A multi-stage sampling technique was used to select the respondents. In the first-stage, the cluster sampling was used to group the 13 districts of the Upper East Region into three (3) zones. These were Eastern, Central and Western zones. The Eastern, Central and Western zones had 5, 4 and 4 districts respectively. Out of these, the simple random sampling method was used to select one (1) district each for the study. These districts were Kasena-Nankana West, Bawku West & Talensi .

In the second-stage, two (2) communities were randomly selected from each of the 3 districts. A total of six (6) communities were visited for the study. In the third and final stage, a total of forty (40) farmers from each of the selected communities were also selected randomly. In all, a total of two hundred and forty (240) farmers were selected for the study.

3.4 Data Collection Methods

The study collected mainly primary data from maize farmers in three districts (Kassena-Nankana West, Bawku West and Talensi) in the month of March 2018. Data were elicited through face-to-face interviews using semi- structured questionnaires.



3.5 Data Analysis

The data were processed and analysed using various descriptive and econometric methods in STATA version 14. The probit model was used to analyse the factors influencing access to credit by farmers while the multivariate probit model was used to analyse the factors influencing adoption of maize production technologies in the Upper East Region. To analyse the effect of access to credit on the intensity of adoption, the Poisson with Endogenous Treatment model was employed. Also, the Cobb-Douglas stochastic frontier approach with sample selection was used to analyse the effect of adoption of improved technologies on maize output. Finally, the Kendall's Coefficient of Concordance was employed to examine whether there exists an agreement between maize farmers' adoption constraints.

3.6 Conceptual Framework

Farmers in Ghana especially in the Upper East Region are faced with problems of degradable farm soils, erratic rainfall conditions coupled with the recent climate change threat. This is even worsened by the seemingly continuous adoption of bad or inappropriate farming practices in their farming activities. The effects or consequences of the situation cannot be underestimated as these challenges lead to often occurrences of drought, low soil fertility in the area with their negative effects on crop yields and productivity.

Farmers have to respond to these emerging challenges by adopting innovations or improved production technologies in order to improve upon their crop yields and productivity. Some of these improved production technologies in maize include improved

maize varieties, Row/line planting, maize intercropped with legume, inorganic fertilizer, stone/soil bunding among others.

The promotion of improved production technology adoption is one of the agricultural interventions in maize production in the Upper East Region. However, the farmer's decision to adopt the innovations might strongly be influenced by some socioeconomic factors such as age, education, extension contacts, land tenure, membership of farmer based organisation (FBOs), farm size, household size, sex, distance to input market, credit, experience among others.

It is expected that if these factors positively influence the farmer's decision to adopt and his eventual adoption of the improved production technologies, it would lead to some positive and significant economic output such as improved maize output.



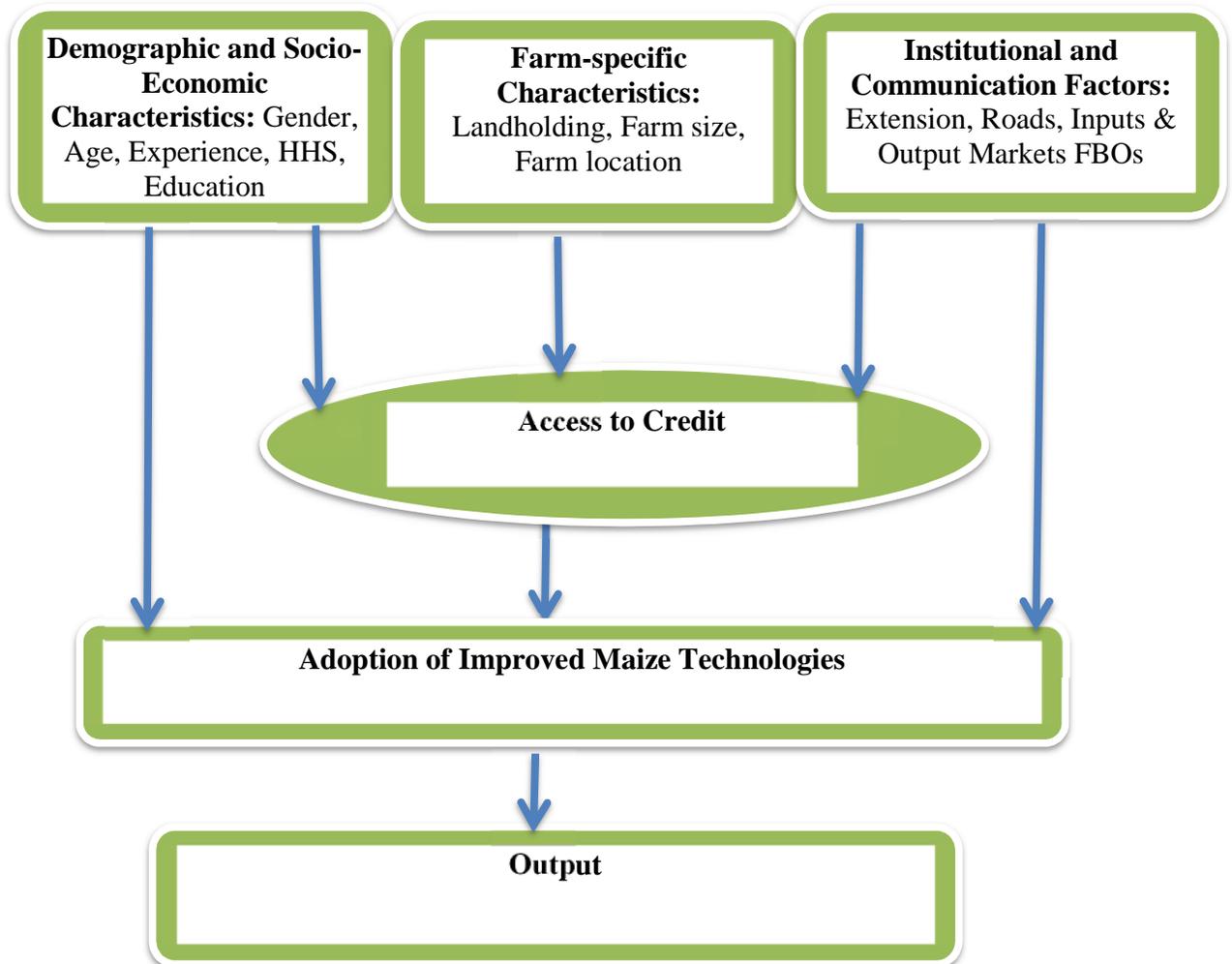


Figure 3. 2: Conceptual framework of factors influencing adoption
Source: Author's own construct.

3.7 Theoretical framework

There are two types of technology adoption; these include individual (farm-level) adoption and aggregate adoption (Feder *et al.*, 1985). This study targeted the adoption of improved production technologies in maize at the farm-level, where the adopter of a given technology is the person who used the technology at the time of the survey (i.e.



2017/2018 cropping year). The adoption of the following five (5) different technologies was analysed: improved maize varieties (IMVT), row/line planting (RPT), legume- maize inter-cropped (LMIT), inorganic fertilizer (IFT) and stone/soil bunding (SBT).

This study adopted the random utility theory to explain farmers' adoption decisions. The adoption decision is a behaviour response by an individual towards a new innovation or technology. This decision is influenced by expected utility a person gains from adopting or not adopting the technology. Thus, farmers are assumed to be rational persons with the objective of maximising expected utility from the improved production technologies (IPTs) they adopt. A farmer will therefore adopt the improved technology package or part of it if the expected utility of adoption is greater or equal to that of non-adoption (Llewellyn *et al.*, 2007). Since the utility derived from the technologies is neither observable nor known to the researcher with certainty, it is considered to be random (Fernandez-Cornejo, 1996). The utility associated with adoption of the technologies is a function of both the deterministic component (V_i) and the stochastic component ε_i such that;

$$U_{i,j} = V_{i,j} + \varepsilon_{i,j} \quad (3.1)$$

$$U_{i,k} = V_{i,k} + \varepsilon_{i,k} \quad (3.2)$$

where; $U_{i,j}$ and $U_{i,k}$ are utilities derived from adopting and not adopting IPTs respectively.

and

$$V_i = X_i' \beta$$

X is a vector of explanatory variables, while β is a vector of unknown parameters to be estimated. Therefore, a farmer will adopt the IPTs if the expected utility of adoption exceeds that of non-adoption as defined in Equation (3.3).

$$U_{i,j} \geq U_{i,k} \quad (3.3)$$

The utility derived from choosing a given alternative, adoption or non-adoption, is not observable. What is observable is the choice of the IPTs and subsequent adoption if the farmer derives higher utility from that specific choice. Thus a 'yes' response (adopted IPTs) is observed if the farmer's expected utility from the IPTs is higher and a 'no' response (has not adopted IPTs) if the farmer's expected utility from IPTs package is lower. For this study, the binary (logit and probit) choice models are not considered suitable for modelling the data since the dependent variable, adoption of the improved technologies is not binary rather it is a count variable (number of improved technologies) with a minimum of zero and a maximum of six.

3.7.1 Binary probit model analysis of factors influencing access to credit by farmers

The probit model was used to determine the factors influencing access to credit by farmers. This model is plausible and appropriate because the outcome (dependent) variable of interest (access to credit) is a dichotomous variable, which assume the value 1 if the farmer accesses credit and 0 otherwise. An important characteristic of the probit (or logit) model is that it has the ability to constrain the estimated probabilities to lie between 0 and 1, which is a limitation of the linear probability model (LPM) (Maddala, 1998). Under standard assumption of binary regression model, the probit model assumes that the error component is normally distributed as opposed to the logit model, which is



logistically distributed. The probit model assumes that the value of the observed variable (A) is dependent on whether a latent (continuous) variable (A^*) lie below or above 0 such that:

$$A_i^* = \beta_0 + X_i' \beta + \varepsilon_i \quad (3.4)$$

and

$$A_i = \begin{cases} 1 & \text{if } A_i^* > 0 \text{ if farmer accesses credit} \\ 0 & \text{if } A_i^* \leq 0 \text{ otherwise} \end{cases}$$

where A_i^* is the latent (continuous) variable, A_i is the observed binary dependent variable for access to credit, X are the explanatory variables, β_0 is the constant; β are unknown regression parameters to be estimated and ε_i is the error term.

In the probit model functional distribution of the error is very important to constrain the values of the latent variable into a desirable property of probability values of 0 and 1. The probit model assumes a cumulative distribution function of standard normal distribution represented by $F(\bullet)$.

$$\begin{aligned} \pi_i &= \Pr(A_i = 1) = \text{Prob } y(X_i' \beta + \varepsilon_i > 0) \\ &= \Pr(\varepsilon_i > -X_i' \beta) \\ &= \Pr(\varepsilon_i < X_i' \beta) \\ &= F(X_i' \beta) \end{aligned}$$

(3.5)



The general formal for the probit model can be stated as:

$$\pi(A_i = 1) = (X_i' \beta) \int_{-\infty}^{X_i' \beta} \frac{1}{\sqrt{2\pi}} \exp\left[-\frac{z^2}{2}\right] dz \quad (3.6)$$

where

π is the probability of accessing credit by farmer i and Z = standard normal variable ($Z \sim N(0, \delta^2)$). The method of estimation of the probit model was the maximum likelihood, which is given by:

$$\log \ell = \sum_{i=1}^9 Y_i \log(\pi_i) + \sum_{i=1}^9 (1 - A_i) \log(1 - \pi_i) \quad (3.7)$$

and the empirical probit model is specified in the following form

$$A_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \beta_4 X_{4i} + \beta_5 X_{5i} + \beta_6 X_{6i} + \beta_7 X_{7i} + \beta_8 X_{8i} + \beta_9 X_{9i} + \beta_{10} X_{10i} + \varepsilon_i \quad (3.8)$$

where X_1 = Gender of respondent; X_2 = Age of respondent; X_3 = Education of respondent; X_4 = Household size of respondent; X_5 = Major occupation of respondent; X_6 = Farm size; X_7 = Farm location; X_8 = Hired labour; X_9 = Extension contact and X_{10} = Membership in FBOs; $\beta_1 - \beta_{10}$ are unknown parameters to be estimated and ε is the error term.





3.7.2 The Multivariate Probit Model

The multivariate probit (MVP) model was used to analyse the factors influencing the adoption of five (5) improved maize technologies. The MVP model allows for simultaneous estimation of multiple outcomes allowing the observed and unmeasured factors (error terms) to be freely correlated (Belderbos *et al.* 2004). The correlation between the improved technologies may be complementary (positive correlation) or substitutes (negative correlation) between different practices (Belderbos *et al.* 2004). In the adoption of improved technologies, farmers consider some practices as complementary and others as competing to deal with several production constraints. The MVP model produces unbiased and efficient estimates by correcting for the unobserved factors and inter-relationships among adoption decisions regarding different practices.

In the study of adoption, we assume that farmers consider a set (or bundle) of possible technologies and choose the particular technology bundle that maximizes expected utility conditional on the adoption. Thus, the adoption decision is inherently a multivariate one and attempting univariate modelling excludes useful economic information contained in interdependent and simultaneous adoption decisions.

The multivariate probit econometric model is dependent on a latent variables (Y_{ij}) which is linearly related to a set of observed characteristics and an error term such that;

$$Y_{i,j}^* = X'_{i,j} \beta_j + u_{i,j}, \quad j=1, \quad 2, \quad \dots, \quad m$$

(3.9)

and

$$Y_{i,j} = \begin{cases} 1 & \text{if } Y_{i,j}^* > 0 \\ 0 & \text{if } Y_{i,j}^* \leq 0 \end{cases} \quad (3.10)$$

where Y_{ij}^* is the latent variable measuring the propensity of adopting improved technologies; Y_{ij} is the observed binary outcomes; β_j are unknown parameters to be estimated and μ_{ij} are the error terms which are independently and identically distributed with a standard normal distribution. The error terms follow a joint multivariate normal (MVN) distribution, with mean 0 and variance 1 and covariance matrix:

$$\Sigma = \begin{bmatrix} 1 & & & & \\ \rho_{12} & 1 & & & \\ \rho_{13} & \rho_{32} & 1 & & \\ \rho_{14} & \rho_{42} & \rho_{43} & 1 & \\ \rho_{15} & \rho_{52} & \rho_{53} & \rho_{54} & 1 \end{bmatrix} \quad (3.11)$$

The particular interest is the off-diagonal elements in the covariance matrix, ρ_m , which represent the unobserved correlation between the stochastic component of the j^{th} type of IPTs. This assumption means that equation (3.11) gives a MVP model that jointly represents decisions to adopt a particular production technology. This specification with non-zero off-diagonal elements allows for correlation across the error terms of the five (5) latent equations, which represent unobserved characteristics for the same individual farmer.

Empirical models

From the theoretical model indicated above, the empirical model to investigate the factors that influence the adoption of improved production technologies (IPTs) is specified as;



$$\text{Adoption } (A_{i,j}) = \beta_{0,j} + \beta_{1,j} X_{1,j} + \beta_{2,j} X_{2,j} + \beta_{3,j} X_{3,j} + \beta_{4,j} X_{4,j} + \beta_{5,j} X_{5,j} + \beta_{6,j} X_{6,j} + \beta_{7,j} X_{7,j} + \beta_{8,j} X_{8,j} + \beta_{9,j} X_{9,j} + \beta_{10,j} X_{10,j} + u_{i,j} \quad (3.12)$$

Table 3. 1: Description of Variables used in the MVP model

Variable	Description	Measurement
X_1	Gender of respondent	Dummy; 1 if respondent is male; 0 otherwise
X_2	Age of respondent	Years of respondent
X_3	Education	Years in schooling
X_4	Farming experience	Years in farming maize
X_5	Farm size	Number of acres of maize farm
X_6	Farm location	Dummy; 1 if Upland area; 0 other wise
X_7	Access to training	Dummy; 1 if yes; 0 otherwise
X_8	Extension contacts	Number of visits
X_9	Membership to FBO	Dummy; 1 if yes; 0 otherwise
X_{10}	Distance to inputs shop	Distance in km

3.7.3 Poisson Regression with Endogenous Treatment

The effect of access to credit on adoption intensity was determined using the Poisson regression with endogenous treatment. Adoption intensity was measured as the number of improved maize technologies adopted by the farmer, which is a non-negative variable, ranging from 0 to 5. The Poisson regression can be modeled as a random variable drawn from a Poisson distribution. In the Poisson regression, the decision to adopt a certain number of technologies is purely based on preference rather than ranking. In other words, there is often no natural upper bound to the outcomes but is limited to zero.



In specifying the Poisson regression with endogenous treatment, we first present the standard Poisson model for count data. Let $y_i, i = 1, \dots, N$ denote the dependent count variable, which is independently Poisson distributed, and its conditional mean is given as:

$$E(y_i|x_i) = \mu_i = \exp(x_i'\beta) \quad (3.13)$$

where x_i is a k-vector of explanatory variables and β is a k-vector unknown parameters to be estimated. The conditional mean specification in Equation (3.13) can be rewritten as a regression model such that:

$$Y_i = \mu_i + u_i = \exp(x_i'\beta) + u_i \quad (3.14)$$

and the probability of the individual i choosing Y improved technologies is computed using the formula below:

$$\Pr(Y_i = y_i|\mu_i) = \frac{e^{-\mu_i}\mu_i^{y_i}}{y_i!} (y_i = 0,1,2, \dots) \quad (3.15)$$

where Y_i is the observed count (number of improved technologies to be adopted); Pr the probability of choosing y_i number of improved technologies by i^{th} individual, μ is the mean incidence rate of the number of technologies adopted per unit of *exposure*, which is given by:

$$\mu_i = \exp(\gamma_0 + \gamma_1x_1 + \gamma_2x_2 + \gamma_3x_3 + \dots + \gamma_kx_k) \quad (3.16)$$

The coefficients of the regression are more often computed using the maximum likelihood estimation as follows:



$$\ln[L(y_i, \gamma)] = \sum_i^n y_i \ln[\mu_i(x_i' \gamma)] - \sum_i^n y_i \ln[y_i!] \quad (3.17)$$

Following Greene (1998), the Poisson regression with endogenous treatment allows for a potential correlation structure between the unobservable variables that affect access to credit and adoption intensity to be estimated such that:

$$E(Y_i | x_i, c, u_i) = \exp(x_i' \gamma + c\lambda + u_i) \quad (3.18)$$

where x_i is a k-vector of other explanatory variables influencing adoption intensity, γ is a k-vector of unknown parameters to be estimated, c is the treatment variable, which account sample selectivity bias and u_i is the error term.

Table 3. 2: Description of variables in the standard Poisson model

Variable	Description	Measurement
x_1	Gender of respondent	Dummy; 1 for male; 0 otherwise
x_2	Age of respondent	Years of farmer
x_3	Education of respondent	Years in schooling
x_4	Farming experience	Number of years in farming maize
x_5	Farm size	Acreages of cultivated maize farm
x_6	Farm location	Dummy; 1 if upland area; 0 otherwise
x_7	Access to training	Dummy; 1 if yes; 0 otherwise
x_8	Extension contact	Number of visits
x_9	Membership to FBOs	Dummy; 1 if yes; 0 otherwise
x_{10}	Distance-to-input shops	Distance in km



Furthermore, the probability function for Y conditional on the treatment c , the covariates x_i and error term u_i is given by:

$$E(Y_i|x_i, c, u_i) = \frac{\exp\{(x_i'\gamma+c\lambda+u_i)\}-\{\exp(x_i'\gamma+c\lambda+u_i)\}^{Y_i}}{Y_i!} \quad (3.19)$$

where the treatment (access to credit) model is given by:

$$c_i = \begin{cases} 1 & \text{if } c_i^* > 0 \\ 0 & \text{if } c_i^* \leq 0 \end{cases} \quad (3.20)$$

and

$$c_i^* = a_o + aW_i' + e_i \quad (3.21)$$

where c_i^* is the propensity to access credit, c_i is the observed dependent variable, representing access to credit, W_i is a k -vector of covariates influencing access to credit, a is a k -vector of unknown parameters to be estimated, and e_i is the error term, which follow bivariate normal distribution with mean zero and covariance matrix. This can be specified as:

$$\begin{bmatrix} \sigma^2 & \sigma\rho \\ \rho\sigma & 1 \end{bmatrix} \quad (3.22)$$

The empirical model of the Probit model specifying the factors that influence access to credit can be represented by:

$$c_i = a_o + a_1W_1 + a_2W_2 + a_3W_3 + a_4W_4 + a_5W_5 + a_6W_6 + a_7W_7 + a_kW_k + a_8W_8 + a_9W_9 + a_{10}W_{10} + e_i \quad (3.23)$$



Table 3. 3: Description of variables in the standard probit model

Variable	Description	Measurement
W_1	Gender of respondent	Dummy; 1 if respondent is male; 0 otherwise
W_2	Age of respondent	Years of farmer
W_3	Education of respondent	Years in schooling
W	Household size of respondent	Number of people in the household
W_5	Major occupation of respondent	Dummy; 1 if Farming; 0 otherwise
W_6	Farming experience	Number of years in farming maize
W_7	Farm size	Number of acres of maize farm
W_8	Farm location	Dummy; 1 if upland area; 0 otherwise
W_9	Extension contact	Number of visits
W_{10}	Membership to FBOs	Dummy; 1 if yes; 0 otherwise



Goodness of Fit Test

The Poisson distribution has the property that the mean and the variance are equal. The overall goodness of fit in terms of the appropriateness of the Poisson model relative to the Negative binomial model can be measured by two chi-square tests. These are the Pearson chi-square statistic;

$$P_p = \sum_{i=1}^n \frac{(y_i - \hat{\mu}_i)^2}{\hat{\mu}_i} \tag{3.24}$$

and the Deviance chi-square statistic;

$$P_p = \sum_{i=1}^n \left\{ y_i \ln \left(\frac{y_i}{\hat{\mu}_i} \right) - (y_i - \hat{\mu}_i) \right\} \quad (3.25)$$

The Deviance formula can be rewritten as:

$$D(y_i, \mu_i) = 2\{LL_{y_i} - LL_{\mu_i}\} \quad (3.26)$$

3.7.4 The Stochastic Frontier Approach

The stochastic frontier approach (SFP) was employed to analyse the effect of adoption on maize output by accounting for selectivity bias. The SFP helps to estimate farm productivity by accounting for both inefficiency and white noise in the data. The SFA has two components; the production function and the inefficiency equation. Coelli (1995) argued that, the SFA is preferred for assessing efficiency because it deals with stochastic noise and permits statistical test of hypothesis pertaining to production structure and degree of inefficiency.

The SFA, the first equation is the production function which shows the relationship between the traditional inputs such as land, labour, fertilizer and seeds while the second equation include the socio-economic and demographic factors, plot-level characteristics, environmental factors and non-physical factors on technical inefficiency. The outcome equation is given by:





$$Q = f(X^s, \beta) \exp(\varepsilon) \tag{3.27}$$

where Q represents output, X^s represents the conventional inputs, β is a vector of unknown parameters to be estimated, and ε is a random disturbance. Equation (3.27) can take the following forms; quadratic functional forms, the linear functional forms and the Cobb-Douglas and transcendental functional forms. The SFA comprises a production function of usual regression type with a composite disturbance term equal to the sum of two error components. This is represented as:

$$\varepsilon_i = v_i - u_i \tag{3.28}$$

where v_i is symmetric, identically and independently distributed error term representing random variation in output due to random exogenous, measurement errors, omitted explanatory variables, and a statistical noise beyond the control of the producing unit. u_i on the other hand, the element is a nonnegative error term representing the stochastic shortfall associated with farm-specific factors which leads to the farm not attaining maximum efficiency of production; is the technical inefficiency of the farm and ranges between zero and one.

Table 3. 4: Variable Description and Measurement in the SFA

Variable	Description	Measurement
X_1	Farm size	Number of acres cultivated
X_2	Labour	Cost per man day
X_3	Inorganic fertilizer	Bags in Kg
X_4	Seed	Kg
X_5	Pesticide	Litres

λ	Adoption	Number of technologies used
-----------	----------	-----------------------------

The technical inefficiency (U_i) can be specified as:

$$U_i = Z'\delta_i \tag{3.29}$$

where Z = vector of explanatory variables associated with the technical inefficiency effects which could include socioeconomic and farm management characteristics and δ = vector of unknown parameters to be estimated. This may follow a half-normal, truncated normal, exponential or gamma.

The technical efficiency (TE) can be calculated as:

$$TE_i = \frac{q_i}{q_i^*} = \frac{f(X_i'\beta)\exp(V_i - U_i)}{f(X_i'\beta)\exp(V_i)} = \exp(-U_i) \tag{3.30}$$

where q_i = observed value of vegetable output and q_i^* = frontier value of vegetable output. This expression shows that the difference between and is embedded in. If $U_i = 0$, then $q_i = q_i^*$, implying that the production lies on the frontier, and hence, technically efficient and the farm obtains its maximum potential output given the level of inputs. However, if $U_i > 0$, production lies below the frontier and the farm is technically inefficient.



$$U_i = \delta_0 + \delta_1 Z_1 + \delta_2 Z_2 + \delta_3 Z_3 + \delta_4 Z_4 + \delta_5 Z_5 + \delta_6 Z_6 + \delta_7 Z_7 + \delta_8 Z_8 + \delta_9 Z_9 + \delta_{10} Z_{10} + e_i \quad (3.31)$$

Table 3. 5: Description of variables in the technical inefficiency model

Variable	Description	Measurement
Z_1	Gender of respondent	Dummy; 1 if male; 0 otherwise
Z_2	Age of respondent	Years of respondent
Z_3	Education of respondent	Number of years in schooling
Z_4	Farming experience	Number of years in farming maize
Z_5	Membership in FBO	Dummy; 1 if yes; 0 otherwise
Z_6	Extension contacts	Dummy; 1 if yes; 0 otherwise
Z_7	Access to credit	Dummy; 1 if yes; 0 otherwise
Z_8	Farm size	Number of acres of maize farm
Z_9	Farm location	Dummy; 1 if upland area; 0 otherwise
Z_{10}	Access to labour	Dummy; 1 if yes; 0 otherwise

3.7.5 Analysis of farmers' constraints in technology adoption in maize production

Kendall's Coefficient of Concordance (W) was employed to rank and test whether there exists significant agreement between farmers' constraints in the adoption of improved technologies. The Kendall's Coefficient of Concordance (W) measures the degree of



concordance or agreement between the constraints of respondents (Edwards, 1964). The general specification of the Kendall's coefficient (W) is:

$$W = \frac{n[\sum T^2 - (\sum T)^2/n]}{nm^2(n^2 - 1)} \quad (3.32)$$

where;

T = sum of ranks for the factors being ranked, m = number of respondents and n = number of factors being ranked.

The maximum variance (T) is given by:

$$T = m^2(n^2 - 1)/12 \quad (3.33)$$

$$VarT = [\sum T^2 - (\sum T)^2/n] \quad (3.34)$$

The significance of the Coefficient of Concordance (W) may then be tested in terms of the F distribution as follows:

$$F\text{-ratio } (F_c) = \frac{(m-1) \times w}{1-w} \quad (3.35)$$

Degree of freedom for numerator (df) = $(n - 1) - (2/ m)$

Degree of freedom for the denominator (df) = $(m - 1) \{ (n - 1) - (2/ m) \}$



CHAPTER FOUR

RESULTS AND DISCUSSION

4.0 Chapter Outline

This chapter presents the results and discussion of the study. The discussions are also compared with past studies.

4.1 Descriptive Statistics of Farmer Characteristics

The study obtained information on demographic and socio-economic characteristics of farmers such as sex, age, education, household size, major occupation and farming experience.

Majority (72.9%) of the farmers were males. This is consistent with Wekem (2013) who found maize production to be dominated by males in the Upper East Region. This could be due to the tedious nature of the work in maize production, which is more demanding in terms of resources, including labour which fit men more due to their greater access to production resources. Besides, it could be that women provide labour on their husbands' maize farms rather than to cultivate their own due to the fact that women are generally constrained in terms of income (Matata *et al.*, 2010).

The minimum and maximum ages of farmers were 20 and 70 years respectively. The farmers were 44.8 years on average. Furthermore, the highest percentage (34.42%) of the



farmers was between the ages of 40-49 years. This positions them in the aging age bracket. The results show that older people are mostly represented in maize farming.

On the average, the farmers attained primary education (mean = 3.50) years of formal education. The education of the farmers ranged from 0 (no formal education) to 16 years (tertiary education). Furthermore, the majority (60%) of the farmers had no formal education while the minority (4%) had tertiary education. This is consistent with Wekem (2013) who found that the majority of farmers in the Upper East region had no formal education. Also, those with primary and secondary educations were 18.75% and 16.67% respectively. Generally, the level of formal education among farmers is still low in the study area, and this can be a stumbling block to the adoption of improved technologies because less-educated farmers may find it difficult to assess the merits and demerits of new technologies to know those that are high yielding and cost-effective (Marenya & Barret, 2006; Randela *et al.*, 2008). According to Minot *et al.* (2006), a higher level of education is expected to be associated with the production of higher value crops and more commercially oriented agriculture.

The mean household size was 6.9 people, with 1 and 15 as the minimum and maximum household sizes respectively. Furthermore, the greatest percentage (61.67%) of farmers had household sizes between 6 to 10 people, 29.17% had up to 5 people and very few respondents (9.17%) had 15 people or more in their household. The mean household size is consistent with the Regional Average of 6 persons per household in the 2010 Population and Housing Census (PHC) (GSS, 2012). This is a potential source of family



labour for increasing crop production by farmers in the study area as bigger household sizes have more people to undertake farm work and minimise the cost of labour.

The experience of farmers engaged in maize farming ranged from 1 to 21 years. Furthermore, mean farming experience was 6.5 years. A further examination revealed that the greatest percentage (52.92%) had spent not more than 5 years in the farming of maize in the Upper East Region, 32.92% had farming experience ranging from six (6) to ten (10) years, 11.25% had farming experience between 11-15 years and the lowest percentage (2.92%) had 16 years and more of experience in their farming. The mean farming experience is relatively low compared to the mean age of farmers indicating that the farmers were engaged in their traditional crops such as millet, rice, sorghum, groundnuts, beans among others and are now shifting to or adding the cultivation of maize to their traditional crops in the region. It offers farmers fair source of knowledge and new skills and it is form of diversification in their farming businesses to help increase their productivity.

The majority of farmers representing 73.3% practiced farming as their major occupation. This confirms the general assertion that agriculture remains the largest source of employment for many rural people in Ghana (GSS, 2012). This is why many development projects are geared toward the agricultural sector to promote productivity to increase income and alleviate poverty. Other major occupations of farmers were: petty trading (6.67%), weavings (3.33%), salary work (4.17%), pito brewing (4.58%), mining (2.08%) and tailoring (5.83%).





Table 4. 1: Summary Statistics of Demographic Characteristics of Respondents

Variable	Frequency	Percentage	Mean	Std. Dev.	Min	Max
Gender						
Male	175	72.9				
Female	65	27.1				
Total	240	100				
Age						
			44.88	10.60	20	70
Less than 30 years	19	7.92				
30-39 years	44	18.33				
40-49 years	85	35.42				
50-59 years	70	29.17				
60 and above	22	9.17				
Total	240	100				
Education						
			3.51	4.78	0	16
No formal	144	60				
Primary	45	18.75				
Secondary	40	16.67				
Tertiary	11	4.58				
Total	240	100				
Household size						
			6.93	2.44	3	15
5 people and below	70	29.17				
6-10 people	148	61.67				
10 people or more	22	9.17				
Total	240	100				
Experience in farming						
			6.55	4.29	1	21
Up to 5 years	127	52.92				
6-10 years	79	32.92				
11-15 years	27	11.25				
Above 15 years	7	2.92				
Total	240	100				
Major occupation						

Farming	176	73.3
Others	64	26.7
Total	240	100

Source: Field Data, 2018

4.2 Farm-specific characteristics

Farm size was computed as the size of arable land actually cultivated for maize in the 2017/2018 farming season, and it ranged from 0.5 to 6 acres. The highest percentage (67.5%) of farmers were found to work on farm sizes ranging between 1 and 2.9 acres, 25% worked on farm sizes ranging between 3 and 4.9 acres, 6.7% worked on 5 acres or more and only 0.83% worked on less than one acre. Furthermore, the mean maize farm size farmers cultivated was 2.17 acres. This is consistent with Wekem (2013). The study observed that overall, farmers in the study area cultivate maize on a relatively small farm sizes, and could imply smaller output, other things held equal.

The majority of the farms representing 64.2% were situated on uplands. This signifies that farmers prefer uplands for the cultivation of maize compared to lowlands. A reason for this could be that lowland farms may be prone to flooding.

The land tenure system or mode of land ownership among farmers evidenced by the survey results were inheritance, purchase and rented. From the results, the majority (74.6%) of the farmers owned land through inheritance from their families, 16.7% of those lands was purchase from neighbours, relatives, friends or private land sellers and 8.8% were rented, and those farmers are only allowed to grow annual crops and strictly not to grow perennial crops. Of those who bought their land, all of them stated to have land title deeds. From the study, there is a growing shift from family land ownership to



individual land ownership with title deeds to the land they use. This finding is consistent with Wekem (2013) in the Upper East Region who reported that the main form of land ownership among farmers is through inheritance

Table 4. 2: Summary Statistics of Farm-specific Characteristics of Respondents

Variable	Frequency	Percentage	Mean	Std. Dev.	Min	Max
Farm size			2.17	1.30	0.5	6
Less than 1 acre	2	0.83				
1 - 2.99 acres	162	67.50				
3 - 4.99 acres	60	25.0				
5 acres and more	16	6.67				
Total	240	100				
Farm Location						
Upland	154	64.17				
Lowland	86	35.83				
Total	240	100				
Land Ownership						
Inherited	179	74.58				
Purchased	40	16.67				
Rented	21	8.75				
Total	240	100				
Crop output	240		761.08	560.29	10	2700

Source: Field Data, 2018

The farmers obtained 761 kg (7.6 maxi-bags) of output in the 2017/2018 cropping season on the average (**Table 4.2**). Furthermore, the majority (52.08%) of the farmers obtained 500 kg (5 maxi-bags) or less of maize output whereas the minority (3.75%) obtained 2000 kg (20 maxi-bags) or more of maize output (Figure 1). Furthermore, 24.17% obtained maize output ranging from 501 to 1000 kg, 14.58% were found to obtained



maize output ranging from 1001 to 1500 kg and 5.42% obtained maize output ranging from 1501 to 2000 kg (Figure 4.1).

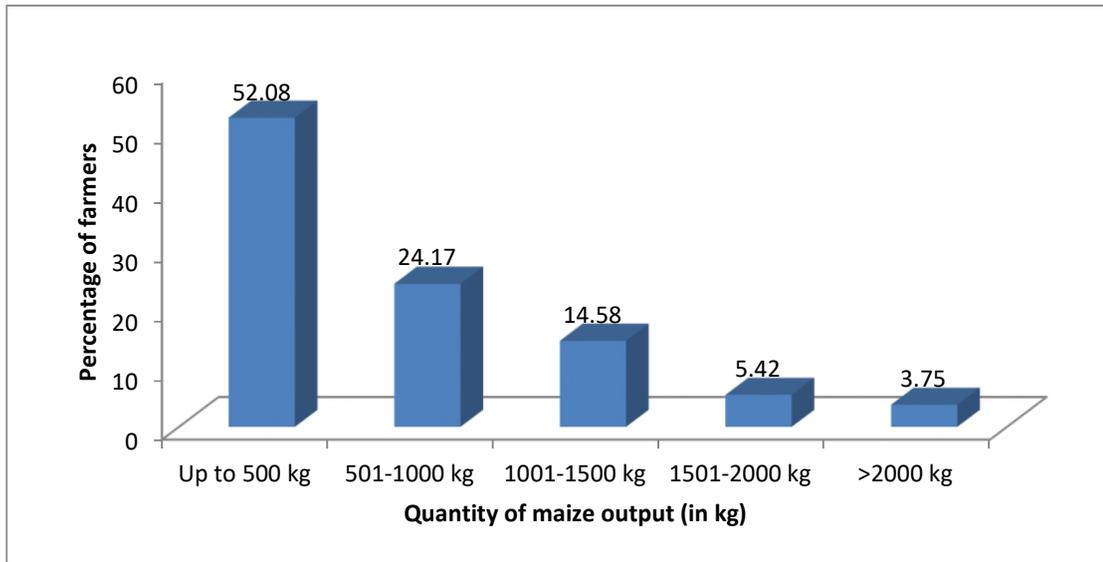


Figure 4. 1: Results of Maize Output of Farmers
Source: Field Data, 2018

4.3 Institutional Factors

The study collected information on certain institutional variables such as extension services, access to training on improved farming methods, distance to nearby input shop, distance to nearby output market and membership in FBOs. Table 4.3 is the summary statistics of these variables.

From the results in Table 4.3, farmers who reported to have at least one extension contact were 34.2%, which implies that the majority of maize farmers in the study area do not have access to extension services. Out of those who had extension contacts, 55.42% had farm visit ranging from 4 to 6, 42.17% had extension visits ranging from 1 to 3 and only





2.41% had extension visits ranging from 7 to 9. Generally, majority of farmers (65.83%) did not have access to extension contacts which is a setback to adoption of improved technologies. Extension agents expose farmers to information about new technologies through training; group discussion, plots demonstration, and this tend to improve their adoption of new technologies. For instance, Pattanayak *et al.* (2003) maintained that the provision of extension services by the government agents, NGOs, and other stakeholders play a very important role in the adoption of new agricultural technologies.

From the results, (48.3%) of the farmers had access to training on improved farming methods. Farmers' participation in training programs increases their knowledge about improved farming methods and these farmers are more likely to have higher adoption and as a result become efficient in resource use than those who do not know about the improved technologies.

From the results in Table 4.3, farmers travelled 10.37% kilometres to access the nearest input shop on the average. The distance between farmers and the nearest input shop ranged from 2 to 21 kilometres. Furthermore, about 29.17% of farmers travelled 5 kilometres or less and 6-10 kilometres to access the nearest input shop respectively, 23.33% travelled between 11 to 15 kilometres and 18.33% travelled 15 kilometres or more to reach the nearest input shop. Referable to the deplorable nature of rural roads, farmers travel fairly longer distances to access nearby input shops. This can reduce farmers' access to farm inputs and limit agricultural commercialisation. Apart from having limited access to inputs as enumerated above, farmers are more likely to incur higher cost

in input accessibility to transportation. Farmers who are closer to input shops are more likely to be exposed to information about the potential benefits of new technologies, and improve the adoption of improved maize technologies.

Table 4. 3: Summary Statistics of Institutional Factors

Variable	Freq.	Percentage	Mean	Std. Dev.	Min	Max
Training on farming practices						
Access	116	48.33				
No Access	124	51.67				
Total	240	100				
Distance to Nearby Input Shop			10.37	5.90	2	21
Up -5 km	70	29.17				
6 - 10 km	70	29.17				
11- 15 km	56	23.33				
More than 15 km	44	18.33				
Total	240	100				
Distance to Nearby Output Market			10.04	5.72	2	20
Up - 5 km	77	32.08				
6 - 10 km	68	28.33				
11 - 15 km	57	23.75				
More than 15 km	38	15.83				
Total	240	100				
Extension Contacts						
No Access	158	65.83				
Access	82	34.17				
1 - 3 times	35	42.17				
4 - 6 times	46	55.42				
7 - 9 times	2	2.41				
Total	240	100				
Membership in FBOs						
Member	69	28.75				
Not a Member	171	71.25				
Total	240	100				
Access to credit						
Borrowers	84	35.0				
Non-borrowers	156	65.0				



Total **240** **100**

Source: Field Data, 2018

The study revealed that farmers travel 10.04 km to reach the nearest major market on the average. The minimum and maximum distances to the nearest output markets were 2 and 20 kilometres respectively. Farmers who are closer to output markets have a better chance to sell more produce by incurring less cost on transportation. The study further put farmers into four categories based on their distance to the nearest output market, and found that 32.08% of them travelled 5 kilometres or less, 28.33% travelled between 6-10 kilometres, 23.75% travelled between 11 to 15 kilometres and 15.83% travelled 15 kilometres or more to reach the nearest output market.

From Table 4.3, farmers who had access to credit for maize production were 35% and the rest, who form the majority use their own income for maize production. This study agrees with Dinye (2013) who found that the majority of farmers do not have access to credit facilities and depend on family and friends to finance crop production. This situation is worrying since lack of access to credit can affect agricultural production. According to Feder *et al.* (1985), adequate, cost-effective and timely access to credit affects adoption. Lack of access to credit in the midst of low or no income by farmers limits the use of modern inputs or technologies (Bhalla 1979).

From Table 4.3, the minority of farmers representing 28.8% belong to FBO while the rest do not belong to FBO. Membership to FBO is an essential tool for disseminating





agricultural information to farmers. Membership to FBO also serves as social collateral for accessing credit. From the perspective of financial institutions, membership to FBO is an essential tool for screening loan applications and for ensuring that loans are repaid to allow prospective members to access credit in subsequent seasons (Aryeetey, 2005). FBOs enable their members to have easy access to credit by overcoming credit market failures, in particular allowing farmers who cannot provide physical collateral or guarantor to benefit from joint liability. Furthermore, membership to FBO also makes it easier for extension officers to visit the farmers and share some knowledge in good agricultural practices with them.

4.4 Adoption of Improved Maize Technologies

This result is to enable us distinguish between the different technologies farmers use in order to achieve the second objective of this study. From the study, farmers practiced one or more of the following improved technologies for maize production: improved maize seeds, inorganic fertilizer, legume-maize intercropping, row-line planting and stone/soil bunding. From the results in Table 4.4, the intensity of adoption of improved technologies ranged from 1 to 5, with a mean of 2.9. Furthermore, the highest percentage (90.42%) of the farmers adopted improved maize variety technology (*IMVT*), 90.0% adopted inorganic fertilizer technology (*IFT*), 30.83% adopted row-line planting technology (*RPT*), 21.25% practiced stone/soil bunding technology (*SBT*) and 20.83% adopted legume-maize intercropping technology (*LMIT*). This can improve maize



productivity and farmers' income as increased use of improved technologies is a precondition for higher productivity. Adoption of improved maize varieties by farmers improves their productivity, increase the rural farmers' income and better their living conditions. Row-line planting provides plants with adequate space, improving accessibility to water, light and nutrients which are vital for plants growth and development. Besides, it enhances weeding efficiency and eases the application of fertilizer and other agrochemicals. On the other hand, inorganic fertilizers are formulated to contain the major nutrients such as Nitrogen, Phosphorus, Potassium, etc. in their right proportions and when applied to the soil the nutrients are made readily available for plant usage which improves growth and development.

Table 4. 4: Farmer Adoption of Improved Maize Technologies

Variable	Frequency	Percentage
Improved Maize Variety		
Yes	217	90.42
No	23	9.58
Total	240	100
Inorganic Fertilizer		
Yes	216	90.0
No	24	10.0
Total	240	100
Legume-Maize Intercropping		
Yes	50	20.83
No	190	79.17
Total	240	100
Row/line Planting		
Yes	74	30.83
No	166	69.17
Total	240	100
Stone Bunding		
Yes	51	21.25
No	189	78.75
Total	240	100

Intensity of Adoption (Mean)	240	2.917
------------------------------	-----	-------

Source: Field Data, 2018

4.5.1 Factors Affecting Access to Credit

Table 4.5 presents the maximum likelihood estimation results of the probit model showing the influence of ten (10) explanatory variables on access to credit. Of these variables, age, education, extension contacts, farm size and membership in FBOs had a positive significant influence on access to credit.

Age and Access to Credit: Age had a positive significant influence on credit access, implying older farmers were more likely to access credit compared to younger farmers. This result agrees with Sedem *et al.* (2016) and Iyanda *et al.* (2014). On the contrary, Denkyirah *et al.* (2016), revealed that age significantly reduces farmers' access to credit.

Education and Access to Credit: Furthermore, the results portray education to be one of the important determinants of access to credit. It was found that education had a positive significant influence on access to credit, indicating that farmers who attained formal education were more likely to access credit, *ceteris paribus*. This result corroborates the results of Hananu *et al.* (2015) and Akudugu *et al.* (2012). A plausible reason could be that educated farmers understand credit schemes and their requirements for satisfying credit application processes better than those without formal education (Hananu *et al.*, 2015). Similarly, being educated increases one's confidence in approaching financial institutions for credit due to the higher possibility of them becoming formally employed, which serves as a security for credit application.





Farm size and Access to Credit: Another significant variable influencing access to credit was farm size. The results showed that farm size increases the likelihood of farmers accessing credit for agricultural production. In other words, larger farm holders were more likely to access credit. This result agrees with Chandio *et al.* (2017) and Awotide *et al.* (2016) who found a positive significant link between farm size and access to credit.

Extension Contact and Access to Credit: The number of extension contacts was also found to have a significant effect on access to credit. The relationship was positive, indicating that farmers with more extension contacts were more likely to access credit. This result is in agreement with Sedem *et al.* (2016) who found that farmers with extension contacts had higher access to credit. This is because extension services provided by government agencies and NGOs provide farmers with information or link them to credit sources.

Membership in FBOs and Access to Credit: Membership in FBO had a positive significant influence on access to credit, which indicates that farmers who are members of FBOs were more likely to access credit, *ceteris paribus*. This result is in tandem with Assogba *et al.* (2017) who analysed the determinants of credit access by smallholder farmers using the logit regression model and found that smallholder farmers' access to credit significantly increases with membership to FBOs. This is probably because membership to FBOs comes with several benefits such as better access to credit information, group lending and social collateral which serves as guarantor for accessing

credit (Akudugu *et al.*, 2009). FBOs can intercede for their members by mediating with formal financial institutions on behalf of smallholder farmers who often lack physical collateral and other securities.

Table 4. 5: Factors Influencing Access to Credit Using the Binary Probit Model

Variable	Coef.	Std. Err.	P>z
Gender	-0.089	0.266	0.738
Age	0.026**	0.010	0.014
Education	0.059***	0.022	0.008
Household size	-0.028	0.051	0.589
Farming as a major occupation	-0.090	0.074	0.228
Farm size	0.282***	0.107	0.008
Farm location	0.160	0.223	0.473
Hired labour	0.026	0.256	0.919
Extension contacts	0.292***	0.070	0.000
Membership in FBOs	0.962***	0.221	0.000
Constant	-2.792	0.592	0.000

Note: Legends (***) (** and *) denote 1%, 5% and 10% significance levels respectively

Source: Field Data, 2018

4.4.2 Factors Influencing the Adoption of Improved Maize Technologies

The factors influencing adoption of improved maize variety technology (*IMVT*), inorganic fertilizer technology (*IFT*), legume-maize intercropping technology (*LMIT*), row-line planting technology (*RPT*) and stone/soil bunding technology (*SBT*) were identified and analysed using the multivariate probit regression model. The model was significant at 1% level under the Wald chi-square test (188.29), implying that at least one of the independent variables in the multivariate probit regression model has a significant influence on at least one improved maize technology adoption.





The parameter measuring correlation between the adoption of at least two improved technologies was statistically significant (at 1% level) under the likelihood ratio (LR) chi-square test (27.20), justifying that the use of the MVP model is correctly specified. In other words, the estimation of separate probit regression models would have produced biased and inconsistent estimates.

There was a positive significant correlation between three paired adoption variables, indicating that farmers' adoption of *RPT* and *LMIT*; *SBT* and *RPT*; and *SBT* and *LMIT* are complements rather than substitutes.

The correlation between *SBT* and *LMIT* was stronger than *RPT* and *LMIT* and *SBT* and *RPT* respectively.

(1) **Improved Maize Variety Technology Adoption**

Firstly, sex was found to be significant and negative, indicating that female farmers were more likely to adopt improved maize variety technology (*IMVT*) for agricultural production.

Secondly, there was a significant (at 10% level) and positive relationship between age and adoption of improved maize variety technology (*IMVT*). The positive relationship means that the probability of adopting *IMVT* increases with age, other things held constant. In other words, older farmers were more likely to adopt *IMVT* compared to younger farmers. This agrees with Islam *et al.* (2012) who found that older and more experienced farmers are more accessible to new technologies. However, this study



disagrees with Danso-Abbeam *et al.* (2017) who cited that older farmers are used to their conventional ways of farming and usually find it difficult to switch, unlike young people who are associated with a higher risk taking behaviour.

Thirdly, education was also found to be significant (at 10% level) and positive indicating that adoption of *IMVT* increases with education. In other words, educated farmers were more likely to adopt *IMVT* for agricultural production. This is consistent with the finding of Danso-Abbeam *et al.* (2017) who cited that better educated farmers can easily assess information about improved technologies and therefore adopt if returns are appealing (Diirro & Sam, 2015). This observation is also consistent with Bruce (2015) who found formal education to be an important determinant of improved variety technology adoption in rice production. Farmers who have knowledge through higher education on improved variety that increases crop productivity and income (Bruins, 2009; Alene *et al.*, 2009; Krishna & Qaim, 2008) will be more likely to adopt *IMVT*.

Farm size had a significant (1% level) and positive, indicating that farm size increases the probability of adopting *IMVT*, *ceteris paribus*. In other words, large-scale farmers were more likely to adopt *IMVT*. This finding is consistent with Onyeneke (2017) who found a positive and significant relationship between farm size and the likelihood of adopting improved rice varieties. Also consistent with this finding is Danso-Abbeam *et al.* (2017) who found that the probability of farmers adopting improved maize variety increases for larger farm size owners in northern Ghana. They cited that larger farm size owners are usually into commercial farming and will usually plant improved maize variety for profit



maximization. Contrary to this, Lunduka *et al.* (2012) found that larger farmland holders had significantly lowered adoption of opened pollinated maize variety in Malawi. In terms of improved rice variety technology (*IRVT*) adoption, Bruce (2015) found that the probability of *IRVT* was higher for smaller farm holders in Ghana.

Farm location was also found to be significant (at 10% level) and positively related to the adoption of *IMVT*, which indicates that farmers whose farms were situated at upland areas were more likely to adopt *IMVT* compared to those whose farms were situated at lowland areas, holding other factors constant. Farms cultivated on uplands are more likely to be safe from excessive soil water and flooding which have negative effects on yield of *IMV* unlike their counterparts whose farms on the lowland areas are prone to waterlogged and flooding under which the *IMV* will not do well.

Distance-to-input shops had a negative significant (at 5% level) influence on the probability of adopting *IMVT*, which means longer distances to nearby input shops reduce the likelihood of adopting *IMVT*, *ceteris paribus*. In other words, farmers who travel shorter distances to access nearby input shops were more likely to adopt *IMVT*. Closeness of farmers to input shops increases accessibility to production resources and lowers input expenditures because farmers can cut down transportation and use that money to purchase more input. This is consistent with Donkoh & Awuni (2011) who revealed that distance to an input store reduces the adoption of the input sold, further arguing that farmers find most inputs, especially chemical fertilizers expensive and so if

they have to transport the inputs from a far place and incur extra costs, given the poor road network, they may feel reluctant.

Finally, extension contact had a positive significant (at 5% level) influence on the adoption of *IMVT*. This means that farmers with an extension contact have a higher probability of adopting *IMVT*, *ceteris paribus*. Extension contact improves accessibility to agricultural innovations because farmers get lots of production information from extension as cited by Danso-Abbeam *et al.* (2017) who also found that the probability of adopting *IMVT* increases with extension contacts in Ghana. Similarly, in northern Tanzania, Nkonya *et al.* (1997) examined the impact of agricultural extension service on adoption of *IMVT*. They revealed that access to extension services significantly increases adoption of *IMVT*.

(2) **Inorganic Fertilizer Technology Adoption**

Age had a significant (10% level) and positive relationship with the probability of adopting inorganic fertilizer technology (IFT), which implies that older farmers were more likely to adopt *IFT*, *ceteris paribus*. This is not consistent with Martey *et al.* (2014) who cited that younger farmers are more dynamic and innovative in terms of technology adoption and will be more likely to adopt improved technologies (Enete & Igbokwe, 2009). On the whole, age tended to influence adoption of *IMVT* and *IFT* only and in the researcher's view, it has to do with financial resource endowments as older household heads are affluent and often able to purchase costly input like *IMVT* and *IFT*.





Farm size was significant (at 1% level) and had positive relationship with adoption of *IFT*, indicating that farm size increases the probability of adopting *IFT*, ceteris paribus. This indicates that large-scale farmers are more likely to adopt *IFT*. This is contrary to Martey *et al.* (2014) who found that large farm size significantly reduces the adoption of inorganic fertilizer technology. This could be because farmers with large farm size often face financial constraints in purchasing adequate inputs with their associated high costs. Furthermore, larger farm sizes favour adoption of *IMVT*, *IFT* and *RPT* only and in the view that larger farm holders are often oriented toward profit-maximization, and adopt technologies that improve yields. This finding is consistent with Onyeneke (2017) who observed that farm size had a positive and significant influence on the likelihood of adopting agrochemicals and inorganic fertilizer.

Access to training on improved farming and the probability of adopting *IFT* were significantly (at 1% level) linked. The relationship was positive, indicating that farmers who obtained training on improved farming methods were more likely to adopt inorganic fertilizer technology.

(3) Legume-Maize Intercropping Technology Adoption

Farming experience was significant (at 10% level) and negatively related to *LMIT*. The negative relationship means that the probability of adopting legume-maize intercropping technology (*LMIT*) declines with experience in farming. In other words, less-experience farmers were more likely to adopt *LMIT* compared to their counterparts, ceteris paribus. This is not consistent with the assertion of Islam *et al.* (2012) who argued that other



things held constant, older and more experienced farmers are more receptive to adopt new technologies. Intercropping has been found to ensure better utilization of resources, increase the quantity and quality of products and reduce crop damage by pests, diseases and weeds (Mousavi & Eskandari, 2011).

Farm location had a significant (at 1% level) negative influence on the probability of adopting legume-maize intercropping technology (*LMIT*) which indicates that farmers whose farms were located around uplands areas were less likely to adopt *LMIT* compared to their counterparts who cultivated their maize around relatively lowland areas, *ceteris paribus*. *LMIT* will produce better yield on lowlands because the crops are more likely to have enough nutrients and soil moisture since intercropping brings about fair competition for soil nutrients and water.

Membership to FBOs was also found to be significant (at 10% level) and positively related to the probability of adopting legume-maize intercropping technology (*LMIT*), indicating that farmers who join FBOs were more likely to adopt *LMIT* compared to their non-member counterparts, *ceteris paribus*. As acknowledged to Danso-Abbeam *et al.* (2017), FBOs serve as social institutions that provide essential information to farmers on improved farming methods.

(4) Row-line Planting Technology Adoption

Farm size and adoption of row-line planting technology (*RPT*) were significantly (at 10% level) linked. The relationship was positive, indicating that the farm size increases the



probability of adopting *RPT*, *ceteris paribus*. This indicates that large-scale farmers are more likely to adopt *RPT*. This is contrary to a priori expectation in the view that *RPT* is labour-intensive and will turn to favour smaller farms. This result is consistent with Tafese (2016) who found that large farm size significantly increases adoption and level of adoption of row planting in Wolaita zone of Ethiopia.

Farm location was also found to have a negative significant (at 1% level) influence on the probability of adopting *RPT* which indicates that farmers who cultivated maize on relatively upland areas were more likely to adopt *RPT* compared to their counterparts, *ceteris paribus*. This is consistent with adoption of *IMVT* but inconsistent with adoption of *LMIT*.

(5) Stone/Soil Bunding Technology Adoption

Sex was significant (at 5% level) and negatively related to the probability of adopting stone bunding technology (*SBT*), which means that female farmers were more likely to adopt *SBT* for agricultural production. This finding is also consistent with the adoption of *LMIT*. In Ethiopia, Amsalu & De Graaff (2007) studied about factors influencing adoption of *SBT*. However, they did not find any significant relationship between sex and adoption of *SBT*.

Membership to FBO showed a positive significant (at 5% level) influence on the probability of adopting stone bunding technology (*SBT*), indicating that farmers who join FBOs were more likely to adopt *SBT* compared to their non-member counterparts, *ceteris*

paribus. This finding is also consistent with the adoption of *LMIT*. This could be due to the fact that FBO members assist each other with on-farm labour and also have easy access to training on how to undertake such a rigorous and skillful activity during agricultural production.



Table 4. 6: Maximum likelihood estimation results of factors influencing the adoption of five (5) improved technologies

Variable	<i>IMVT</i>		<i>IFT</i>		<i>LMIT</i>		<i>RPT</i>		<i>SBT</i>	
	(1)		(2)		(3)		(4)		(5)	
	Coeff.	Std. Err.								
Constant	-0.776	0.741	-0.755	0.720	-0.882	0.478	-0.511	0.424	-1.063	0.497
Gender	-0.691*	0.367	-0.087	0.355	0.081	0.251	-0.034	0.220	-0.493**	0.248
Age	0.028*	0.017	0.029*	0.017	0.005	0.011	0.008	0.010	0.014	0.012
Education	0.075*	0.039	0.050	0.034	0.022	0.022	-0.004	0.019	-0.018	0.022
Farming experience	0.042	0.068	-0.069	0.042	-0.076**	0.033	0.011	0.030	-0.054	0.036
Farm size	0.650***	0.216	0.543***	0.192	0.141	0.096	0.157*	0.089	0.126	0.102
Farm location	0.573*	0.311	-0.107	0.279	-0.940***	0.208	0.490***	0.190	-0.299	0.214
Access to training	0.986	0.706	1.227***	0.293	0.163	0.242	-0.274	0.225	-0.085	0.255
Extension contact	5.269**	2.138	0.481	0.393	0.248	0.266	0.254	0.257	0.299	0.258
Membership in FBOs	0.703	0.814	0.178	0.332	0.446*	0.259	0.105	0.242	0.535**	0.249
Distance-to-input shops	-0.105**	0.042	-0.020	0.031						
rho21	0.200	0.174								
rho31	-0.116	0.193								
rho41	0.213	0.170								
rho51	0.148	0.224								
rho32	0.080	0.200								
rho42	-0.004	0.141								
rho52	0.185	0.209								
rho43	0.248**	0.108								
rho53	0.441***	0.114								
rho54	0.221**	0.102								

Number of observation = 240; Wald chi2 = 188.29***; Likelihood ratio (LR) chi-square test for paired correlations = 27.20***

Legends *, **, * indicate significance levels at 1%, 5% and 10% levels**

Source: Field Data, 2018

4.5 Effect of Access to Credit on Improved Maize Technology Intensity-Poisson Regression with Endogenous Treatment

Here, effect of access to credit on the adoption intensity of improved maize technologies is discussed as shown in Table 4.7. A Poisson model with endogenous treatment was used to address possible sample selection problem. Referable to the Heckman selection framework, there was an initial estimation of a selection (access to credit) and substantive equations (adoption intensity) to correct for such selection problem under the Poisson model with endogenous treatment.

The Wald χ^2 test showing the model fitness shows that the model is statistically significant, indicating that all the independent variables jointly determined the dependent variables. In other words, one or more of the independent variables has a significant influence on the dependent variables.

In testing for sample selection bias and the appropriateness of the Poisson Regression with Endogenous Treatment, the Wald χ^2 test of independent equations is used. From the estimation, the Wald χ^2 test of independent equations was 55.73 and significant at 1%, indicating that selectivity bias problem is present in the model and has been corrected. This shows that there were unobserved factors influencing both access to credit and adoption intensity of improved maize technologies; hence, the use of the Poisson Regression with Endogenous Treatment is justified.

Table 4.7 shows the results from a Binary Probit and Poisson estimation that indicates the factors influencing access to credit and adoption intensity of improved maize technologies respectively.

From the substantive model, farm size, access to training on improved farming methods and access to credit had positive effect on adoption of IFTs. These findings



are consistent with the finding of the multivariate probit model results, which show that farm size had a positive significant influence on improved maize variety, inorganic fertilizer and row-line planting technologies adoption. In that same model, access to extension services had a positive significant influence on improved maize variety adoption while access to training on improved farming methods had a positive significant effect on inorganic fertilizer technology adoption.

4.5.1 Factors Affecting the Intensity of Adoption of Improved Maize Technologies

Farm Size and Adoption Intensity: Farm size had a significant (at 5% level) and positive relationship with the intensity of adoption of improved maize technologies. This implies that farm size increases the probability of adopting more improved maize technologies, *ceteris paribus*. In other words, bigger farm holders are more likely to increase their adoption of improved maize technologies. This result is not consistent with Nkonya *et al.* (1997) who revealed that larger farms tended to adopt improved technologies, particularly fertilizer less intensively than smaller farms. Bigger farm holders are often oriented toward profit-maximization, and will adopt technologies more to improve productivity and to increase incomes. For instance, Uaiene *et al.* (2009) argued that farmers with larger farms are more likely to adopt an improved technology compared with those with small farmers as they can afford to devote part of their fields to try out the improved technology. Similarly, adopting sophisticated technologies, such as mechanized equipment, require economies of size to ensure profitability.





Extension Contact and Adoption Intensity: Extension contact was found to be significant at 1% level and positively related to the intensity of adoption of improved maize technologies, which means that farmers who had access to extension services were more likely to increase their adoption of improved maize technology than their counterparts who had no access to extension service. Extension services serve as important source of information on agricultural production, which expose farmers to new or improved agricultural technologies and this can facilitate the up-take of improved technologies. Farmers who have significant extension contacts have better chances to be aware of various management practices that they can use to increase production (Onyeneke, 2017).

Access to Training on Improved Farming Methods and Adoption Intensity: Access to training on improved farming was also found to be significant and positively related to adoption intensity. This implies that farmers who obtained training on improved farming methods were more likely to increase their adoption of improved maize technologies. Training provides farmers with enough information on improved farming methods on demonstration plots where they can assess the efficiency and cost associated with those technologies.

Membership in FBOs and Adoption Intensity: Membership to FBOs was significant (at 5% level). The relationship was positive, indicating that the probability of adopting improved maize technologies increases with FBO membership. In other words, farmers who join FBOs were more likely to increase their adoption of improved maize technologies compared to their non-member counterparts, *ceteris paribus*. A plausible reason could be that being a member of an FBO increases access

to information and other services that enable them to adopt more improved technologies. Moreover, FBO members enjoy easy access to labour, because members usually assist each other with resources including labour which enable them to undertake rigorous activities associated with improved technologies such as stone bunding and row or line planting during agricultural production.

Access to Credit and Adoption Intensity: Of particular interest was the effect of access to credit on adoption intensity. The coefficient of access to credit was positive significant at 1%. This means that farmers who had access to credit increase their adoption of improved maize technologies by 15.6% compared to their counterparts who had no access. This is probably because credit is an important source of capital which can be used to purchase improved technologies when incomes from farm and non-farm employment are missing or inadequate. This result is consistent with Obisesan *et al.* (2016) who found a significant and positive relationship between access to credit and adoption of improved cassava production technology. From their study, access to credit facilities leads to 15.82% increase in the adoption level, attributing it to the fact that credit increases the farmers' economy to purchase improved seed, fertilizer and other inputs.



Table 4. 7: Poisson Regression Results showing the Factors Influencing Adoption Intensity, Including Access to Credit

Variable	Coef.	Std. Err.	P>z
Gender	-0.051	0.058	0.380
Age	0.003	0.002	0.258
Education	0.003	0.005	0.544
Household size	0.007	0.011	0.499
Major occupation	-0.079	0.055	0.151
Farming experience	-0.003	0.008	0.731
Farm size	0.049**	0.021	0.021
Farm location	-0.035	0.057	0.538
Access to training on improved farming methods	0.119**	0.055	0.032
Distance to nearby input shop	-0.005	0.005	0.298
Extension contact	0.176***	0.060	0.003
Membership in FBOs	0.143**	0.057	0.013
Access to credit	0.156**	0.069	0.022
Constant	0.690	0.143	0.000

Number of Observation = 240; Wald χ^2 (13) = 56.81; P rob > χ^2 = 0.0000; Wald test of independent eqns. ($\rho = 0$): χ^2 (1) = 77.38 Prob > χ^2 = 0.0000

Note: Legends (***); (**) and (*) denote 1%, 5% and 10% significance levels respectively

Source: Field Data, 2018

4.6 Improved Technology Adoption and Output of Maize Farmers

This section presents the stochastic frontier results showing the effect of adoption of improved technologies on output and technical inefficiency of maize farmers in the Upper East Region as demonstrated in Table 4.10.





4.6.1 Stochastic frontier results

A likelihood ratio (LR) test was conducted to determine the appropriate functional form of the data, thus, the choice between Cobb-Douglas and transcendental (trans-log) functional forms. From the results, the LR statistic was 24.44 and significant at 10%, implying that the null hypothesis that the translog stochastic frontier is a better specification of the data is rejected. In other words, the Cobb-Douglas stochastic frontier is the appropriate functional form compared to the trans-log production function. This result is in line with that of Seyoum *et al.* (1998) who found the Cobb-Douglas stochastic frontier to be an adequate representation of their data.

The null hypothesis of ‘no inefficiency component’ was also rejected, implying that the use of the stochastic frontier framework is ideal compared to using the average response model (see Table 4.8). Ibrahim *et al.* (2014) also revealed that there is technical inefficiency in the use of inputs among maize producers in Nigeria. Additionally, the gamma parameter associated with the variance of the technical inefficiency effect in the stochastic frontier was estimated to be 0.925 and significant at 1% level (see Table 4.10). This means that the technical inefficiency effect is a significant component of the total variance of the output of maize farmers.

Table 4. 8: Results of hypothesis test

Test Type	Null Hypothesis	Statistic	Rule	Decision
Functional form	$H_0 : \beta_{ij} = 0$	24.44 (0.058)	Reject H_0 : Cobb-Douglas is appropriate	
Frontier Test	$H_0 : \delta_1 = \delta_2 \dots \delta_{14} = 0$	802.67 (0.000)	Reject H_0 : MLE is appropriate, inefficiency effects exists	

Source: Frontier Regression



The Wald chi-square statistic was 409.05 and significant at 1% level, implying that the explanatory variables used in the model collectively or jointly explain the variations in output of maize farmers. A sum of all coefficients of the Cobb-Douglas function depicts decreasing returns to scale (0.742) meaning that output changes less proportionally than when all inputs included in the model are changed in the same proportion. This indicates that maize farmers in the study area are producing in stage III of the production function.

From Table 4.9, the results show that the stochastic frontier model performs better when the adoption variable is included in both the output and inefficiency equations compared to when it is included in the output or inefficiency model or in none of the equations. This is based on the AIC statistic because a model with the smallest AIC is superior over a model with a larger AIC.

Table 4. 9: Hypothesis tests showing the appropriate inclusion of the adoption in the stochastic frontier production function.

Tests	df	AIC	BIC
Adoption in output and inefficiency equation	20.00	155.94	225.55
Adoption in output equation only	19.00	173.35	239.48
Adoption in inefficiency only	19.00	183.75	249.88
Adoption in none	18.00	181.75	244.40

Source: Stochastic frontier results

The results of the stochastic frontier production function further indicate that a total of four out of the five conventional inputs included in the model exhibited statistically significant effect on output at 1% significance level respectively. These were farm size, inorganic fertilizer, seed and pesticides (see Table 4.10).



The study realised that a 1% increase in farm size, inorganic fertilizer and seeds increases maize output by 0.602%, 0.067% and 0.274% respectively whereas a 1% increase in pesticides reduces output by 0.231% holding other variables constant. The positive relationship between farm size and output agrees with Chiona *et al.* (2014). This means that a farmer who uses more inorganic fertilizer and seeds and less pesticides stands the chance of increasing maize output.

Adoption intensity of improved technologies exhibited a significant and positive effect on output of maize farmers. This means that farmers who adopt more improved maize technologies thus 1% increase in intensity of adoption increases their output by 0.026% compared to their counterparts who adopt little or no improved technology. This result is consistent with Asante *et al.* (2014) who revealed that adoption influences output of farmer.

Table 4. 10: Maximum Likelihood Estimates of Stochastic Frontier Estimation

Variable	Parameter	Coef.	Std. Err.	P>z
<i>ln</i> farm size	β_1	0.602 ^a	0.069	0.000
<i>ln</i> fertilizer	β_2	0.067 ^a	0.016	0.000
<i>ln</i> seed	β_3	0.274 ^a	0.041	0.000
<i>ln</i> labour	β_4	0.030	0.072	0.676
<i>ln</i> pesticides	β_5	-0.231 ^a	0.063	0.000
Adoption intensity	γ	0.026^a	0.005	0.000
Constant	β_0	6.085	0.270	0.000
Returns to scale		0.742		
Gamma (γ)		0.925 ^a	0.074	
Sigma ($\delta = \delta_u^2 + \delta_v^2$)		0.762 ^a		
lambda ($\lambda = \delta_u^2 / \delta_v^2$)		12.351 ^a		

Number of observation = 240; Wald chi2 = 409.05^a

Note: superscript “a” denotes 1% significance level

4.6.2 Determinants of Technical Inefficiency

Table 4.11 contains the results of factors influencing technical inefficiency of maize farmers. A negative coefficient depicts a decreasing effect on technical inefficiency and the opposite is true for positive coefficients (Abdulai *et al.*, 2013). Out of the 10 variables included in the efficiency model, four exhibited significant effect on technical inefficiency. These were farming experience, membership in FBOs, access to credit and adoption.

Farming experience had a negative significant influence on technical inefficiency, implying that farmers who have spent more years in farming were more likely to be efficient than those who have spent few years in farming. In short, more farming experience reduces technical inefficiency. This is probably because highly experience farmers are able to maximise output through the adequate knowledge and skills they have acquire than those with less experience.

Membership in FBO was also an important factor influencing technical inefficiency negatively. The negative effect of membership in FBO means that farmers who belong to FBOs were more efficient than their counterparts who do not belong to FBO. Farmers in FBOs often have access to information and training that enable them to improve their farming practices and achieve higher efficiency. This result is not consistent with Abdul-Hanan & Abdul-Rahman (2017) who revealed that membership to association decreases efficiency in maize production. The result of Chirwa (2007) on the other hand agrees with that of the present study with regards to the effect of membership in farmer-based associations on technical inefficiency.

Access to credit was also significant and positive and therefore relates positively to inefficiency. In other words, farmers who obtained credit for their maize production



were more likely to be technically inefficient compared to their counterparts who had no access to credit. This is because the credit accessed may not be used for the intended purpose of maize production within such time period. However, this result disagrees with that of Abdul-Hanan & Abdul-Rahman (2017) who attested that credit enable farmers to pay for the new technology and undertake long-term investments that improve efficiency.

Adoption had a significant positive effect on technical inefficiency. This means that farmers who adopt more improved maize technologies were more likely to be technically inefficient compared to their counterparts who adopted little or no improved maize technologies. This may probably occur because most farmers often fail to comply with recommended application of improved technologies that improve efficiency. For instance, it is recommended that farmers apply 3-4 bags of fertilizer per an acre in order to achieve the desired level of output.

Table 4. 11: Maximum Likelihood Estimation Results of Technical Inefficiency

Variable		Coef.	Std. Err.
Sex	z_1	0.225	0.312
Age	z_2	0.012	0.013
Education	z_3	-0.016	0.028
Farming experience	z_3	-0.080*	0.042
Membership in FBO	z_4	-0.817**	0.355
Extension contacts	z_5	-0.066	0.106
Access to credit	z_6	1.284***	0.408
Farm size	z_7	0.181	0.165
Farm location	z_8	-0.033	0.283
Access labour	z_9	0.453	0.869
Adoption intensity	γ	0.043***	0.014
Constant	δ_0	-3.562	1.604
<i>Mean (Std. Dev) TE</i>		<i>0.750</i>	
<i>Maximum TE</i>		<i>0.944</i>	
<i>Minimum TE</i>		<i>0.047</i>	





4.6.3 Distribution of Technical Efficiency

The mean technical efficient was 0.75, indicating that maize farmers in the Upper East Region are producing with 75% efficiency. Binam *et al.* (2004) attested that high technical efficiency scores indicate the existence of substantial gains in output and/or decreases in cost with available technology and resources. Also, the minimum technical efficiency score among maize farmers was 4.7% and the maximum was 94.4% (see Figure 4.2). Furthermore, the highest proportion of maize farmers had technical efficiency score between 80-89%. There is also evidence that the technical efficiency of maize farmers is highly clustered around 60 to 90%, indicating very high technical efficiencies among maize farmers in the Upper East Region.

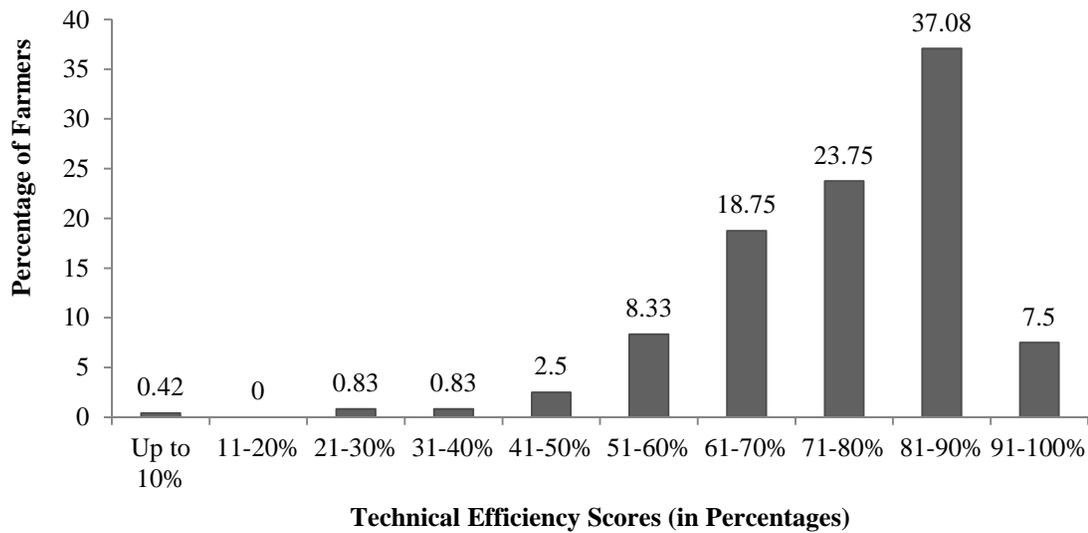


Figure 4. 2: Efficiency scores of maize farmers

Source: Stochastic frontier results



4.7 Ranking of Constraints Facing Farmers in the Adoption of Improved Technologies in Maize Production

The farmers cited several constraints to agricultural production: high cost of improved technologies, inadequate availability of improved technologies, untimely access to agrochemicals, difficulty in access to credit facilities, limited available information on improved technologies, limited access to land and unreliable markets. Among these constraints, high cost of improved technologies was ranked as the first most important constraint that farmers face and unreliable markets as the least important constraint that farmers face. These findings are consistent with Wekem (2013). Furthermore, the chi-square (636.3) of the Kendall's test of concordance was significant at 1% level. The Kendall's coefficient value of 0.444, implying the farmers were about 44.4% in agreement that the above constraints were worrying them in their pursuit to adopting improved maize technologies.

Table 4. 12: Ranking of Constraints in Improved Technology Adoption

Constraints	Mean	Ranking
High cost of improved technologies	2.10	1 st
Inadequate availability of improved technologies	2.36	2 nd
Untimely access to agrochemicals	3.43	3 rd
Difficulty in access to credit fertilities	4.41	4 th
Limited available information on improved technologies	4.42	5 th
Limited access to land	5.47	6 th
Unreliable markets	5.81	7 th
Kendall's W	0.444	
Chi-Square	636.3	
Df	6	
Asymp. Sig.	0	

Source: Field Data, 2018

CHAPTER FIVE

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.0 Chapter Outline

This chapter of the study presents the summary of findings, conclusions and policy recommendations.

5.1 Summary

The agricultural sector in Ghana is expected to achieve productivity at 6% growth per annum. Nevertheless, actual crop yields, especially for maize are still far below achievable yields partly due to low adoption of improved technologies. The study examines credit accessibility, adoption of improved technologies and the technical efficiency of maize farmers in the Upper East Region of Ghana. A cross section of farmers (n = 240) was selected using a multi-stage sampling approach. Data were collected through face-to-face interviews using semi-structured questionnaire. Demographic and socio-economic characteristics and farm-specific factors of maize farmers were summarized using descriptive statistics such as frequencies, percentages, means and standard deviations.

Specifically, the study determined the factors influencing access to credit by maize farmers using the binary probit model while the determinants of improved technology adoption were measured using the multivariate probit model. The effect of access to credit on the intensity of improved technology adoption was estimated using the Poisson regression with endogenous treatment model while the effect of improved technology adoption on maize output was determined using the Stochastic frontier



production estimation by allowing for selectivity bias. Finally, the Kendall's coefficient of concordance was employed to rank and determine whether there exist significant differences in maize farmers' agreement with constraints facing them in adoption of improved technologies.

The study identified five major improved technologies: improved seed varieties, inorganic fertilizer, legume-maize intercropping, row-line planting and stone bunding. The results showed that row-line technology (*RPT*), legume-maize intercropping technology (*LMIT*) and soil/stone bunding technology (*SBT*) were adopted together by farmers. Adoption of improved maize technologies was significantly affected by demographic and socio-economic, farm-specific and institutional factors.

Access to credit was positively and significantly influenced by age, education, extension contacts, farm size and membership in FBOs. On the other hand, access to credit exhibited a positive significant effect on the intensity of improved maize technology adoption. Specifically, the results showed that farmers who had access to credit increase their adoption of improved maize technologies by 15.2% compared to their counterparts who had no access to credit. Other variables that positively affected adoption intensity were extension contact, membership in FBOs, access to training and farm size respectively.

From the stochastic frontier production estimation results, adoption intensity of improved technologies significantly increases maize output. The study also revealed that farm size, inorganic fertilizer and seed increase maize output whereas pesticides



significantly reduces maize output. Furthermore, maize technical inefficiency was positively affected by adoption intensity of improved technologies and access to credit while farming experience and membership in FBOs were negatively related to maize technical inefficiency. The mean technical efficient was 0.75, which means that farmers were about 75% technically efficient in their maize production. High cost of improved maize technologies was the most important constraint facing maize farmers, among other constraints like lack of access to improved maize seeds, high cost of fertilizer, untimely access to agrochemicals, lack of access to credit facilities, limited available information, limited access to land and unreliable market.

5.2 Conclusions

The broad aim of the study which was to analyse the factors influencing access to credit, improved technology adoption and technical efficiency of maize farmers in the Upper East Region of Ghana was achieved. Specifically, the interplay between access to credit, improved technology adoption and technical efficiency was also assessed. The study observed that maize farmers were adopting five different types of improved maize technologies; improved seed varieties, inorganic fertilizer, legume-maize intercropping, row-line planting and stone bunding. Besides, the adoption of row-line technology (*RPT*), legume-maize intercropping technology (*LMIT*) and soil/stone bunding technology (*SBT*) is a complementary decision by farmers. Also, sex of farmer, age, education, farm size, farm location, distance to local input-shop, extension contacts, FBO membership and access to training on improved farming were significantly related to the adoption of improved technologies. The study also revealed that access to credit is a positive factor for increasing the adoption of improved technologies in maize production. It was also realised that increasing the



adoption of improved technologies, farm size, inorganic fertilizer and seeds were associated with higher maize output. Adopting more improved technologies on the other hand reduces technical efficiency of maize farmers. The mean maize technical efficiency was 0.75, which meant that 25% of maize output was lost due to technical inefficiency. High cost of improved maize technologies was the most important constraint facing maize farmers in the production.

5.3 Recommendations

Based on the conclusions, the following recommendations were made;

1. Government and NGOs should strengthen the provision of extension services to farmers to improve their access to credit and the adoption of improved technologies.
2. Maize farmers should be encouraged to join FBOs in order to increase their access to credit and the adoption of improved maize technologies.
3. Government, NGOs and financial institutions should assist farmers with credit facilities to enable them purchase improved technologies to tackle the high cost of production.
4. Farmers should adopt more improved technologies in their maize production to obtain higher yields.
5. Farmers should also increase their farm sizes and follow the recommended usage of chemical fertilizer and improved seeds to achieve higher output.



REFERENCES

- Abdul-Hanan, A., & Abdul-Rahman, A. (2017).** Technical Efficiency of Maize Farmers in Ghana: A Stochastic Frontier Approach. *International Journal of Innovation and Scientific Research*, 29(2), 110-118.
- Abdulai, S., Nkegbe, P. K., & Donkoh, S. A. (2013).** Technical efficiency of maize production in Northern Ghana. *African Journal of Agricultural Research*, 8(43), 5251-5259.
- Abdulai, S., Zakariah, A., & Donkoh, S. A. (2018).** Adoption of rice cultivation technologies and its effect on technical efficiency in Sagnarigu District of Ghana. *Cogent Food & Agriculture*, 4(1), 1424296.
- Abdul-Hanan, A., Ayamga, M., & Donkoh, S. A. (2014).** Smallholder adoption of soil and water conservation techniques in Ghana.
- Adeyeye, A. D., Jegede, O. O., Oluwadare, A. J., & Aremu, F. S. (2016).** Micro-level determinants of innovation: analysis of the Nigerian manufacturing sector. *Innovation and Development*, 6(1), 1-14.
- Afolami, C. A., Obayelu, A. E., & Vaughan, I. I. (2015).** Welfare impact of adoption of improved cassava varieties by rural households in South Western Nigeria. *Agricultural and Food Economics*, 3(1), 18.
- African Development Bank (AfDB), Organisation for Economic Co-operation and Development (OECD) and United Nations Development Programme (UNDP).**
- Africa, R. E. O.-S.-S. (2011).** Sustaining the Expansion,". *Washington, DC: International Monetary Fund*, 48.
- Agbamu, J. U. (1993).** Analysis of farmers' characteristics associated with adoption of soil management innovations in Ikorodu LGA of Lagos State. *The Nigerian Journal of Rural Extension and Development*, 1(2&3), 57-67.



- Akino, M., & Hayami, Y. (1975).** Efficiency and equity in public research: Rice breeding in Japan's economic development. *American Journal of Agricultural Economics*, 57(1), 1-10.
- Akudugu, M. A., Egyir, I. S., & Mensah-Bonsu, A. (2009).** Women farmers' access to credit from rural banks in Ghana. *Agricultural Finance Review*, 69(3), 284-299.
- Akudugu, M. A., Guo, E., & Dadzie, S. K. (2012).** Adoption of modern agricultural production technologies by farm households in Ghana: What factors influence their decisions.
- Alene, A. D., Menkir, A., Ajala, S. O., Badu-Apraku, B., Olanrewaju, A. S., Manyong, V. M., & Ndiaye, A. (2009).** The economic and poverty impacts of maize research in West and Central Africa. *Agricultural Economics*, 40(5), 535-550.
- Alene, A. D., Poonyth, D., & Hassan, R. M. (2000).** Determinants of adoption and intensity of use of improved maize varieties in the central highlands of Ethiopia: A tobit analysis. *Agrekon*, 39(4), 633-643.
- Amanor-Boadu, V., Zereyesus, Y. and Ross, K. (2015).** Agricultural Production Survey for the Northern Regions of Ghana: 2013-2014 Results. Manhattan: Agricultural Economics Department, Kansas State University. https://www.agmanager.info/sites/default/files/APS_Report_2016_Final.pdf
- Amare, M., Asfaw, S., & Shiferaw, B. (2012).** Welfare impacts of maize–pigeonpea intensification in Tanzania. *Agricultural Economics*, 43(1), 27-43.
- Amemiya, T. (1981).** Qualitative response models: A survey. *Journal of Economic Literature*, 19:1483-1536.





- Amsalu, A., & De Graaff, J. (2007).** Determinants of adoption and continued use of stone terraces for soil and water conservation in an Ethiopian highland watershed. *Ecological economics*, 61(2-3), 294-302.
- Anang, B. T., Sipilainen, T., Backman, S., & Kola, J. (2015).** Factors influencing smallholder farmers access to agricultural microcredit in Northern Ghana. *African Journal of Agricultural Research*, 10(24), 2460-2469.
- Anyaebulam, H. N., Ezeh, C. I., Chukwu, G. O., & Asumugha, G. N. (1995).** Credit availability in relation to adoption and profitability of selected farm technologies in Abia state, Nigeria. In *Proceedings of the 30th annual conference of the Agricultural Society of Nigeria* (pp. 358-361).
- Aryeetey, E. (2005).** Informal finance for private sector development in Sub-Saharan Africa. *Journal of Microfinance/ESR Review*, 7(1), 3.
- Asante, B. O., Villano, R. A., & Battese, G. E. (2014).** The effect of the adoption of yam miniset technology on the technical efficiency of yam farmers in the forest-savanna transition zone of Ghana. *African Journal of Agricultural and Resource Economics*, 9(2), 75-90.
- Asfaw, S., Kassie, M., Simtowe, F., & Lipper, L. (2012).** Poverty reduction effects of agricultural technology adoption: a micro-evidence from rural Tanzania. *Journal of Development Studies*, 48(9), 1288-1305.
- Asfaw, S., Kassie, M., Simtowe, F., & Lipper, L. (2012).** Poverty reduction effects of agricultural technology adoption: a micro-evidence from rural Tanzania. *Journal of Development Studies*, 48(9), 1288-1305.
- Assogba, P. N., Kokoye, S. E. H., Yegbemey, R. N., Djenontin, J. A., Tassou, Z., Pardoe, J., & Yabi, J. A. (2017).** Determinants of credit access by smallholder farmers in North-East Benin. *Journal of Development and Agricultural Economics*, 9(8), 210-216.



- ATC (2013).** Construction and Mitigation Plan - American Transmission Co. projects. www.atc-projects.com/.../Badger-Coulee-Construction-and-Mitigation-Plan-Segment-...
- Awika, J. M. (2011).** Major cereal grains production and use around the world. In *Advances in cereal science: implications to food processing and health promotion* (pp. 1-13). American chemical society.
- Awotide, B. A., Karimov, A. A., & Diagne, A. (2016).** Agricultural technology adoption, commercialisation and smallholder rice farmers' welfare in rural Nigeria. *Agricultural and Food Economics*, 4(1), 3.
- Barrett, C.B., C.M. Moser, O.V. McHugh, & Barison, J. (2004).** "Better Technology, Better Plots, or Better Farmers? Identifying Changes in Productivity and Risk among Malagasy Rice Farmers", *American Journal of Agricultural Economics*, 86(4): 869-888.
- Belderbos, R., Carree, M., Diederer, B., Lokshin, B., & Veugelers, R. (2004).** Heterogeneity in R&D cooperation strategies. *International journal of industrial organisation*, 22(8-9), 1237-1263.
- Bempomaa, B., & Acquah, H. D. G. (2014).** Technical efficiency analysis of maize production: evidence from Ghana. APSTRACT: *Applied Studies in Agribusiness and Commerce*, 8(2-3), 73-79.
- Bhalla, G. S. (1979).** Transfer of technology and agricultural development in India. *Economic and Political Weekly*, A130-A142.
- Binam, J. N., Tonye, J., Nyambi, G., & Akoa, M. (2004).** Factors affecting the technical efficiency among smallholder farmers in the slash and burn agriculture zone of Cameroon. *Food policy*, 29(5), 531-545.
- Bisanda, S., Mwangi, W. M., Verkuijl, H., Moshi, A. J., & Anandajayasekeram, P. (1998).** Adoption of maize production technologies in the southern highlands of Tanzania. CIMMYT.



- Bonabana-Wabbi, J. (2002).** Assessing factors affecting adoption of agricultural technologies: The case of Integrated Pest Management (IPM) in Kumi District, Eastern Uganda (Doctoral dissertation, Virginia Tech).
- Brooks, C. (2008).** RATS Handbook to accompany introductory econometrics for finance. *Cambridge Books*.
- Bruce, A. K. K. (2015).** Improved Rice Variety Adoption and its Effects on Farmers' Output in Ghana. A Thesis Submitted to the Department of Agricultural and Resource Economics, Faculty of Agribusiness and Communication Sciences, University for Development Studies for the Award of Master of Philosophy Degree in Agricultural Economics. (Accessed at: <http://udsspace.uds.edu.gh/bitstream/123456789/607/1/IMPROVED%20RI%20CE%20VARIETY%20ADOPTION%20AND%20ITS%20EFFECTS%20ON%20FARMERS%E2%80%99%20OUTPUT%20IN%20GHANA.pdf>. April, 2018)
- Bruins, M. (2009).** The evolution and contribution of plant breeding to global agriculture, In: UPOV, responding to the challenges of a changing world: The role of new plant varieties and high quality seed in agriculture. In Proceedings of the Second World Seed Conference held at the FAO Headquarters, Rome (pp. 18–29). September 8-10, 2009. Geneva: UPOV.
- Buyinza, M., & Wambede, N. (2008).** Extension for agroforestry technology adoption: mixed intercropping of croton (Croton grahamiana) and maize (Zea mays L.) in Kabale district, Uganda. *Environmental Research Journal*, 2(3), 131-137.
- Cappellari, L., & Jenkins, S. P. (2003).** Multivariate probit regression using simulated maximum likelihood. *The Stata Journal*, 3(3), 278-294.
- Capps Jr, O., & Kramer, R. A. (1985).** Analysis of food stamp participation using qualitative choice models. *American Journal of Agricultural Economics*, 67(1), 49-59.



- Challa, M. (2013).** Determining factors and impacts of modern agricultural technology adoption in West Wollega.
- Chandio, A. A., Magsi, H., Rehman, A., & Sahito, J. G. M. (2017).** Types, sources and importance of agricultural credits in Pakistan. *Journal of Applied Environmental and Biological Sciences*, 7, 144-149.
- Chi, T. T. N., & Yamada, R. (2002).** Factors affecting farmers' adoption of technologies in farming system: A case study in Omon district, Can Tho province, Mekong Delta. *Omonrice*, 10, 94-100.
- Chib, S., & Greenberg, E. (1998).** Analysis of multivariate probit models. *Biometrika*, 85(2), 347-361.
- Chiona, S., Kalinda, T., & Tembo, G. (2014).** Stochastic frontier analysis of the technical efficiency of smallholder maize farmers in Central Province, Zambia. *Journal of Agricultural Science*, 6(10), 108.
- Chirwa, E. W. (2007).** Sources of technical efficiency among smallholder maize farmers in Southern Malawi.
- Coelli, T. J. (1995).** Recent developments in frontier modelling and efficiency measurement. *Australian Journal of agricultural economics*, 39(3), 219-245.
- Cowan, R., & Gunby, P. (1996).** Sprayed to death: path dependence, lock-in and pest control strategies. *The economic journal*, 521-542.
- Dankwa, J. B. (2001).** Factors affecting adoption levels of cocoa technologies in the Ashanti Region of Ghana (Doctoral dissertation, University of Cape Coast).
- Danso-Abbeam, G., Bosiako, J. A., Ehiakpor, D. S., & Mabe, F. N. (2017).** Adoption of improved maize variety among farm households in the northern region of Ghana. *Cogent Economics & Finance*, 5(1), 1416896.



- Denkyirah, E. K., Aziz, A. A., Denkyirah, E. K., Nketiah, O. O., & Okoffo, E. D. (2016).** Access to Credit and Constraint Analysis: The Case of Smallholder Rice Farmers in Ghana. *Journal of Agricultural Studies*, 4(2), 53-72.
- Diagne, A., & Demont, M. (2007).** Taking a new look at empirical models of adoption: Average treatment effect estimation of adoption rates and their determinants. *Agricultural Economics*, 37(2-3), 201-210.
- Diiro, G. M., & Sam, A. G. (2015).** Agricultural technology adoption and Nonfarm earnings in Uganda: a Semi-parametric analysis. *The Journal of Developing Areas*, 49(2), 145-162.
- Dinye, R. D. (2013).** Irrigated agriculture and poverty reduction in Kassena Nankana district in the upper-east region, Ghana. *Journal of Science and Technology*, 33(2), 59-72.
- Donkoh, S. A. (2006).** Technology adoption and efficiency in Ghanaian agriculture (Doctoral dissertation, University of Reading).
- Donkoh, S. A., & Awuni, J. A. (2011).** Adoption of farm management practices in lowland rice production in Northern Ghana.
- Doss, C. R. (2003).** Understanding farm level technology adoption: lessons learned from CIMMYT's micro surveys in Eastern Africa.
- Dzene, R. (2010).** What drives efficiency on the Ghanaian cocoa farm. Ghana Institute of Management and Public Administration (GIMPA), Accra.
- Eaton, C., & Shepherd, A. (2001).** Contract farming: partnerships for growth (No. 145). Food & Agriculture Organisation.
- Edwards, S. F. (1964).** The statistical dynamics of homogeneous turbulence. *Journal of Fluid Mechanics*, 18(2), 239-273.



- Emmanuel, D., Owusu-Sekyere, E., Owusu, V., & Jordaan, H. (2016).** Impact of agricultural extension service on adoption of chemical fertilizer: Implications for rice productivity and development in Ghana. *NJAS-Wageningen, Journal of Life Sciences*, 79, 41-49.
- Enete, A. A., & Igbokwe, E. M. (2009).** Cassava market participation decisions of producing households in Africa. *Tropicultura*, 27(3), 129-136.
- Eskandari, H., Ghanbari, A., & Javanmard, A. (2009).** Intercropping of cereals and legumes for forage production. *Notulae Scientia Biologicae*, 1(1), 07-13.
- Essilfie, F. L., Asiamah, M. T., & Nimoh, F. (2011).** Estimation of farm level technical efficiency in small scale maize production in the Mfantseman Municipality in the Central Region of Ghana: A stochastic frontier approach. *Journal of Development and Agricultural Economics*, 3(14), 645-654.
- FAO (2005).** Fertilizer use by crop in Ghana. FAO.
- FAO (2015).** Socio-economic context and role of agriculture Country Fact Sheet on food and agriculture policy trends: Ghana, March 2015, FAPDA, Food and Agriculture Policy Decision Analysis.
- FAO (2003).** Statement at the Ministerial Conference of the WTO - Circulated by H.E. Hartwig de Haen, Assistant Director-General, Fifth Session, Cancun, 10-14 September, Doc No: WT/MIN (03)/ST/61.
- Feder, G., Just, R. E., & Zilberman, D. (1985).** Adoption of agricultural innovations in developing countries: A survey. *Economic development and cultural change*, 33(2), 255-298.
- Fernandez-Cornejo, J. (1996).** The microeconomic impact of IPM adoption: theory and application. *Agricultural and Resource Economics Review*, 25(2), 149-160.



- Førsund, F. R., Lovell, C. K., & Schmidt, P. (1980).** A survey of frontier production functions and of their relationship to efficiency measurement. *Journal of econometrics*, 13(1), 5-25.
- Fufa, B., Behute, B., Simons, R., & Berhe, T. (2011).** Tef Diagnostic Report: Strengthening the Tef Value Chain in Ethiopia. *Addis Ababa, Ethiopia*.
- Ghana Statistical Service (2012).** 2010 Population and Housing Census. Regional Analytical Report, Upper West Region.
- Ghana Statistical Service (GSS) (2017).** Annual Gross Domestic Production (GDP) Report, Ghana Statistical Service, Accra. www.statsghana.gov.gh/.../GDP/GDP2018/2017%20Quarter%204%20and%20annual
- Ghanbari-Bonjar, A., & Lee, H. C. (2003).** Intercropped wheat (*Triticum aestivum* L.) and bean (*Vicia faba* L.) as a whole-crop forage: effect of harvest time on forage yield and quality. *Grass and Forage Science*, 58(1), 28-36.
- Ghimire, R., & Huang, W. C. (2016).** Adoption pattern and welfare impact of agricultural technology: empirical evidence from rice farmers in Nepal. *Journal of South Asian Development*, 11(1), 113-137.
- Gockowski, J., & Ndoumbe, M. (2004).** The adoption of intensive monocrop horticulture in southern Cameroon. *Agricultural economics*, 30(3), 195-202.
- Goldberger, A. S. (1964).** *Econometric theory* Wiley. New York.
- Greene, W. (2003).** *Econometric Analysis*, 5th ed. New Jersey: Prentice Hall
- Gujarati, D. N. (2009).** *Basic econometrics*. Tata McGraw-Hill Education.
- Hananu, B., Abdul-Hanan, A., & Zakaria, H. (2015).** Factors influencing agricultural credit demand in Northern Ghana. *African Journal of Agricultural Research*, 10(7), 645-652.



- Herdt, R. W., & Capule, C. (1983).** Adoption, spread, and production impact of modern rice varieties in Asia. *Int. Rice Res. Inst.*.
- Hossen, M. M. (2016).** Adoption of Intercropping with Jackfruit by the Farmers of Bhaluka Upazilla under Mymensingh District. Bangladesh, Dhaka (unpublished thesis).
- Hussain, S. A., Amiruzzaman, M., & Hossain, Z. (2003).** Combining ability estimates in maize. *Bangladesh. J. Agril. Res*, 28, 435-440.
- Ibrahim, K., Shamsudin, M. N., Yacob, R., & Radam, A. B. (2014).** Technical Efficiency in Maize Production and its Determinants: A Survey of Farms across Agro Ecological Zones in Northern Nigeria. *Trends in Agricultural Economics*, 7(2), 57-68.
- IFDC (2006).** International Fertilizer Development Center, IFDC.
- Inocencio, A., Sally, H. and Merrey, D. J. (2003).** Innovative Approaches to Agricultural Water Use for Improving Food Security in Sub-Saharan African. International Water Management Institute, Colombo, Sri Lanka.
- Institute of Statistical, Social and Economic Research (ISSER) (2017).** State of the Ghanaian economy. Institute of Statistical, Social and Economic Research, University of Ghana, Legon.
- Isife, B. I., Albert, C. O., Ezeano, E. I., & Idibia, E. (2010).** Institutional arrangement for agricultural technology transfer and adoption in southern Nigeria agricultural development: An appraisal. *International Journal of Agriculture*, 2(2), 106-111.
- Islam, K. Z., Sumelius, J., & Bäckman, S. (2012).** Do differences in technical efficiency explain the adoption rate of HYV rice? Evidence from Bangladesh. *Agricultural Economics Review*, 13(1), 93.
- Iyanda, J. O., Afolami, C. A., Obayelu, A. E., & Ladebo, O. J. (2014).** Social capital and access to credit among cassava farming households in Ogun

State, Nigeria. *Journal of Agriculture and Environmental Sciences*, 3(2), 175-196.

Jain R. Arora A & Raju S. (2009). A Novel Adoption Index of Selected Agricultural Technologies: Linkages with Infrastructure and Productivity. *Agricultural Economics Research Review*, 22(1).

Jayne, T. S., Mason, N., Myers, R., Ferris, J., Mather, D., Beaver, M., Lenski, N., Chapoto, A. & Boughton, D. (2010). Patterns and Trends in Food Staples Markets in Eastern and Southern Africa: Toward the Identification of Priority Investments and Strategies for Developing Markets and Promoting Smallholder Productivity Growth. International Development Working Paper 104, Michigan State University, East Lansing.

Jones, P. G., and Thornton, P. K. (2003). The Potential Impacts of Climate Change and Maize Production and Latin America in 2055. *Global Environmental Change*, 13: 51-59.

Kebede, T. A. (2001). Farm household technical efficiency: A stochastic frontier analysis. A study of Rice producers in Mardi Watershed in the Western Development Region of Nepal, A Masters Thesis Submitted to Department of Economics and Social Sciences, Agricultural University of Norway.

Kebede, Y., Gunjal, K., & Coffin, G. (1990). Adoption of new technologies in Ethiopian agriculture: The case of Tegulet-Bulga district Shoa province. *Agricultural economics*, 4(1), 27-43.

Kebede, Y., Gunjal, K., & Coffin, G. (1990). Adoption of new technologies in Ethiopian agriculture: The case of Tegulet-Bulga district Shoa province. *Agricultural economics*, 4(1), 27-43.

Kotu, B. H., Verkuil, H., Mwangi, W. M., & Tanner, D. G. (2000). Adoption of improved wheat technologies in Adaba and Dodola Woredas of the Bale Highlands, Ethiopia. CIMMYT.





- Krishna, V. V., & Qaim, M. (2008).** Potential impacts of Bt eggplant on economic surplus and farmers' health in India. *Agricultural Economics*, 38(2), 167-180.
- Kuwornu, J. K., Amoah, E., & Seini, W. (2013).** Technical efficiency analysis of maize farmers in the Eastern Region of Ghana. *Journal of Social and Development Sciences*, 4(2), 84.
- Kuwornu, J. K., Ohene-Ntow, I. D., & Asuming-Brempong, S. (2012).** Agricultural credit allocation and constraint analyses of selected maize farmers in Ghana. *Challenge*, 71, 72.
- Lavison, R. K. (2013).** Factors influencing the adoption of organic fertilizers in vegetable production in Accra (Doctoral dissertation, University of Ghana).
- Leibenstein, H. (1966).** Allocative efficiency vs. "X-efficiency". *The American Economic Review*, 56(3), 392-415.
- Llewellyn, R. S., Lindner, R. K., Pannell, D. J., & Powles, S. B. (2007).** Herbicide resistance and the adoption of integrated weed management by Western Australian grain growers. *Agricultural Economics*, 36(1), 123-130.
- Loevinsohn M, Sumberg J, Diagne A (2012).** Under what circumstances and conditions does adoption of technology result in increased agricultural productivity? Protocol. London: EPPI Centre, Social Science Research Unit, Institute of Education, University of London
- Loevinsohn, M., Sumberg, J., Diagne, A., & Whitfield, S. (2013).** Under what circumstances and conditions does adoption of technology result in increased agricultural productivity? A Systematic Review.
- Lowder, S. K., Scoet, J., & Raney, T. (2016).** The number, size, and distribution of farms, smallholder farms, and family farms worldwide. *World Development*, 87, 16–29.

- Lunduka, R., Fisher, M., & Snapp, S. (2012).** Could farmer interest in a diversity of seed attributes explain adoption plateaus for modern maize varieties in Malawi. *Food Policy*, 37(5), 504-510.
- Maddala, G. S. (1983).** Limited-dependent and qualitative variables in econometrics (No. 3). Cambridge university press.
- Maiangwa, M. G., Ogunbile, A. O., Olukosi, J. O., & Atala, T. K. (2010).** Adoption of chemical fertilizer for land management in the North-West Zone of Nigeria. *Tropical Agricultural Research and Extension*.
- Maiga, E. W. H. (2005).** Determinants of adoption of soil and water conservation techniques in Burkina Faso (Doctoral dissertation, Oklahoma State University).
- Mal, P., Anik, A. R., Bauer, S., & Schmitz, P. M. (2013).** Bt cotton adoption: a double-hurdle approach for north Indian farmers.
- Marenja, P. P., & Barrett, C. B. (2006).** Household-level determinants of adoption of improved natural resources management practices among smallholder farmers in western Kenya. *Food policy*, 32(4), 515-536.
- Martey, E., Wiredu, A. N., Etwire, P. M., Fosu, M., Buah, S. S. J., Bidzakin, J., & Kusi, F. (2013).** Fertilizer adoption and use intensity among smallholder farmers in Northern Ghana: A case study of the AGRA soil health project. *Sustainable Agriculture Research*, 3(1), 24.
- Matata, P. Z., Ajay, O. C., Oduol, P. A., & Agumya, A. (2010).** Socio-economic factors influencing adoption of improved fallow practices among smallholder farmers in western Tanzania. *African journal of agricultural research*, 5(9), 818-823.
- McFadden, D. (1974).** The measurement of urban travel demand. *Journal of public economics*, 3(4), 303-328.





- McNamara, K. T., Wetzstein, M. E., & Douce, G. K. (1991).** Factors affecting peanut producer adoption of integrated pest management. *Review of agricultural economics*, 13(1), 129-139.
- Mentire W. & Gecho Y. (2017).** Factors Affecting Adoption of Wheat Row Planting Technology: The Case of Sodo Zuriya Woreda, Wolaita Zone, Southern Ethiopia. December, 2016. *Innovative Systems Design and Engineering*. 2222-1727.
- Min, S., Huang, J., Bai, J., & Waibel, H. (2017).** Adoption of intercropping among smallholder rubber farmers in Xishuangbanna, China. *International Journal of Agricultural Sustainability*, 15(3), 223-237.
- Ministry of Foreign Affairs (2011c).** Resultaten in on twikkeling 2009–2010, Dutch contributing to international development goals, The Hague.
- Minot, N., Joshi, P. K., Birthal, P. S. (2006).** Sources of agricultural growth in India: Role of diversification towards high-value crops (No. 98). *International Food Policy Research Institute (IFPRI)*.
- Mmbando, F. E., & Baiyegunhi, L. J. (2016).** Socio-economic and institutional factors influencing adoption of improved maize varieties in Hai District, Tanzania. *Journal of Human Ecology*, 53(1), 49-56.
- MoFA (2016).** Agriculture in Ghana, Facts and Figures (2015): Statistics, Research and Information Directorate, Accra – Ghana.
- MoFA, (2015).** Medium Term Agricultural Sector Investment Plan (METASIP) II, 2014 – 2017. Accra – Ghana.
- Morris M., Mekuria, M. and Gerpacio, R. (2003).** Impacts of CIMMYT Maize Breeding Research. In *Crop Variety Improvement and its Effect on Productivity* (eds.). Evenson R. E. and D. Gollin. CABI, Wallingford, UK.



- Mousavi, S. R., & Eskandari, H. (2011).** A general overview on intercropping and its advantages in sustainable agriculture. *Journal of Applied Environmental and Biological Sciences*, 1(11), 482-486.
- Muzari, W. Gatsi, W & Muvhunzi, S. (2012).** The Impacts of Technology Adoption on Smallholder Agricultural Productivity in Sub-Saharan Africa: A Review, *Journal of Sustainable Development*; 5 (8), 69.
- Mwabu, G., Mwangi, W., & Nyangito, H. (2006).** Does adoption of improved maize varieties reduce poverty? Evidence from Kenya. In *International Association of Agricultural Economists Conference, Gold Coast, Australia* (pp. 12-18).
- Nhemachena, C., Matchaya, G., Nhemachena, C. R., Karuaihe, S., Muchara, B., & Nhlengethwa, S. (2018).** Measuring Baseline Agriculture-Related Sustainable Development Goals Index for Southern Africa. *Sustainability*, 10(3), 849.
- Njogu, G. K., Njeru, A., and Olweny T., (2017).** Influence of Technology Adoption on Credit Access among Small Holder Farmers: A Double-Hurdle Analysis. *Africa International Journal of Management Education and Governance* (AIJMEG), 2 (3), 60-72.
- Nkegbe, P. K., & Shankar, B. (2014).** Adoption intensity of soil and water conservation practices by smallholders: evidence from Northern Ghana. *Bio-based and Applied Economics*, 3(2), 159-174.
- Nkonya, E., Schroeder, T., & Norman, D. (1997).** Factors affecting adoption of improved maize seed and fertilizer in northern Tanzania. *Journal of Agricultural Economics*, 48(1-3), 1-12.
- Nmadu, J. N., Sallawu, H., & Omojoso, B. V. (2015).** Socio-economic factors affecting adoption of innovations by cocoa farmers in Ondo State, Nigeria. *European Journal of Business, Economics and Accountancy*, 3(2), 58-66.



- Nmadu, J. N., Sallawu, H., & Omojeso, B. V. (2015).** Socio-economic factors affecting adoption of innovations by cocoa farmers in Ondo State, Nigeria. *European Journal of Business, Economics and Accountancy*, 3(2), 58-66.
- Obisesan, A., Amos, T. T., & Akinlade, R. J. (2016).** Causal Effect of Credit and Technology Adoption on Farm Output and Income: The Case of Cassava Farmers in Southwest Nigeria. In 2016 AAAE Fifth International Conference, September 23-26, 2016, Addis Ababa, Ethiopia (No. 246443). African Association of Agricultural Economists (AAAE).
- Odhiambo, G. D., & Ariga, E. S. (2001).** Effect of intercropping maize and beans on striga incidence and grain yield.
- OECD/PBL (2012).** OECD Environmental Outlook, Organisation for Economic Co-operation and Development
- Ofori, E. and Kyei-Baffour, N. (2006).** Agrometeorology and Maize Production. Available at: www.wmo.ch/web/wcp/aggm.
- Ofori, F., & Stern, W. R. (1987).** Cereal–legume intercropping systems. *In Advances in agronomy*, 41, (41-90). Academic Press.
- Okudzeto, E., Mariki, W. A., Lal, R. and Senu, S. S. (2015).** Ghana 2015– African Economic Outlook. Paris: African.
- Okwoche, V. A., Voh, J. P., & Ogunwale, S. A. (1998).** Socio-economic characteristics influencing the adoption behaviour of women Cooperators and non-Cooperators in Oju LGA of Benue State. *Journal of Agricultural Extension*, 2(3), 143-152.
- Olson, R. A. (1970).** The Fertilizer Programme of the Freedom from Hunger Campaign. In: AH Bunting (Ed.): *Change in Agriculture*. London: Duckworth and Co. Ltd., pp. 599-605.



- Onyeneke, R. U. (2017).** Determinants of adoption of improved technologies in rice production in Imo State, Nigeria. *African Journal of Agricultural Research*, 12(11), 888-896.
- Ouma, J. O., & De Groote, H. (2011).** Determinants of improved maize seed and fertilizer adoption in Kenya. *Journal of Development and Agricultural Economics*, 3(11), 529-536.
- Ouma, J. O., Murithi, F. M., Mwangi, W., Verkuijl, H., Gethi, M., & De Groote, H. (2002).** Adoption of maize seed and fertilizer technologies in Embu district, Kenya. CIMMYT.
- Owusu, W. (2016).** Adoption of Improved Maize Technologies and Maize Yield in The Kwahu Afram Plains North District (Doctoral dissertation, University of Ghana).
- Pattanayak, S. K., Mercer, D. E., Sills, E., & Yang, J. C. (2003).** Taking stock of agroforestry adoption studies. *Agroforestry systems*, 57(3), 173-186.
- Payne, J., Fernandez-Cornejo, J., & Daberkow, S. (2003).** Factors affecting the likelihood of corn rootworm Bt seed adoption.
- Pindyck, R. S., & Rubinfeld, D. L. L. (1981).** Econometric Models and Economic Forecasts.
- Rajasekharan, P., & Veeraputhran, S. (2002).** Adoption of intercropping in rubber smallholdings in Kerala, India: a tobit analysis. *Agroforestry Systems*, 56(1), 1-11.
- Randela, R., Alemu, Z. G., & Groenewald, J. A. (2008).** Factors enhancing market participation by small-scale cotton farmers. *Agrekon*, 47(4), 451-469.
- Ravallion, M., & Chen, S. (2004).** "How have the world's poorest fared since the early 1980s?" *World Bank Research Observer*, 19 (2), 141-170.
- Rogers, E. M. (1983).** Diffusion of innovations. *New York: Free.*

- Rogers, E. M. (2003).** Elements of diffusion. *Diffusion of innovations*, 5(1.38).
- Rogers, E. M. (2010).** *Diffusion of innovations*. Simon and Schuster.
- Rogers, E. M., & Shoemaker, F. F. (1971).** *Communication of Innovations; A Cross-Cultural Approach*.
- Rogers, E.M. (1962).** *Diffusion of Innovation*. New York: Free Press.
- Rosegrant, M.W., C. Ringler, S. Msangi, T. Zhu, T. Sulser, R. Valmonte-Santos, and S. Wood. (2007).** “Agriculture and Food Security in Asia: The Role of Agricultural Resources Knowledge in a Changing Environment,” *Journal of Semi-Arid Tropical Agricultural Resources*, 4: 1-35.
- Rosegrant, M.W., C. Ringler, T. Sulser, M. Ewing, A. Palazzo, T. Zhu, G.C. Nelson, J. Koo, R. Robertson, S. Msangi, and M. Batka. (2009).** “Agriculture and Food Security under Global Change: Prospects for 2025/2050. Background note for supporting the development of CGIAR strategy and Results Framework.” Washington, D.C.: *International Food Policy Research Institute*.
- Ruttan, V. W. (1977).** Induced innovation and agricultural development. *Food Policy*, 2(3), 196-216.
- Saqib, S. E., Kuwornu, J. K., Panezia, S., & Ali, U. (2017).** Factors determining subsistence farmers' access to agricultural credit in flood-prone areas of Pakistan. *Kasetsart Journal of Social Sciences*.
- SARI. (1996).** Savanna Agricultural Research Institute. Annual Report, 1996.
- Sedem, E. D., William, A., & Gideon, D. A. (2016).** Effect of access to agriculture credit on farm income in the Talensi district of northern Ghana. **Russian Journal of Agricultural and Socio-Economic Sciences**, 55(7).
- Seyoum, E. T., Battese, G. E., & Fleming, E. M. (1998).** Technical efficiency and productivity of maize producers in eastern Ethiopia: a study of farmers



within and outside the Sasakawa-Global 2000 project. *Agricultural economics*, 19(3), 341-348.

Simtowe, F., Asfaw, S., & Abate, T. (2016). Determinants of agricultural technology adoption under partial population awareness: the case of pigeonpea in Malawi. *Agricultural and Food Economics*, 4(1), 7.

Sodjinou, E., Glin, L. C., Nicolay, G., Tovignan, S., & Hinvi, J. (2015). Socioeconomic determinants of organic cotton adoption in Benin, West Africa. *Agricultural and Food Economics*, 3(1), 12.

Suri, T. (2011). "Selection and Comparative Advantage in Technology Adoption," *Econometrica*, 79(1): 159–209.

Tafese T. (2016). Adoption and Intensity of Row-Seeding (Case of Wolaita Zone) Ethiopia. *Open Access Library Journal*. 10.4236/oalib.1102443

Tesfaye, Z., & Alemu, H. (2001). *Adoption of improved maize technologies and inorganic fertilizer in Northwestern Ethiopia. Ethiopian Agricultural Research Organisation (EARO) (No. 40, p. 51). Research report.*

Traore, K., Sidibe, D. K., Coulibaly, H., & Bayala, J. (2017). Optimizing yield of improved varieties of millet and sorghum under highly variable rainfall conditions using contour ridges in Cinzana, Mali. *Agriculture & Food Security*, 6(1), 11.

Uaiene, R. N., Arndt, C., & Masters, W. A. (2009). Determinants of agricultural technology adoption in Mozambique. *Discussion papers*, 67.

UN (2011). World population prospects: the 2010 revision. United Nations, Department for Economic and Social Information and Policy Analysis, New York.

USAID (2014). The Market for Maize, rice, Soy, and Warehousing in northern Ghana. United States Agency for International Development.



- Vandercasteelen, J., Dereje, M., Minten, B., & Taffesse, A. (2014).** Perceptions, impacts and rewards of row planting of teff.
- Vandermeer, J. H. (1992).** The ecology of intercropping. Cambridge University Press.
- Verbeek, M. (2004).** A guide to modern econometrics. southern gate, chichester, west sussex, england hoboken: NJ: John Wiley & Sons.
- Verma, S. and Sharma, P.K. (2007).** Effect of long-term manuring and fertilizers on carbon pools, soil structure, and sustainability under different cropping systems in wet-temperate zone of northwest Himalayas. In: *Biology and Fertility Soils*, 44 (1): 235-240.
- Wekem, A. D. (2013).** Barriers to entry and farmers' participation in dry season irrigation farming in the Upper East Region of Ghana (Doctoral dissertation, Department of Agricultural Economics, University of Ghana).
- Wiredu, A. N., Zeller, M., & Diagne, A. (2015).** What determines adoption of fertilizers among rice-producing households in Northern Ghana. *Quarterly Journal of International Agriculture*, 54(3), 263-283.
- Wolka, K., & Negash, M. (2014).** Farmers' adoption of soil and water conservation technology: a case study of the Bokole and Toni sub-watersheds, southern Ethiopia. *Journal of Science & Development*, 2(1), 35-48.
- Wood, T. N. (2013).** Agricultural development in the northern savannah of Ghana (Doctoral dissertation, The University of Nebraska-Lincoln).
- Wooldridge, J. M. (2002).** Inverse probability weighted M-estimators for sample selection, attrition, and stratification. *Portuguese Economic Journal*, 1(2), 117-139.
- World Bank (2011).** Africa's Future and the World Bank's Support to It, Washington D.C.



World Bank (2012): World Development Indicators. Washington, D.C.

World Bank (2015). Country Data: Ghana. Washington D.C.: World Bank
(<http://www.worldbank.org/en/country/ghan>)

Wu, J., & Babcock, B. A. (1998). The choice of tillage, rotation, and soil testing practices: Economic and environmental implications. *American Journal of Agricultural Economics*, 80(3), 494-511.

Yawson, D. O., Armah, F. A., Afrifa, E. K., & Dadzie, S. K. (2010). Ghana's fertilizer subsidy policy: Early field lessons from farmers in the central region. *Journal of sustainable development in Africa*, 12(3), 191-203.

Yigezu, Y. A., Tizale, C. Y., & Aw-Hassan, A. (2015). Modeling Farmers' Adoption Decisions of Multiple Crop Technologies: The Case of Barley and Potatoes in Ethiopia. In *2015 Conference, August 9-14, 2015, Milan, Italy* (No. 211867). *International Association of Agricultural Economists*.

Yirga, C., & Hassan, R. M. (2013). Determinants of inorganic fertilizer use in the mixed crop-livestock farming systems of the central highlands of Ethiopia. *African Crop Science Journal*, 21(1), 669-682.



Appendix I: Research Questionnaire

**MPHIL RESEARCH PROJECT
FARMER QUESTIONNAIRE- 2017/2018 FARMING SEASON**

**ADOPTION OF IMPROVED TECHNOLOGIES IN MAIZE PRODUCTION
AND ITS EFFECT ON OUTPUT IN THE UPPER EAST REGION, GHANA**

My name is Tampoling Emmanuel Manbey, an Mphil student of Agricultural and Resource Economics Department, University for Development Studies, Tamale. I am undertaking a research on the topic: *Adoption of Improved Technologies in Maize Production and the Effect on Output in the Upper East Region of Ghana*. I would like to solicit some information from you while assuring you that it is purely for academic purposes and any information provided would be treated as confidential and your name would not be mentioned anywhere in the research work. I would therefore be grateful if you could be as accurate and objective as possible in your responses.

SECTION A1: SOCIO-DEMOGRAPHIC AND ECONOMIC FACTORS

This section contains questions about the demographic and socio-economic characteristics of farmers in the study area. Please indicate the code for each question where applicable.

Table 1: Farmer Characteristics

1.Respondent ID	2.Sex of respondent (Code 1)	3.Age of respondent	4.Respondents ethnic group	5.Marital status of respondent (Code 2)	6.Religion of respondent (Code 3)	7.Educational level of respondent (Code 4)	8. Number of years in schooling
	Code 1 Male -1 Female-0		Talensi-1 Gurune-2 Kusaasi-3 Kasena- Nankana-4 Nabdram- 5	Code 2 Married-1 Single – 2 Divorced -3 Widow/Widower - 4	Code 3 Christian-1 Muslim-2 Tradition alist-3	Code 4 No formal -1 Primary -2 JHS -3 SHS -4 Tertiary -5 Non-formal -6	

SECTION A2: Household size, Employment status-Farm and Non-farm & Farming experience

This section contains questions about the household size, employment status and farming experience of farmers in the study area. Please indicate the code for each question where applicable.



Table 2: Household size, employment and farming experience

9. Sex of household head	10. Age (yrs)	11. How many people currently live in your household?	12. # HH age under < 18 yrs [] 18-60 yrs [] 60+ yrs []	13. What is your major occupation? (Code 6)	14. What is your minor occupation? (Code 6)	15. What other source of income generating activities do you engage in? (Code 6)	16. How many years have you been farming maize?

Code 5

Male - 1
Female - 0

Use Code 6 for Q. 11-13

Farming-1 Petty trading-2Weaving-3Salaried worker-4 Pito-Brewing-5 Galamsey - 6 Tailoring - 7
Others (please specify).....

SECTION B: FARM-SPECIFIC CHARACTERISTICS

17. Indicate the main type of land ownership for your maize farm

1= own land [] 2= inherited land [] 3 = rented land []

18. What method do you engage in during land preparation? (1) Tractor [] (2) Bullock [] (3) Hand tillage []

19. Please, indicate the size of your farm and production estimates of maize in the 2017/18 farming season in the Table 3 below:

Table 3: Farm characteristics

Crop type	Farm size (acres)	Quantity harvested (kg)	Quantity Stored/ consumed (kg)	Quantity sold (kg)	Unit price/kg (GH¢)	Total Amount (GH¢)
Maize						

20. Please indicate by ticking the main location of your maize farm:

1= Upland [] 2 = low-land []

21. Did you have access to labour in 2017/2018 farming season? Yes [] No []

22. Indicate the type of main source of labour employed in 2017/18 farming season

1= family labour [] 2 = hired labour []

23. Please, indicate the number of labour employed for your maize farm in the 2017/18 farming **Table 4**

#	Farm Activity	Family labour		Hired labour		Total cost of labour (GH¢)
		# of people employed	Cost per worker (GH¢)	# of people employed	Cost per worker (GH¢)	
1.1.	Land preparation (ploughing, land clearing, harrowing spraying)					



1.2.	Planting / Sowing					
1.3.	Weed control 1& 2					
1.4.	Fertilizer application					
1.5.	Harvesting					
1.6.	Threshing					
1.7.	Bagging, loading and transportation					

SECTION C: IMPROVED PRODUCTION TECHNOLOGY (IPT) FACTORS

24. Do you have knowledge of any maize technology? (Please tick the correct response)

Yes [] No []

26. Which of the following do you have knowledge on? *Table 5*

Knowledge on improved technology	Response Yes = 1 No = 2	Rate of knowledge			
		Poor	Fair	Good	Very Good
Improved varieties					
Inorganic/Chemical fertilizer					
Legume intercropped with Maize					
Row or line planting					
Stone/soil bunding					
Manure					

27. Which of these technologies have you adopted *Table 6?*

Type	Response Yes = 1 No = 2	Reasons for adopting	Reasons for not adopting
Improved varieties			
Inorganic/Chemical fertilizer			
Legume intercropped with Maize			
Row or line planting			
Stone/soil bunding			
Manure			

28. Source of Information on Improved Production Technology *Table 7*

Source	Response Yes = 1 No = 2	Please rate the quality of information you received by ticking (√)			
		Excellent	Very good	Good	Poor
Colleague farmer					
Farmer groups					
Extension agents					
Radio/television					
NGOs (Workshop/seminars)					

29. Did you receive training on these improved technologies? Yes [] No []

30. Which of the following improved technologies were you trained on? **Table 8**

Type of Technology	Tick
Improved maize varieties	
Legume intercropped with Maize	
Row/Line Planting	
Minimum Tillage	
Stone Bunding	
Contour Plough or Ridging	
Crop Rotation	
Chemical fertilizer application	

31. Which variety did you cultivate for the last season? a. Local variety [] b. mamaba [] c. Golden Crystal [] d. Obatanpa [] e. Panaar [] f. Others (please specify.....)

32. Please, indicate the kinds of inputs used in the production of maize in the 2017/18 farming season in the **Table 9** below:

Inputs (Agro-chemicals)	1 Quantity of input accessed (kg/litres)	Unit Price	Total cost
I. Chemical Fertilizer 15-15-15 NPK (50 kg)			
II. Organic fertilizer (kg)			
III. Sulphate of ammonia (50 kg)			
IV. Improved seed (kg)			
V. Weedicide (litres)			
VI. Pesticide (litres)			

33. Method of fertilizer application? a. Broadcasting [] b. Placement method [] c. Dig and bury []

SECTION D: INSTITUTIONAL FACTORS

34. What is the distance from your house to the nearest input shop?km

35. What is the distance from your house to the nearest output market?

.....km

36. Did you receive extension contact during the 2017/2018 farming season?

a. Yes [] b. No []

37. If yes, how many times did you come into contact with extension agents during the 2017/18 season?

38. Which aspect of farming did you receive extension advice? (Tick where applicable) a. Field preparation [] b. Planting/sowing [] c. Fertilizer application [] d. Weeding/spraying [] e. Harvesting [] f. Threshing/shelling [] g. improved maize varieties []



39. Do you belong to any maize farmer organisation in your area?
a. Yes [] b. No []
40. Did you request for credit for your farming during the 2017/2018 season?
Yes [] b. No []
41. Did you obtain the credit facility? a. Yes [] b. No []
42. If yes, what kind of credit did you obtain? a. Cash [] b. Input [] c. Mechanisation []
43. Did you arranged with a marketer for the purchase of your produce?
a. Yes [] b. No []
44. Did you engage in contract farming for the 2017/2018 season?
a. Yes [] b. No []
45. What is the distance from your house to farm?km

SECTION E: ELICITATION OF CONSTRAINTS

46. Please rank in the appropriate constraints inhibiting the adoption of improved maize technologies in your area

Constraints	Rank in order of severity (from 1-8)
i. Lack of access to improved maize seed	
ii. High cost of improved maize seed	
iii. Untimely access to agrochemicals	
iv. High cost of fertilizer	
v. Limited access to land	
vi. Access to information	
vii. Lack of reliable market	
viii. Lack of access to credit facilities	

Suggests solutions

.....
.....
.....

Thank you for your time

