UNIVERSITY FOR DEVELOPMENT STUDIES, TAMALE

AGRICULTURAL TECHNOLOGY TRANSFER, ADOPTION AND TECHNICAL EFFICIENCY OF RICE FARMERS IN NORTHERN GHANA

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BY

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SEPTEMBER 2019

DECLARATION

STUDENT'S DECLARATION

I hereby declare that this thesis 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.

Candidate's Signature: .... Date: ....

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SUPERVISORS' DECLARATION

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.

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ABSTRACT

The demand for rice continues to outstrip supply in Ghana, making the country a net importer of the commodity. Low productivity due to poor technology dissemination and adoption by rice farmers is said to be the major reason for the supply deficit. The main objective of this study was therefore, to draw the link between agricultural technology transfer mechanisms, adoption and technical efficiency of rice farmers in northern Ghana. Specifically, the study assessed various agricultural technology transfer methods and their perceived effectiveness; examined the determinants of adoption of selected improved agricultural technologies; and also estimated the technical efficiency of rice farmers, using data randomly collected from 543 rice farmers. Kendall's *W* and Chi squared tests were employed to identify and assess the various agricultural technology transfer methods and their perceived effectiveness. Multivariate probit and Zero Inflated Poisson models were estimated to examine the determinants of adoption of improved agricultural technologies. Also, a framework that corrects for sample selection in stochastic production frontier (SPF) model with propensity score matching (PSM) to resolve biases stemming from both observed and unobserved variables was employed to estimate the technical efficiency of rice farmers. The empirical results show that farmer-to-farmer extension approach, demonstration field, household extension method, and radio were the main extension methods used to disseminate information to farmers. Among the explanatory variables, farmers who attended demonstration field days, and had access to television (TV), radio, and training, had a higher probability to adopt improved technologies such as bunding, irrigation, line planting, briquetting, spacing, harrowing and nursery establishment. On the other hand, farmers who were located in the northern region with larger farm sizes, and

received information via household extension method, had lower probabilities of adopting improved rice production technologies. Irrigation farmers were more technically efficient (68%) than their counterparts rainfed farmers (63.4%). Technical efficiency (TE) estimates improved marginally from 60.6% to 62.2% upon implementing the sample selection framework in SFA. TE was enhanced by location in the northern region, credit access, household size, and farmer's perception of climate change; but was lower for male farmers, household heads, commercial and experienced farmers as well as beneficiaries of fertilizer subsidy programmes. Among others, the Government of Ghana (GoG) should collaborate with NGOs to empower nucleus farmers to establish technology demonstration farms where they can train other farmers on improved technologies. The nucleus farmers could be assisted to use ICT and mass media mechanisms such as video, mobile phones, and radio since these methods can be used to reach out to many farmers at a lower cost. Also, farmers are advised to join or form groups to be able to learn new techniques of production from their colleague farmers, and also stand the chance of contracting loans and technologies which could increase their efficiency and output of rice.

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DEDICATION

To my wife, Mrs. Olivia Abakisi-Shaibu, and my children, Wuntima, Wunveila and Wunmalia-Dede for your spiritual and emotional support.

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LIST OF ABBREVIATIONS

ADVANCE – Agricultural Development and Value Chain Enhancement Project

CRS – Catholic Relief Services

DAES – Directorate of Agricultural Extension Services

ERP – Economic Recovery Programme

FAO – Food and Agriculture Organisation

FASDEP – Food and Agriculture Sector Development Policy

FBO – Farmer Based Organisation

FGD – Focus Group Discussion

GDP – Gross Domestic Product

GoG – Government of Ghana

GSS – Ghana Statistical Service

Ha – Hectare

IFDC – International Fertilizer Development Centre

IFAD – International Fund for Agricultural Development

IFPRI – International Food Policy Research Institute

METASIP – Medium Term Agricultural Sector Investment Plan

MoFA – Ministry of Food and Agriculture

MT – Metric Tonne

NGO – Non-Governmental Organisation

RSSP –Rice Sector Support Project

SAP – Structural Adjustment Programme

SARI – Savannah Agricultural Research Institute

SFA	– Stochastic Frontier Analysis
SPF	– Stochastic Production Frontier
SRID	– Statistics, Research and Information Directorate
TE	– Technical Efficiency
TGR	– Technology Gap Ratio
UN	– United Nations
UNFCCC	– United Nations Framework Convention on Climate Change
USAID	– United States Agency for International Development
ZIP	– Zero Inflated Poisson Model

CHAPTER ONE

INTRODUCTION

1.1 Background to the Study

The Food and Agricultural Organisation estimates that food production must increase by at least 60 percent to respond to the demand of the 9 billion people that are expected to inhabit the planet by 2050 (FAO, 2013). New evidence continues to point to a rise in world hunger in recent years after a prolonged decline. An estimated 821 million people – approximately one out of every nine people in the world are undernourished (FAO, IFAD, UNICEF, WFP and WHO, 2018). Ensuring global food security over the next decades will be herculean task. In meeting this challenge, there is the need to create sustainable economic growth in rural areas of developing countries (including northern Ghana) where food insecurity and poverty are most prevalent (Darfour and Rosentrater, 2016).

It has been predicted by the United Nations Framework Convention on Climate Change (UNFCCC, 2007) that over the next few decades, billions of people, especially those living in developing countries will face shortages of water and food, and greater risks to health and life because of climate change (Connor, 2015). With fewer social, technological and financial resources for adapting to changing conditions, developing countries are the most vulnerable to the impacts of climate change (UNFCCC, 2007). Although some crops in some regions of the world may benefit, the overall impacts of climate change on agriculture are expected to be negative (International Food Policy Research Institute, IFPRI, 2009). Furthermore, crop failures and long-term declines in productions will occur (IFPRI, 2009). The impact of climate change will hit developing countries the hardest, and it is in these countries where food security will be most threatened (IFPRI, 2009). Because agricultural production remains the main source of income for most rural communities, adaptation of the agricultural sector to the adverse effects of climate change will be imperative for protecting and improving the livelihoods of the poor and ensuring food security (FAO, 2012).

Crop output (including cereal production) in sub-Sahara Africa has generally been low for a long time due to a number of factors including poor adoption and use of improved production methods (Ragasa et al., 2013). The impact is being felt more severely in impoverished communities (Nakano, Tsusaka, Aida, and Pede, 2018). In contrast, the green revolution has drastically improved the yields of grains (including rice) for several decades in Asian countries (Nakano et al., 2018). Tsusaka and Otsuka (2013) mentioned rice to be one of the most important cereal crops that could help Africa achieve the African Green Revolution. Communicating improved rice production technologies to farmers and the subsequent adoption of improved agricultural and environmentally friendly technologies for rice production is therefore necessary to support in meeting the food demand by mitigating against the effect of climate change.

In this study, improved agricultural technologies are specific methods which, when applied to rice production, enhance productivity and increased incomes. While there could be numerous competing definitions of what methods constitute good agricultural practice, there are several broadly accepted schemes that producers can adhere to. The Food and Agricultural Organization of the United Nations (FAO) considers improved agricultural technologies as a collection of principles to applied to on-farm production and post-production processes, resulting in safe and healthy food, while taking into account economic, social and environmental sustainability. Seventeen (17) of such technologies have been identified (and used in this study) based on information from active projects that were ongoing at the time of this study. However, seven of the technologies were found to be most promoted and applied by majority of the farmers. This are: bunding, irrigation, line planting, briquetting, spacing, harrowing and nursery establishment. These technologies have been found to be interdependent and mostly adopted together by the farmers for effectiveness. Irrigation technology is particularly popular among rice farmers in the study area. For this reason, this study sought to assess the impact of adoption of irrigation technology on technical efficiency.

The northern regions of Ghana (Upper east, Upper west and the Northern regions) together cover about 41% of Ghana's land mass, with about 66% of the households engaged in agriculture (Ministry of Food and Agriculture, MoFA, 2013). Sadly, most statistical surveys and studies (e.g. GSS, 2014) have shown that the northern parts of Ghana remain the poorest areas of the country. Improvement in agricultural production and sustainability depend largely on the willingness of farmers and their ability to access improved production technologies (Dobermann, 2013). Agricultural advisory services play a crucial role in addressing these challenges by ensuring that farmers are exposed to improved and time-tested production techniques and that their concerns are addressed adequately by relevant authorities and service providers.

The purpose of extension in recent times, for agriculture, goes beyond technology transfer and training, as it now extends to facilitation and learning, which include assisting in the formation of farmer groups and dealing with marketing issues that border the farmers (Barungi, Guloba, and Adong, 2015; Davis, 2008). It also includes addressing issues of public interest such as health and nutrition, conservation of resources, agricultural production processes and monitoring of food security, food safety, education of families, and youth empowerment by forming partnerships with a broad range of service providers and development organisation and projects (Directorate of Agricultural Extension Services, DAES, 2010).

When new agricultural technologies such as the Urea Deep Placement (UDP) technology are generated by stakeholders, the agricultural extension system is expected to transfer these technologies to the end user, being the farmers. The role of research and extension is to give critical technical and management information that responds to the needs of farmers (Anderson and Feder, 2003). The issue of low agricultural productivity among farmers in most African countries has been attributed largely to poor linkages between research and extension services. The problem is also due to the fact we have ineffective technology delivery systems beset with poor packaging of technical information and poor delivery methodologies (DAES, 2010).

Extension service is organised and delivered in several ways, with the prime objective of increasing production and incomes (Barungi, Guloba, and Adong, 2015). The success of agricultural extension in achieving these will however depend on the extension method that is employed to reach out to the end user. The application of innovative methods to increase coverage is therefore of concern to all the actors involved in the business of agricultural extension and information advisory mechanisms. A range of approaches to agricultural extension, mostly from top-down, and usually commodity-based approaches to more participatory approaches, have been promoted over the last few years in Ghana by MoFA as the main actor in the extension delivery system (DAES, 2010). Other non-governmental organisations and projects such as the International Fertilizer Development Centre (IFDC), Ghana Agriculture Technology Transfer Project, ESOKO Ghana, Catholic Relief Services (CRS), and Care International have adopted similar approaches to extend technologies to farmers. The ineffectiveness of some of the extension methods to meet their goals coupled with inadequate extension officers and low budgetary allocations for supporting public agricultural extension, has led to continuous modification and experimentation with existing methods. This present study examines the various agricultural technology transfer mechanisms, adoption of improved production techniques, and technical efficiency of rice farmers in Northern Ghana.

1.2 Problem Statement

In Ghana, rice imports continue to surge ahead of production. Increasing rice production and yields have therefore become a priority and necessity for stakeholders in the rice value chain (MoFA, 2013). Annual per capita consumption of rice in Ghana grew from 17.5 kg during 1999–2001 to 24 kg during 2010–2011 (MoFA, 2013; Ragasa et al., 2014). This has seen a further increase to about 32kg in 2015 (MoFA SRID, 2016). Also, the demand for rice is projected to increase at an annual growth rate of 11.8%, exceeding that of maize (2.6%) in the medium term (Millennium Development Authority (MiDA), 2010). As only 5% of global production is traded, local production would also protect consumers from price shocks in the world rice market (World Bank, 2013). While substantial investments in national rice production have been made, local production is still not able to keep up with the growing demand for rice in Ghana (MoFA SRID, 2016). Although local production of milled rice recently has grown by 10.5% annually, from 242,000 metric tons (MT) in 2004 to 481,000 MT in 2012, most of this growth in production has come from expansion in farm sizes (7.5%), with the remaining 3.0% coming from productivity improvements (MoFA SRID, 2016). Despite these efforts, Ghana imported 656,232.06 MT of rice in 2017 alone, accounting for only 47% of net local demand (MoFA SRID, 2018).

Meanwhile, several interventions have been implemented in northern Ghana to address the situation of low adoption and application of improved production techniques by farmers. Improved agricultural technologies and practices have been introduced to rice farmers through interventions such as the Feed the Future (FtF) USAID-Ghana Agriculture Technology Transfer (ATT) project (2013-2018), Agricultural Development and Value Chain Enhancement (ADVANCE) I and II projects (2009-2012 and 2013-2018 respectively), and the Rice Sector Support Project (RSSP) (2013-2016). These interventions have come in the form of improved seed and innovative agronomic practices (Zereyesus, Ross, Amanor-Boadu, and Dalton, 2014).

Despite all the efforts, average rice yield continues to stay low at about 3.01 MT/Ha, while the achievable yield based on on-farm trials is estimated to be about 6. MT/Ha (MoFA SRID, 2018). Low adoption of inputs and improved technologies are often cited as the major reason for this gap. Again, there exist some technology transfer and adoption challenges which have to be addressed to make a headway with improvements in the rice sector of northern Ghana. For instance, Ragasa et al. (2013) reported of a low adoption level of 48% for improved modern rice varieties from certified sources for the northern savannah zone as compared with the national average of 58%. Again, just about 34% of the total area under rice production in the northern savannah zone was planted with modern rice varieties from certified source, with only 13% of the total area planted in rows. While Ragasa et al. (2013) reported low levels of fertilizer usage and the adoption of improved agricultural practices such as bunding, nursery establishment, row planting and irrigation among rice farmers in northern Ghana, Abdulai, Zakariah and Donkoh (2018) established a positive correlation between the adoption of improved rice production technologies and technical efficiency of rice farmers in the study area. The foregoing discussions indicate that poor agricultural technology transfer methods can result in poor adoption and utilisation of innovative agricultural technologies among farmers. A study on technology transfer, adoption and technical efficiency of rice farmers would therefore be worthwhile.

1.3 Research questions

The study therefore sought to answer the following questions:

1. What is the perception of rice farmers about the effectiveness of the various agricultural technology transfer approaches used in northern Ghana?
2. What factors influence the adoption of improved agricultural technologies by rice farmers in northern Ghana?
3. What are the technical efficiency levels of rice farmers in northern Ghana? And
4. What factors influence the technical efficiency of rice farmers in northern Ghana?

1.4 Objectives of the Study

The main focus of the study was to look at the various agricultural technology transfer approaches, adoption constraints, and technical efficiency among rice farmers in northern Ghana. Specifically, the study sought to:

1. To assess the perception of farmers about the effectiveness of identified agricultural technology transfer methods in northern Ghana;
2. Examine the factors influencing the adoption of improved agricultural technologies by rice farmers in northern Ghana;
3. Estimate the technical efficiency of rice farmers in northern Ghana; and
4. Investigate the determinants of technical efficiency of farmers in northern Ghana.

1.5 Significance of the Study

Rice has become a major part of the diet of many Ghanaians, thereby, attracting the attention of many actors in the agrifood sector (MoFA, 2016). The production of rice is however challenged by many factors including low technology adoption and climate change. According to Darko and Atazona (2013), northern Ghana has become more vulnerable to the volatile weather patterns than the rest of the country resulting from climate change.

This study adds to scholarly research and literature by teasing out the applicable technology extension approaches or methods to reach out to rice farmers in northern Ghana. Previous studies (Ragasa et al., 2013) have reported of low adoption of improved agricultural practices by rice farmers in northern Ghana. However, to the best of the researcher's knowledge, there is no sufficient literature to explain how technology transfer processes or approaches (those commonly used in Ghana) affect adoption of improved agricultural practices such as bunding and Urea Deep Placement (UDP) Technology by rice farmers. The study adds to the empirics of technical efficiency (TE). For instance, Donkoh, Ayambila, and Abdulai (2013), Anang et al. (2016), and Abdulai, Zakaria and Donkoh (2018) have found some level of technical inefficiency among rice farmers in northern Ghana. The studies of the above mentioned authors could not also address unobserved biases in estimating TE based on Greene's (2010) framework or addressing sample selection in SFA

Also, the study could prove useful to stakeholders such as the government of Ghana, farmers and farmer associations, agricultural NGOs and all the actors in the rice value chain by aiding in the design of solutions for adoption and productivity challenges. The findings to a large extent, can shape agricultural policy in Ghana, as well as help in the design of donor funded projects and programmes by local and international NGOs.

1.6 Scope of the Study

This study was limited to rice farmers (both under irrigation and rainfed systems) in the Upper East region and Northern region of Ghana. These two regions have evidence of rice production potentials due to the availability of vast lowlands and valleys that characterize rice production (MoFA, 2016). The two regions also have irrigation schemes which make rice production possible even in the dry season. These schemes include the Via and Tono irrigation schemes located in the Upper East region, and Libga, Golinga and Bontanga irrigation schemes located in the Northern region of Ghana. Farmers located in communities where there are natural low-lands for rice production, as well as those located near the various irrigation schemes were considered as sample units for the study. In terms of content, the study models the relationship between technology transfer approaches, adoption of improved rice production technologies and technical efficiency (TE) of rice farmers under the two production systems (i.e. rain fed and irrigated conditions). This is done using Stochastic Production Frontier (SPF) estimations accounting for sample selection. The study builds on previous works on TE conducted in northern Ghana (i.e Nkegbe 2012; Donkoh, Ayambila, and Abdulai, 2013; Anang et al., 2018; Abdulai, Zakaria and Donkoh, 2018) that could not address unobserved biases based on Greene's (2010) framework or addressing sample selection in SFA.

1.7 Organisation of the Study

The thesis is organised under six (6) chapters. The first chapter provides the general introduction of the thesis, outlining the problem statement and the objectives, the significance of the study, and the scope of the study. Chapter two provides a background to agriculture and the national economy of Ghana. In the third chapter, conceptual, theoretical, and empirical literature is reviewed to guide the scope of the study. Chapter four focuses on the methodology adopted for the study. In chapter five, the results are presented and discussed. The last chapter of the thesis (chapter six) provides a summary of the study, draws conclusions, and makes recommendations for policy formulation and improvements in the rice sector of Ghana.

CHAPTER TWO

AGRICULTURE AND THE NATIONAL ECONOMY OF GHANA

2.1 Agriculture in Ghana

This section of the thesis provides a background to the agricultural sector in Ghana. The section discusses briefly, the performance and contribution of the agricultural sector to the national economy. According to McKay and Aryeetey (2004), agriculture has been the bedrock of Ghana's economy since independence. The agricultural sector continues to contribute substantially to Ghana's Gross Domestic Product (GDP) (MoFA, 2016; GSS, 2014; MoFA, 2013). Meanwhile, growth of the sector is still primarily led by smallholders for subsistence purpose (MoFA, 2016). The World Bank (2009), indicates that economic growth rate of Ghana was negative in the 1970s until the late 1980s when the economy started to recover. Within the same period, agricultural growth rate was also low. However, the contribution of the agriculture to GDP increased to about 60% around the late 1970s and early 1980s. When growth started to recover after 1983, the service and industrial sectors needed more recovery as they declined more in the previous period. The GDP share of agriculture was about 40% in the late 1990s and was above 35% till 2007 when we started experiencing a drop. Between 2012 and 2013, the share of agriculture to Ghana's GDP fell below 30% at about 23% and 22% respectively. It dropped to 20.2% in 2015 (MoFA, 2016; GSS, 2016). The projected contribution of the agriculture sector to the GDP of Ghana by the end of 2017 is 18.5%, a reduction of 0.3% from the 2016 figure (GoG, 2017). Recent decline in the agricultural GDP share is the result of faster growth in the service sector, which has increased the share in GDP to more than 53% in 2015 alone. Meanwhile, the share of the industrial sector to the GDP of Ghana has not changed much after the 1990s. The growth in the non-agricultural sectors is not consistent with the transformation or economic theory and also based on experiences from other developing countries in which the role of industry has increased in the development process (Breisinger and Diao, 2008).

Table 2.1 gives further details about the contribution of the subsectors to Ghana's GDP. Within the agricultural sector, root and tuber crops such as cassava, yams and cocoyam, contributed up to 16.9% of the agricultural GDP in 2013 alone. Export crops, such as cocoa, oil palm, fruits, vegetables, rubber, and cotton, accounted for about 22% of the agricultural GDP. Cereals accounted only for 10% and other staple crops accounted for 21%. The livestock sector also contributed 7% to the agricultural GDP of 2013.

Though the estimates in Table 2.2 show an improvement in the growth of the Agriculture sector in the last few years, i.e. 5.7% in 2013, compared to 2.3% in 2012 and 0.8 in 2011, its contribution to the economy continues to decline as discussed above. In 2014 however, agricultural growth in Ghana further reduced to 4.6% from 5.7% in the previous year and further reduced to 2.5% in 2015 (GSS, 2016). The sector is however expected to grow by about 4.3% towards the end of 2017 (GoG, 2017). Ghana has recently discovered oil, which attracts a lot of government's attention. Budgetary allocation to the agriculture sector has also declined considerably over the years (GoG, 2017). This situation, if unchecked, could lead to the infamous phenomenon of Dutch disease commonly described by some scholars as "resource curse" where the discovery of natural resources may lead to a decline in the performance of the agricultural sector as is the case of Ghana presently.

Table 2. 1: Distribution of GDP (at basic price) by economic activity (%)

Sector	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016*	2017*
Agric.	30.4	29.1	31	31.8	29.8	25.3	22.9	22.4	21.5	20.3	18.9	18.5
Industry	20.8	20.7	20.4	19	19.1	25.6	28	27.8	26.6	26.6	24.3	25.6
Service	48.8	50.2	48.6	49.2	51.1	49.1	49.1	49.8	51.9	53.3	56.8	55.9

Source: GSS (2016), *GoG (2017)

Table 2. 2: Growth rate of GDP by economic activity (at constant price) %

Sector	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016*	2017*
Agric.	-1.7	7.4	7.2	5.3	0.8	2.3	5.7	4.6	2.5	3.0	4.3
Industry	6.1	15.1	4.5	6.9	41.6	11	6.6	0.8	1	-0.5	17.7
Service	7.7	8.0	5.6	9.8	9.4	12.1	10	5.6	5.2	5.7	4.7

Source: GSS (2016), *GoG (2017)

The structure and distribution of agricultural GDP significantly differ across Ghana's agro ecological zones. The regional differences pose some implications for subsector level agricultural growth strategies. The Forest zone of Ghana is still a major agricultural producer, accounting for the greatest percentage of agricultural GDP of the country, compared to the Coastal belt, and the Southern and Northern Savannah areas respectively (MoFA, 2016). The Northern savannah region is the major basket for cereals and livestock in Ghana, producing over 70% of the country's rice sorghum, millet, cowpeas, groundnuts, beef and soybeans (MoFA, 2016; 2013). The forest regions supply a large share of high-value products such as cocoa and timber and some livestock (mainly commercial poultry) (ibid). The diverse agricultural production system accounts for some differences in the income structure across the various agricultural zones and regions.

In Ghana, agriculture is predominantly on a small-scale with about 90% of farm holdings being less than 2 hectares. The relatively large-scale farms are for the production of cash crops such as cocoa and oil palm. The major crops grown among the starchy and cereal staples include cassava, yam, cocoyam, maize, millet, sorghum and plantain. For the northern part of Ghana, it is predominantly maize, rice, cowpea, groundnuts, sorghum, millet, and a few other crops including yam. The total production area for these crops was estimated to be 3,275,000 Ha in 2011 which increased to 3,462,000 Ha in the 2012 production season (MoFA, 2013). The main tools for production are the hoe and the cutlass although there are few farmers who use the bullock, especially in the northern part of the country. MoFA (2013) also noted that most food crop farms are intercropped while mono-cropping is practiced by large-scale commercial farms. Intercropping/mixed cropping system is noted as a means of diversifying the production processes to withstand the shocks of climate change (Azumah, Donkoh and Ansah, 2017).

To support smallholder farmers in ensuring food security, efforts towards productivity improvements should consider intensification methods. For instance, MoFA set a target of improving technologies adopted by smallholder farmers and yields of rice, maize, sorghum, cassava and yam by 50% and cowpea by 25% by 2015 (MoFA, 2013). According to MoFA (2013b), the yields of most food crops except cassava and yam have been decreasing over the past five-year period (2009 - 2013). For instance, in comparing the yields of 2013 with 2012, yield of rice, maize, millet, sorghum, cowpea and soya bean recorded a decrease of 7.86%, 7.36%, 6.26%, 7.46%, and 8.13% respectively. Among the reasons for such decrease was uneven rainfall distribution and poor cropping methods.

2.2 Overview of agricultural policy in Ghana

This section provides a historical run down of agricultural policies in Ghana dating far back to the colonial period. As a result of the important contributions of agriculture to the economic growth and development of Ghana as well as the myriad of challenges bedeviling the sector, several policies to improving agricultural production in the country have been formulated and implemented over the years. The trajectory of agricultural policy dates back to the post-colonial era. During this period, agricultural policies were towards the production of export commodities and raw materials for metropolitan manufacturers and farmers abroad (Dapaah, 1996). According to Seini (2002), the passing of the poll tax law at the beginning of the 20th century forced subsistence farmers and fisher folks to find wage employment or become self-employed in export crop production, mainly cocoa.

In the final years of colonial rule in Ghana, and towards independence, there was a shift in agricultural policies influenced by the desire of the nationalist government to please the urban youth, who were in the forefront of the independence struggle, many of whom were unemployed or underemployed. This was also to satisfy the perception that industrialisation was the best way to bring about rapid structural changes, economic growth and economic independence. As a result, it became necessary to have an agricultural policy that created more jobs by reducing the dependence on small-scale farmers or total food supply (Seini, 2002). Therefore, the Agricultural Development Corporation (ADC) was established in the first 5-year Development Plan from 1951 to 1956 to promote agricultural development in Ghana. The ADC was expanded under the second 5-year Development Plan spanning from 1959 to 1964. However, it is asserted by Dapaah (1996) that overall, policies in the early years of independence did not address agricultural and food production challenges generally. This was because agricultural policies were designed to deal primarily with urban unemployment and not to deal with rural poverty.

Between 1966 and 1972; that is after the change of government in 1966, the emphasis of agricultural policy was on private capitalist development. Government at the time became particularly interested in promoting rice farming in the northern Ghana as a means of increasing food production and availability. State Farms were therefore sold to private rice farmers and the extension service was revived to offer advisory services to small-scale farmers all over Ghana. The implication is that emphasis in the period was on private ownership, units of more modest size and bank financing. Another notable characteristic of agricultural policy at the time was the formation of single product development boards. Policy makers believed that the ingenuity of the peasant farmer could be further successfully exploited by the establishment of development boards to offer advice, incentives and oversee the production of agricultural raw materials that were necessary to support newly established factories. Subsequently, the continued interest in raising agricultural productivity to self-sufficiency level led to the implementation of the Operation Feed Yourself (OFY) and Operation Feed Your Industries (OFYI) programmes during the 1970s (Seini, 2002).

According to Seini (2002), small scale development programmes were initiated to provide avenues for small farmers in the late 1970s and the early 1980s. One such project was the World Bank scheme which sought to raise incomes of the rural small scaled farmers of the upper regions. The Ghanaian German agricultural development project was also established. This was to assist small scaled farmers to increase food production via effective distribution of inputs. Research into the development of new technologies for farmers was also a core mandate. The Volta Regional Agricultural Development programme (VORADEP), the Northern Regional Rural Integrated Project (NORRIP) and the Managed Inputs Delivery and Agricultural Services (MIDAS) were also established around the 1980s with the aim of increasing agricultural production, particularly for small scale farmers. These policies and projects provided agricultural inputs and services in a timely and on regular basis to farmers. Around the early 1990s, the International Fund for Agricultural Development (IFAD), designed and implemented programmes that sought to improve the productivity of small-scale farmers in the Northern parts of Ghana as well as the transitional zone, Ashanti and Volta Regions. Some of the programmes include small–scale/micro–scale irrigation and drainage Projects to ensure two production seasons in a year.

However, a major downturn in Ghana's economic growth and development in the 1980s due to both domestic and external factors lead to the initiation of the Structural Adjustment Programme (SAP) and subsequently the Economic Recovery Programme (ERP) in the 1980s. Being the major sector of the economy, agriculture invariably became the target of most policy interventions. Specifically, as part of the Economic Recovery Programme (ERP), a programme for the agricultural sector dubbed "Ghana Agricultural Policy - Action Plans and Strategies (1984 - 86)" was implemented. The plan highlighted self-sufficiency in production and maintenance of adequate levels of buffer stocks of maize and rice. This was to ensure availability of food during the lean periods. It was also to ensure price stability and the provision of maximum food and nutrition security against unforeseen crop failures and natural hazards (Seini, 2002).

Also, the government launched Ghana's Vision 2020 programme in 1995 to usher the country into an era of sustained accelerated growth. The programme was to transform Ghana from a poor highly indebted low-income country into a prosperous middle-income country by the year 2020. The Ghana Poverty Reduction Strategy (GPRS) I, and the Growth and Poverty Reduction Strategy (GPRS) II also contained policies and programmes aimed at improving agricultural gains in the country. Subsequent to GPRS II were the Ghana Shared Growth and Development Agenda (GSGDA I and GSGDA II) under which the strategy for agricultural growth was "Accelerated agricultural modernisation and natural resource management" (NDPC, 2015). Other plans and programmes on improving the agriculture sector include the Agricultural Services Sub-Sector Investment Program (AgSSIP), Medium Term Agriculture Sector Investment Plan (METASIP). In recent times, one major factor that has been identified to be a threat to growth in agricultural production is climate change (Yaro et al., 2010). As a result, recent policies and strategies on agriculture are geared towards mitigating the negative effects of climate change.

According to MoFA (2007), the Food and Agriculture Sector Development Policy (FASDEP) I, was developed as a policy to guide development and interventions in the agriculture sector of Ghana. FASDEP I was formulated in 2002 building on the key elements of Accelerated Agricultural Growth and Development Strategy (AAGDS). FASDEP I also focused on strengthening the private sector as the engine of growth, and meant to provide a framework for modernising the agricultural sector and to make it a catalyst for rural transformation, in accordance with the goal of the Ghana Poverty Reduction Strategy (GPRS I).

A poverty and social impact analysis (PSIA) of FASDEP I (MoFA, 2007), however, concluded that the policies would not be able to achieve the desired impacts for a number of reasons including the fact that:

- The expectation of modernising subsistent agriculture was unachievable largely because of improper targeting of the poor within an environment where the drivers of modernisation, access to credit and improved agricultural technology, good infrastructure, and markets are lacking.
- Problem analysis was weak. This did not adequately reflect the perspectives of clients on their priorities; and
- The process by which MoFA was to stimulate response from other MDAs for interventions that fell outside the domain of MoFA was not properly stated.

There was therefore the need for FASDEP II which sought to enhance the environment for all categories of farmers. It also targeted poor and risk prone and risk-averse producers. This made it possible through an extensive stakeholder consultation processes which incorporated lessons learned from implementation of FASDEP I, and sub-sector policies and strategies that were developed in the past. The policy also ensured consistency with national development goals as stated in the GPRS II, which aimed to achieve accelerated and sustainable shared growth, poverty reduction, gender equity, social protection and empowerment of the vulnerable and excluded. This was to be achieved within a decentralised and democratic political environment (MoFA, 2007).

To implement the Food and Agriculture Sector Development Policy (FASDEP II), the Government of Ghana developed the Medium-Term Agriculture Sector Investment Plan (METASIP). This was to be implemented over the medium term between 2011-2015

(MoFA, 2009). In the context of the Ghana Shared Growth and Development Agenda (GSGDA), METASIP had a framework of interventions for the agriculture sector to play its role in the national economy. GSGDA which was coordinated by the National Development Planning Commission (NDPC) was supposed to be the national programme of economic and social development policies in Ghana. The first phase of METASIP was also to fulfil Ghana's participation in agriculture related initiatives of the ECOWAS and the Africa Union Commission (AUC), under the structure of the ECOWAS Agriculture Policy (ECOWAP), and the Comprehensive Africa Agriculture Development Programme (CAADP) (MoFA, 2009).

The formulation of METASIP was done through a consultative process, and involved both technical and budgetary planning. It took into account ongoing projects and adopted the sector-wide approach (SWAp) and mechanisms to bring on board key actors and agencies in the agriculture sector through coordination and participation in synchrony with the CAADP principles for implementation.

METASIP comprised the following six (6) programmes areas which correspond to FASDEP II. It represents Ghana's priorities within the four CAADP Pillars:

1. Food security and emergency preparedness
2. Improved growth in incomes
3. Increased competitiveness and enhanced integration into domestic and international markets
4. Sustainable management of land and environment
5. Science and technology applied in food and agriculture development
6. Enhanced institutional coordination

Boateng and Nyaaba (2014) analysed the perceptions of households on the impact of METASIP on Food Security in Ghana. They concluded that METASIP must do more to guide and sustain its successes. Boateng and Nyaaba (2014) highlighted that more efforts needed to be put in for improved production, mechanization, irrigation and water management and enhanced off-farm activities by actively engaging communities, households and all stakeholders in the agricultural value chain. This meant adopting a holistic approach in public investment, stakeholder participation and commitment from policy makers.

The Medium-Term Agricultural Sector Investment Plan (METASIP II) 2014-2017 has been developed as a continuation of the efforts from METASIP I (MoFA, 2015). This is based on the guidelines of the Ghana Shared Growth and Development Agenda (GSGDA II), and also based on the Maputo and Malabo declarations of government expenditure allocation of at least 10 percent of the national budget into the agricultural sector, and expected GDP growth of at least 6 percent within the plan period. The targets mentioned above are also in conformity with the agricultural performance targets of the ECOWAP of ECOWAS, CAADP of NEPAD and is expected to contribute significantly to the achievement of the Sustainable Development Goals of the United Nations.

The plan has been developed with a strong emphasis on the Accelerated Agriculture Modernization and Sustainable Natural Resource Management which will transform the agricultural sector to increase productivity and output, create jobs, increase incomes, and ensure food security over the medium term. Innovative interventions have been planned based on the adopted objectives and key strategies that will be systematically implemented under the programme areas to ensure that the goals set for the agricultural sector under the

GSGDA II are achieved. This plan also has six programmes with its corresponding sub-programmes. The programmes are:

- Management and administration;
- Food and nutrition security and emergency preparedness;
- Increased growth in incomes;
- Marketing of agricultural products;
- Management of land and environment; and
- Science and technology in food and agricultural development.

Cross cutting issues such as climate change and environment, gender, HIV/AIDs, population, decentralization, disasters, vulnerability, culture, security and technological innovations are also taken into consideration in all programmes, projects and activities of stakeholders in the agricultural sector.

The plan is implemented along programme areas that address the key challenges to the modernization and transformation of agriculture in Ghana. It will be implemented by the existing structures of the MDAs, particularly the District Departments of Agriculture (DDAs) which are now departments within the District Assemblies. Complexities of implementation are bound to arise as the Sector Plan will have to be largely implemented together with other stakeholders. It is therefore expected that, the DDA must not only understand the various aspects of the plan but also incorporate relevant aspects into the district assembly MTDP and also be able to convince the district authorities why priority should be given to planned activities in order to receive funding.

2.3 Rice production and consumption pattern in Ghana

2.3.1 Rice production patterns in Ghana

This section discusses and provides information on the rice sector of Ghana. It provides information also about the consumption patterns, and rice production. A major boost in rice production as a result of government policy was realised in the 1970s. By instituting Operation Feed Yourself (OFY) and Operation Feed Your Industry (OFYI) programmes between 1972 and 1975, there was a massive boost in rice production (Seini, 2002). The programmes were to increase food production and raw materials to feed industry. One of the objectives of the programmes was to make sure that smallholder farmers increased their production through expansion of farm sizes and the use of fertilizers. Under the OFY in particular, much attention was focused on the cultivation of rice and maize, with rice being more successful. The country became self-sufficient (but not secured) in production of rice between 1974 and 1975 (Seini, 2002).

However, under the 3rd phase of the structural adjustment programme (SAP) in the 1980s, dubbed liberalisation and growth phase, the major goals included deregulation of commodity and service markets. This was to reduce domestic price distortions, as well as liberalisation of export and import markets. As part of the trade liberalisation programmes, the guaranteed minimum prices for maize and rice were abolished. All subsidies including subsidies for agricultural inputs, notably fertilizers and insecticides were also removed. On the average, the prices of most agricultural inputs such as herbicides used in cereal production increased by about 40% annually during the periods of 1986 to 1992 (Asuming-Brempong, 1998). The trade liberalization agenda had a dire consequence on the rice sector. Local production started to decline as there was no more subsidies to support the sector. Because of the free market system, the country was flooded with cheap imported rice, making domestic production uncompetitive. This notwithstanding, rice production in Ghana has increased significantly from year 2000.

For instance, MoFA (2013) reported that the land area under the production of rice has increased from 123, 000 Ha in 2002 to about 189, 000 Ha in 2012 (see Table 2.3). However, average yield per hectare is still 2.5 as against the achievable yield of 6.5 MT/Ha (MoFA, 2013). Until 2008, the total output of paddy rice for Ghana was below 300, 000 MT. However, local production has increased from 391, 000 MT in 2009 to 481, 000 MT in 2012 (see Table 2.3).

The expansion in the production of rice is largely attributable to the expansion on area under productions. Favourable rain patterns, the national fertilizer subsidy programme and the block farm programme could also have accounted for the increase in the national rice output. Only about 80% of the rice produced in Ghana is by smallholder farmers, mostly on farmlands less than one hectare in size (Angelucci et al., 2013). Past projects and government interventions such as the MiDA Commercial Development of Farmer Based Organisations were not successful in commercialising the rice sector of Ghana.

Rain-fed rice production contributes 84% of total current production in Ghana, generating average paddy yields of 1.0 - 2.4 MT/Ha while irrigated production accounts for just about 16% of production but produces higher average paddy yield of about 4.5 MT/ha (CARD, 2010). Due to increased investment and attention towards the local rice sector by both the government and its development partners, domestic paddy rice production in Ghana has increased by 160% between 2007 and 2012 while yield increased by about 59% (MoFA, 2013). In addition to the increase in production, there has been a tremendous improvement in the finishing and the quality of the local rice over the years. For instance, Ghana can now boast of premium long grain perfumed rice such as “AGRA rice”, “Jamine 85”, and Northern Star Rice” based on research of scientists from Alliance for a Green Revolution in Africa (AGRA) and the Savannah Agricultural Research Institute (SARI).

Even though rice is produced in all the ten regions of Ghana, Northern, Upper East and Volta regions are mainly responsible for the majority of rice produced in Ghana (MoFA SRID, 2016; 2013). Average yield of 2.96 MT/Ha in these three regions exceeds the national average of 2.5 MT/Ha but is significantly lower than the average yield of 5.48 MT/Ha in the Greater Accra Region, suggesting that the adoption of the right technologies could enhance yields and output (Angelucci et al., 2013). Meanwhile national averages have only improved marginally from 2.64MT/Ha in 2013 to about 3MT/Ha in 2017 due the implementation of the “Planting for Food and Jobs” programme (MoFA SRID, 2018) as shown by Table 2.3.

Table 2. 3: Rice production and importation in Ghana

Parameter	Year													
	2002	2003	2004	2005	2006	*2007*	2008	2009	2010	2011	2012	2013	2014	2015
Planted a	124	118	119	120	125	109	133	162	181	197	189	216	224	233
Paddy P MT)	280	239	242	237	250	185	302	391	492	463	481	570	604	641
Imports	297	798	254	485	390	442	395	384	320	543	509	-	-	621
Value of million)	68.85	124.66	119.15	138.94	159.47	157.86	187.28	218.5	200.88	391.17	639.4	-	-	-
Yield (p	-	-	-	-	-	-	-	-	-	-	-	2.64	2.69	2.75

FA SRID, 2013; 2016). The yield for 2016 and 2017 is 2.92 and 3.01 MT/Ha respectively according to SRID, 2018.

CHAPTER THREE

LITERATURE REVIEW

3.0 Introduction

This chapter provides a review of the conceptual, theoretical and empirical literature relevant to the study. First, the concept of extension approaches, methods and models are examined in relation to the Ghanaian agricultural extension system. Conceptual and theoretical discussions about technology diffusion and adoption have also been addressed in this chapter. Finally, the chapter looks at the concept of efficiency and discusses some selected empirical studies on technology adoption and technical efficiency.

3.1 The Concept of Extension Approaches, Extension Models and Extension Methods

3.1.1 The Concept of Agricultural Extension

According to Davis (2008), agricultural extension was originally used to mean 'extend' research-based knowledge from its source to the rural sector, primarily to improve the lives of farmers. Anandajayasekeram, Puskur, Workneh, and Hoekstra (2008), and Moris (1991) also defined agricultural extension as the delivery of technical information to farmers, resulting in a technology transfer model of extension which is seen by many as the main purpose of agricultural extension. The model is based on the idea that improved information or knowledge is transferred through extension workers to the end user who are usually the farmers. This means that extension is a conscious process of communicating information to help people form sound opinions and make decisive choices.

Also, agricultural extension is seen as a human-centred endeavour aimed at changing or improving knowledge. It also aims at improving attitude, practices and skills of beneficiaries through education and the provision of support services. In the view of Ackah-Nyamike (2007), extension attempts to empower farmers with the requisite knowledge, attitude, and opportunity to practice for enhancing productivity and welfare. This is philosophized as helping people to help themselves. Traditionally, extension in developing countries was centred on increasing production and yield improvements, training of farmers, and transferring technology to them (Davis, 2008).

The traditional approaches to research and development are linear. It was assumed that innovations originate from agricultural researchers, transferred by extension agents and other intermediaries and are applied by farmers. According to Christoplos (2010) “Extension is part of agricultural knowledge and information systems, which are in turn part of the agrifood and rural development innovation systems that frame the prospects for rural poverty alleviation and food security”.

As the problems faced by the agricultural sector change over time, we will have to adapt our ideas about the role of agricultural extension in meeting modern day challenges (Leeuwis, 2004). Current understanding of agricultural extension transcends technology transfer to even facilitation and learning. This includes helping farmers form groups, deal with marketing issues and environmental sustainability, and partner with a range of service providers and development actors (DAES, 2010). Extension has a crucial contribution to make to these broader systems. New meanings of agricultural extension involve the concept of Agricultural Knowledge System (AKS) which is comprised of agricultural research, agricultural extension and agricultural education in one system. The AKS focuses on how the three activities (mentioned above) generate new knowledge and information for beneficiaries being the farmers (Anandajayasekeram et al., 2008). The emphasis is on the agricultural research, extension and education components with the purpose of working together to support decision making process, problem solving initiatives and innovation in agriculture.

From the above definitions, it can be deduced that agricultural extension involves three key stakeholders who can either be linked cyclically or in a linear manner. It involves the researcher, the extension agent and the farmer who is at the receiving end. The relationship is said to be linear if there is no feedback or interaction between the farmers and the originators of the information that the farmers consume (van Rooyen et al., 2017).

It is also important to make a distinction between extension approaches, extension models and extension methods as used in this thesis. From literature, the terms extension approaches and extension models have been used interchangeably (Anandajayasekeram et al., 2008). For example, Rivera (1989) used "extension system". Worth (2002), calls it "extension approach", while Duvel (2000), referred to it as an "extension model".

3.1.2 The Concept of Extension Approach

According to Singh and Shekhar (2015), extension approach is the very essence of an agricultural extension system. An extension approach is the style of action within a system. It embodies the philosophy of the system and works like a doctrine for the system. This informs, stimulates and guides such aspects of the system as its structure, its leadership, and its programmes. It also guides its resources and provides linkages. Leeuwis (2004) referred to an extension approach as the basic planning philosophy which could be adopted by an agricultural extension organisation to help extension agents understand the fundamental concepts and functional methods of extension that is adopted to fulfill its goal. Seven dimensions characterise each extension approach in Ghana (DAES, 2010). These are:

1. The main identified problem to which the approach is to be applied and to address;
2. The goals for which it was designed to achieve;
3. The way in which planning is done, and the relation of those who control programme planning to those who are the programme's main beneficiaries;
4. The nature of the field personnel. This includes aspects such as their density in relation to clients, levels of training, reward packages, origin, and gender;
5. The resources needed and various costs items;
6. The implementation strategy used; and
7. How it accumulates and measures its successes.

Table 3.1 presents a number of extension approaches that are used to transmit information on improved technologies to farmers. Axinn (1998) identified eight (8) extension approaches which include the General Agricultural Extension Approach, the Commodity Specialised Approach, the Training and Visit (T&V) Approach, the Farming Systems Development Approach, and the Participatory Agricultural Extension Approach. The rest are the Project Approach, the Cost Sharing Approach, and the Educational Institution Approach. Gemo et al. (2005) also identified other forms of extension approaches which include public extension approach, NGO approach and the private sector approach. What is common to both Axinn (1998) and Gemo et al. (2005) is the commodity specialised approach, and training and visit approach which are widely used in Ghana.

Table 3. 1: Categorization of agricultural extension approaches

Axinn (1998)		Gemo et al. (2005)	
1	General agriculture	1	Public extension approach
2	Commodity specialised	2	Commodity specialised approach
3	Training and Visit (T&V) approach	3	Training and Visit (T&V)
4	Agricultural participatory approach	4	NGO approach
5	Project approach	5	Private sector approach
6	Farming systems research and extension (FSR/E)	6	Technology transfer model
7	Cost sharing approach	7	Innovation linkages model
8	Educational institutions approach		

Source: DAES (2010)

3.1.3 Extension Models

Anandajayasekeram et al. (2008), stated that a model could be viewed as a schematic description of a system, or phenomenon that takes care of its known or inferred properties and may be used for further study of its characteristics. For many years, a number of agricultural extension models have been used to enhance the effectiveness of extension services delivery. In the real-world situation however, you would find a combination of elements of various model simultaneously being implemented.

Gemo et al. (2005) identified seven (7) extension models being used in Africa. These models are however, imported from other regions of the world. These are: the technology transfer model (which is basically a top-down model), the public extension model (usually operated by public institutions such MoFA of Ghana), the commodity extension model, and the T&V model. The rest are the NGO (international and local) model, the private sector model, the Farmer Field School (FFS) model, and the Innovative linkage models.

3.1.4 Extension Methods

An extension method refers to the techniques used by an extension system as it functions. For example, demonstration, or a visit by an extension officer to a farmer. Having looked at the concepts of extension approach, extension model and extension method, the discussions below outlines some of the main approaches, models and methods employed in the agricultural extension service delivery in Ghana and the world at large. Major emphasis is however placed on the agricultural extension methods as this applies to this study. Some of these include individual/household extension method, group method, and mass media method.

It is difficult to single out one extension method as being the best one as they all come with some merits and demerits. However, the choice of methods depends on various factors such as the tenure system in the area, community organisation, and resources available for extension (Nakano, Tsusaka, Aida, and Pede, 2018; Anandajayasekeram et al., 2008). A combination of extension methods is seen to be more effective than just applying one method. For example, in an area where land tenure system is communal, a group approach is likely to be more effective. Meetings and field days as well as school approaches may also be very good options.

3.1.4.1 The Individual/Household Extension Method

This approach is most effective for activities within the full control of the individual farmer or his or her household. In this sense, discussion with the whole family highlights more problems, with more experience brought to bear. Anandajayasekeram et al. (2008), highlights some merits of the individual extension method as follows:

- Unclear messages that was fully und not understood during group sessions can easily be clarified when using this method;
- The extension officer is able to secure cooperation by inspiring confidence in the family through personal contact;
- It facilitates immediate feedback on the effectiveness of the issues discussed;
- It may be the best way to ensure that everyone in the family participate in decision-making that concerns farm business.

Disadvantages of the individual extension method however include its high cost in terms of time and transport. Only a few farmers can be and may actually be visited. Also, the area covered is small since all the effort is concentrated on a few farmers.

3.1.4.2 Group Extension Method

This approach involves working with groups or the community as a whole. It is suitable when discussing matters related to the whole community (such as postharvest technology transfer, grazing, protection, and management of indigenous forests) and when there are activities to be undertaken by a group (e.g. group nurseries). The direct target group may be a women's group, a church organisation, a cooperative society or the community in general.

Extension work can be carried out at meetings, either organised specifically for the selected purpose or by making use of meetings that were already organised for some other purpose. Meetings are effective venues for receiving information from the community, for discussing issues of communal or individual interest and for spreading new ideas. Field days and demonstration are best organised on individual farms. According to Anandajayasekeram et al. (2008), two kinds of demonstration forms can be used, namely; Result and Method demonstrations.

Result demonstration shows farmers the results of a practice that has been in use for some time. It is intended to arouse the farmers' interest in the practice. This can also be used to compare older practices or techniques with new ones. Method demonstrations on the other hand, show farmers how a particular activity or task is carried out. It is among the oldest and effective methods of teaching since farmers can practice, see, hear, and discuss during the demonstration. Under the group approach five different methods are used:

- the catchment approach;
- T&V approach;
- the school approach;
- the mass media approach; and
- Farmer Field Schools.

3.1.4.3 The Catchment Approach

This is a special type of group approach that has been used since 1980s (Anandajayasekeram et al., 2008). All farmers within a certain area, normally some 200–400 ha, are mobilised and trained for conservation efforts. A catchment committee consisting of, and elected by, the local farmers assists the extension staff in awareness creation, layout of contours, implementation and follow up. The group approach is combined with the individual approach since each farm is subject to specific advice and layout.

3.1.4.4 The School Approach

In this approach, the extension work can be in the form of lectures, support for clubs, demonstration plots or discussions held during parents' days. Schools can be approached through lead farmers of extension agents. The attending farmers can be used as a channel for reaching the community and will also be influenced themselves, thus changing the behaviour and attitudes of the new generation. Attending farmers can also be used to trigger discussion in their families. Among others, the schools can afford to make demonstration plots available and these can be seen by many people. It is possible to reach large numbers of people within a short time at minimal cost. The disadvantages of the approach however, is that some farmers who attend the demonstrations are often not decision-makers in their homes (e.g. some women participants) and so considerable time is needed before such farmers who attend demonstrations become influential in their homes or society.

3.1.4.5 Mass Media

This method involves the use of the mass media such as radio, posters, drama, TV, newspapers, films, slide shows) to disseminate information. Mass media are mainly used to create awareness. Advantages of mass extension methods include increase in the impact of extension staff through rapid spread of information (Anderson and Feder, 2003). Many people can be reached within a short time, even in remote areas (Aremu, Kol, Gana, and Adelere, 2015). However, the amount of information that can be transmitted is limited. Radio and television reception are poor in some areas and the target group may not own those sets, particularly television sets. It is also difficult to evaluate the impact since there is no immediate feedback. Again, the production of both programmes and printed materials is costly and requires special skills.

3.2 Technology Diffusion and Adoption

This section discusses the theory and attributes of technology adoption and diffusion by farmers. It gives an understanding of the characterization of rice farmers in northern Ghana who seek to imbibe knowledge on rice production techniques transmitted to them by extension agents.

Various authors define the term “technology” in many ways. Rogers (2003) uses the words ‘technology’ and ‘innovation’ synonymously and defines technology as the design for action that reduces the uncertainty in the cause-effect relationship involved in achieving a desired goal. According to Hall and Khan (2002), technology is the execution of reasoning inherent in practical art and development of knowledge involved in productive and creative activities. Technology involves transfer of information from the developer to a user.

Therefore, the contribution of a new technology to economic growth can only be realised when and if the new technology is widely disseminated and used.

In the view of Rogers (2003), diffusion is the process by which an innovation is transmitted through certain media over time among the members of a social system. Diffusion of an innovation gives knowledge on how ideas are accepted and under what conditions they are most likely to be implemented. In simple terms, diffusion is the process by which something new spreads throughout a population (Hall and Khan, 2002). According to Abdul-Hanan et al. (2014), the extent of use of a new technology or innovation is known as adoption, while diffusion is the dispersal of technology in a community.

Sociologists explain adoption and diffusion in terms of the nature of communication channels and differences in social positions. Economists explain adoption and diffusion in terms of returns or profitability. Anthropologists and geographers also explain the concepts as the compatibility of innovation and information flow (Boahene, 1995).

Rogers (1962), like others found that, diffusion was an S-shape function of time. Diffusion theory represents a complex number of sub-theories that collectively describe the processes of adoption. Diffusion research can be traced to a French sociologist Gabriel (Tarde, 1903; Couros, 2003) although he used slightly different terms from present day, for instance ‘imitation’ to mean ‘adoption’ (Rogers, 2003). The S-shape attribute of the rate of adoption was also attributed to Tarde (1903). Using the S-shape, Tarde was able to identify those innovations with a relatively fast rate of adoption (steep slope) and those with a slower rate of adoption (gradual slope). Ryan and Gross (1943) also noted that the rate of adoption followed an S-curve when plotted on a cumulative basis over time. Based on the time of adoption, Ryan and Gross (1943) classified farmers into five categories as:

1. Innovators, who usually have larger farms, are more educated, more prosperous and more risk-oriented.
2. The early adopters, who are usually younger, more educated, tend to be community leaders, but less prosperous.
3. The early majority, who are said to be more conservative but open to new ideas, active in their various communities and have influence on their neighbours.
4. The late majority, who are relatively older, less educated, fairly conservative and less socially active.
5. The laggards, also known as phobics, who are very conservative, have small farms and capital, oldest and least educated.

Adoption is the decision making process where an individual decides to use (adopt) a new idea (an innovation or technology). An innovation is meant for a whole society and not an individual. However, since individuals have varying levels of uncertainty, the time of adopting a technology may not be the same for all. Researchers including Rogers demonstrated that the adoption of an innovation follows a normal, bell-shaped curve when plotted over time on a frequency basis. But if the cumulative number of adopters is plotted instead of the frequencies, the result is an s-shaped curve as shown by Figure 3.1 (Rogers, 1983; Beal and Rogers, 1960). Therefore, the same adoption data can be represented by either a bell-shaped (frequency) or an s-shaped (cumulative) curve; this is shown in the figure below. The reason for the s-shape is that the distribution rises slowly at first when there are few adopters in each time period. This increases to a peak where half of the persons in the system have adopted the innovation. It then increases at a slower rate as the few remaining individuals finally adopt. Roger (1983) noted that the S-shaped curve is normal because it rests on the role of information and uncertainty reduction in the diffusion of an innovation. According to Roger (1983), different forms of mathematical formulae have been proposed fit, and also explain the shape of adopter distributions with a general agreement that the S-shaped curves are essentially normal.

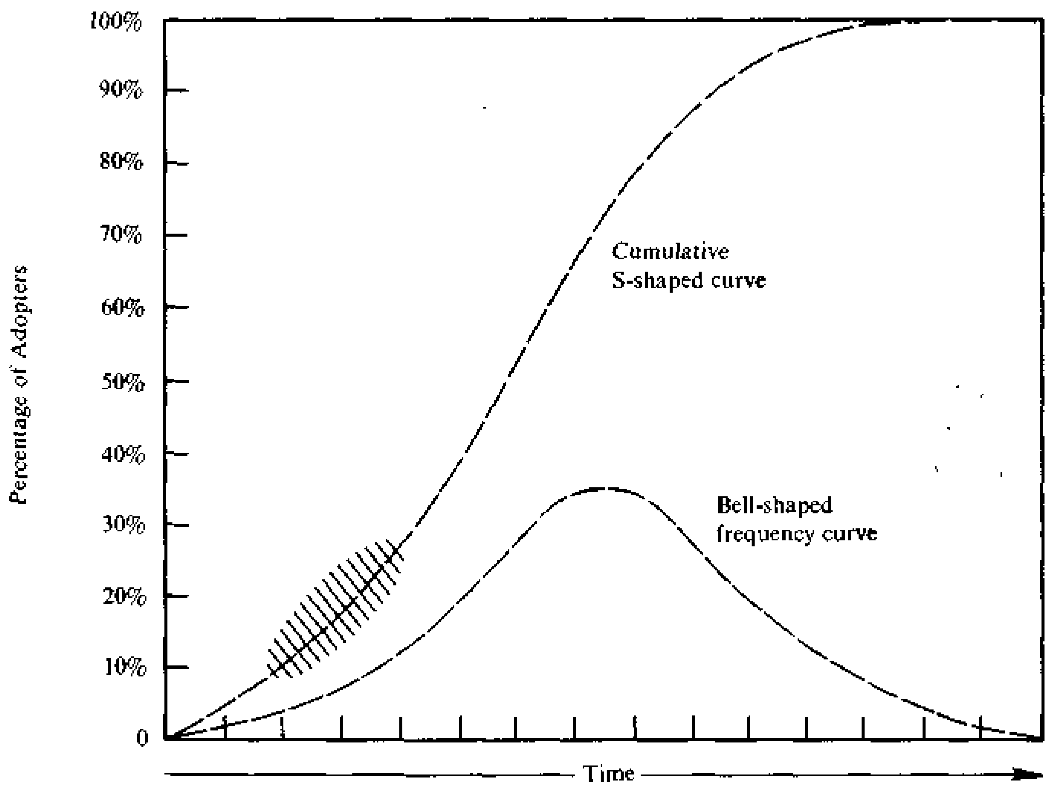

Figure 3. 1: The shape of adoption curve
Source: Rogers (1983)

Since Ryan and Gross's (1943) work, various theorists (i.e. Midgley and Dowling, 1978; Abrahamson and Rosenkopf, 1997; Gladwell, 2000; Rogers, 1995, 2003) have used and modified these basic categories to build upon their work (Couros, 2003). According to Vanderslice (2000), the most widely recognised source of diffusion theory is Everett Rogers seminal work on *Diffusion of Innovations*. Therefore, in recent times, Rogers' (2003) work formed the basis of most adoption studies. Key in his definition of diffusion is the presence of four elements in the diffusion of innovation process. These elements include:

1. The innovation; an idea, practices or objects that is perceived as new by individuals or a group of adopters. Wasson (1960) mentioned that the ease or difficulty of introduction of new ideas ‘depends basically on the nature of the 'new' in the new product’,
2. Communication Channels; the means by which innovations move from individual to individual, or group to group,
3. Time; the non-spatial interval through which the diffusion events occur, and
4. A social system; a set of interrelated units that are engaged in joint problem solving activities to accomplish a goal.

Rogers (2003) also distinctly separated the diffusion process from the adoption process. He noted that while the diffusion process infuses through society and groups, the adoption process is most relevant to the individual. Thus, Rogers (2003) defines the adoption process as “the mental process through which an individual pass from first hearing about an innovation to final adoption”. The five steps in this process are: knowledge (awareness), persuasion (interest), decision (evaluation), implementation (trial), and confirmation (adoption).

- In the awareness stage, the individual is exposed to the innovation but lacks complete information about it.
- At the interest or information stage, the individual becomes interested in the new idea and seeks additional information about it.

- At the evaluation stage the, individual mentally applies the innovation to his/her present and anticipated future situations, and then decides whether or not to try it.
- During the trial stage, the individual makes full use of the innovation.
- At the adoption stage, the individual decides to continue the full use of the innovation.

Throughout the adoption process, the individual seeks knowledge and skills which ultimately affects the adoption process. For a potential adopter however, the process will proceed through the various steps and lead to adoption, or alternately, lead to rejection of the innovation.

3.2.1 Attributes of Innovation (or Technology)

The attributes of innovation/technology are discussed in this section based on Rogers' (2003) descriptions. Rogers (2003) described the innovation-diffusion process as "an uncertainty reduction process" and he proposes attributes of innovations that help to decrease uncertainty about the innovation. Attributes of innovations include five characteristics of innovations: Relative advantage, Compatibility, Complexity, Trialability, and Observability ((Vagnani and Volpe, 2017). Individuals' perceptions of these characteristics predict the rate of adoption of innovations.

Relative Advantage

Vagnani and Volpe (2017) defined relative advantage as the degree to which an innovation is perceived as being better than the idea it supersedes. The cost and social status motivation aspects of innovations are elements of relative advantage. For instance, while innovators, early adopters, and early majority are more status-motivated for adopting innovations, the late majority and laggards perceive status as less significant. Moreover, innovations are categorised into two types: preventive and incremental (non-preventive) innovations. A preventive innovation is a new idea that an individual adopts now in order to lower the probability of some unwanted future event. Preventive innovations usually have a slow rate of adoption so their relative advantage is highly uncertain (Rogers, 2003).

However, incremental innovations provide beneficial outcomes in a short period. To increase the rate of adopting innovations and to make relative advantage more effective, direct or indirect financial payment incentives may be used to support the individuals of a social system in adopting an innovation. Incentives are part of support and motivation factors. Another motivation factor in the diffusion process is the compatibility attribute.

Compatibility

In some diffusion research, relative advantage and compatibility were viewed as similar, although they are conceptually different. Rogers (2003) stated that "compatibility is the degree to which an innovation is perceived as consistent with the existing values, past experiences, and needs of potential adopters". A lack of compatibility in information technology (IT) with individual needs may negatively affect the individual's IT use (McKenzie, 2001). If an innovation is compatible with an individual's needs, then uncertainty will decrease leading to improved rate of adoption of the innovation.

Complexity

Rogers (2003) defined complexity as “the degree to which an innovation is perceived as relatively difficult to understand and use”. He stressed that unlike the other attributes, complexity is negatively correlated with the rate of adoption. Excessive complexity of an innovation is an obstacle to its adoption. An innovation might confront faculty members with the challenge of changing their teaching methodology to integrate the technological innovation into their instructional processes, so it might have different levels of complexity.

Trialability

According to Rogers (2003), trialability is the degree to which an innovation may be experimented with on a limited basis. Also, trialability is positively related with the rate of adoption. The more an innovation is tried, the faster its adoption by clients. As discussed in the implementation stage of the innovation-decision process, reinvention may occur during the trial of the innovation. Then, the innovation may be changed or modified by the potential adopter. Increased reinvention may create faster adoption of the innovation. For the adoption of an innovation, another important factor is the trial, which is especially helpful for later adopters. However, Rogers (2003) stated that early adopters see the trialability attribute of innovations as more important than later adopters.

Observability

The last characteristic of innovations is observability. Rogers (2003, p.16) defined observability as "the degree to which the results of an innovation are visible to others" Role modelling (or peer observation) is the key motivational factor in the adoption and diffusion of technology. Similar to relative advantage, compatibility, and trialability, observability also is positively correlated with the rate of adoption of an innovation. In summary, Rogers (2003) argued that innovations offering more relative advantage, compatibility, simplicity, trialability, and observability will be adopted faster than other innovations. Rogers does caution, "getting a new idea adopted, even when is has obvious advantages, is difficult" (p. 1), so the availability of all of these variables of innovations speed up the innovation-diffusion process.

3.2.2 Rate of Adoption

Rogers (2003) defined the rate of adoption as "the relative speed with which an innovation is adopted by members of a social system". For instance, the number of individuals who adopted the innovation for a period of time can be measured as the rate of adoption of the innovation, and can be classified under the five categories mentioned by Ryan and Gross (1943). The perceived attributes of an innovation are significant predictors of the rate of adoption. Rogers reported that 49-87% of the variance in the rate of adoption of innovations is explained by the five attributes (i.e. observability, triability, complexity, compatibility, and relative advantage). In addition to these attributes, the innovation-decision type (optional, collective, or authority), communication channels (mass media or interpersonal channels), social system (norms or network interconnectedness), and change agents may increase the predictability of the rate of adoption of innovations. For instance, personal and optional innovations usually are adopted faster than the innovations involving an organizational or collective innovation-decision. However, for Rogers, relative advantage is the strongest predictor of the rate of adoption of an innovation.

3.2.3 The Cochrane Treadmill of Adoption

The essential role of economics in innovation and adoption studies is to be able to tell the effect of technology change on economic variables such as prices and, in particular, the wellbeing of the farmers over time. This is the reasoning behind the Cochrane treadmill analysis of adoption.

In Cochrane (1979) analysis of adoption of new technology, he divided the farming population into three subgroups (early adopters, followers, and laggards). The early adopters represent only a small segment of the farming population, in which case the impact of their adoption decision on aggregate supply and, thus, output prices is relatively small. This means that at this stage of the adoption process, these adopters stand to profit more from the innovation. As time progresses, the followers who represent a large share of the farm sector tend to adopt the technology during the take-off stage of the innovation. Because of their large size and the cumulative effect of the early adopters, their adoption decision will ultimately have the tendency to reduce prices as well as profits.

The laggards who either adopt at the last stage or do not adopt at all stand the chance of losing from technological change. Cochrane noted that if they do not adopt, they produce the same quantity as before, at low prices; and if they adopt, the significant price effect may sweep the gain associated with higher yields. Thus, in Cochrane view, farmers are not likely to gain from the introduction of innovation in agriculture, except for a small group of early adopters. This is because it may lead to structural change and worsen the plight of majority of the small farms. Sunding and Zilberman (2000) also noted that when an innovation that is supply-increasing in nature is adopted to a significant degree, it will lead to reduction in output prices, especially in agricultural commodities with low elasticity of demand. Cochrane therefore argued that the real gainers from technological change and agriculture innovation are likely to be consumers, who pay less for their food bill. This means however that in situations where the farmer is as well the consumer of the farm product, then the gain from adoption would be maximized by the farmer. Using empirical models, Kislev and Schori-Bachrach (1973) showed that only small subgroups of farmers (the early innovators who have higher education and other higher human capital) will consistently be able to take advantage of technology change and profit. This argument is similar to the threshold model discussed earlier. Thus, the early adopters with increasing profit are likely to accumulate more of the land thereby increasing their farm size.

3.3 Approaches to the analyses of Adoption

This section provides a review of what determines adoption of technology across space and time. Timothy and Anne (1993) considered three basic empirical approaches that vary according to the type of data available. These are: Time series studies approach, Panel data studies approach, and Cross-sectional studies approach. The study could not obtain any time series nor panel data, hence the reliance on the cross-sectional data collected through a carefully managed process.

There are many studies of technology adoption that use cross-sectional data (e.g. Azumah et al., 2016; Mohammed et al., 2014; Donkoh, 2011; Donkoh and Awuni, 2011; Onweremadu et al., 2007; and Bayard et al., 2006). Such data are broadly of two kinds.

First there are studies that take a look at J farmers' technology use at some date. The gain to a farmer i of using the new technology is typically parameterised as $\gamma x_i + u_i$, where x_i are farm and farmer characteristics and u_i is an independently and identically distributed farm specific $ex\ ante$ shock. γ is a set of parameters to be estimated.

It is often assumed that these shocks are normally distributed, and the model is then run as a probit, so that:

Prob {adoption by farmer i}= $\emptyset(\gamma x_i/\sigma_u)$ .... (3.8)

where $\emptyset(\cdot)$ is the distribution function of the standard normal. The intention of this line of research is often to measure the effect of x_i on adoption decisions (Timothy and Anne, 1993). σ_u is the variance.

However, this model is problematic if, as the time-series analysis suggests, there is some dynamic structure to the adoption decision. The cross section provides only a snapshot; at that point, the technology may incompletely diffuse through the population. This confounds the interpretation of the coefficients in equation 3.8. For example, there may be a time-dependent element in the adoption decision, so that the expected profits are $\gamma x_{it}/\psi_{it,}$ where:

$\psi_{it=}g(\psi_{it-1}, D_{t-1}, x_{it}) + \varepsilon_{it}$ .... (3.9)

where D_{t-1} is a history of the new technology's use up to period $t-1$. There are many possible interpretations of ψ_{it}, including (i) a farmer's knowledge about the new technology or (ii) evolving costs of adoption process.

Cross-sectional studies such as this present one may be able to provide insight into the farm and farmer characteristics associated with ultimately accepting the new technology. However, these data are of limited use in exploring the adoption process itself. Some cross-sectional surveys contain information based on recall, about when a farmer adopted a technology. Under some circumstances, recall data may provide a means for dealing with the problem of adoption process. If, for example, the dynamic structure was well represented by $\psi_{it} = \partial_i x_i$, equation 3.8 can be augmented. Creating for each farmer a set of discrete choice observations, d_{it}, equal to 1 if farmer i was using the technology at time t, $t \in [1, \dots, \tau]$, and zero if otherwise, we estimate a probit:

$$\text{Prob}\ \{d_{it} = 1\}\ = \emptyset(yx_i + pT + \partial[T \times x_i])/\sigma_u) \ldots\ldots\ldots\ldots \ (3.10)$$

where T is a set of $\tau - 1$ year indicators and T× x_i are interaction terms that allow the influence of field and farm characteristics to change over the diffusion process. σ_u is variance. While more flexible than (1), this structure is also extremely limiting. It is necessary to maintain the assumption that influential farm and farmer variables x_i do not change over time. In general, this seems unreasonable since farmer's wealth and credit-worthiness are both to influence and to be influenced by adoption choices taken. If these data are available only at the time when the survey was done, their use in equation 3.10 will bias the parameters of interest. It also seems unlikely that the dynamics of adoption can be captured by allowing time-varying coefficients on variables whose values are assumed to be constant over time. Thus, while one might be able to do better by having information about the year in which the technology was adopted, there are still problems.

3.4 Empirical Studies on Adoption of Agriculture Technologies

This section looks at various adoption studies and the methodologies employed to analyse the data in those studies. To begin with, the study reviews the simplest adoption studies that employed probit/logit models for estimation.

Uddin et al. (2014), studied the factors affecting farmers' adaptation strategies to environmental degradation and climate change effects in Bangladesh. They used randomised lottery method to select 100 farmers. The data was estimated using a logit model. The results showed that age, education, family size, farm size, family income, and involvement in cooperatives were significantly related to the adaptation strategies adopted by the farmers. They concluded that despite different support and technological interventions being available, lack of available water, shortage of cultivable land, and unpredictable weather ranked highest as the respondent group's constraints to coping with environmental degradation and change effects.

Akudugu et al. (2012) also specified a logit model to examine the factors that influenced farm households' modern agricultural production technology adoption decisions using 300 farmers in the Bawku West district of Ghana. The authors defined adoption as binary, thus, those who engaged in modern agricultural production technologies (known as the adopters) and those who did not (known as non-adopters). They found farm size, expected benefits from technology adoption, access to credit and extension services to have a significant influence on technology adoption decisions. They concluded that farm household's agricultural technology adoption decisions depend on their socio-economic circumstances and institutional effectiveness. Donkoh and Awuni (2011) also analysed the adoption of farm management practices in the northern region of Ghana using ordered probit model, and found results corroborating with Abdul-Hanan et al. (2014) who rather applied a count data model.

Again, Bayard et al. (2006), studied the adoption and management of soil conservation practices in Haiti. In this study, they identified and analysed factors influencing farmers' decisions to adopt rock walls. They also examined the factors which played a significant role in the management of land improvement technology. A sample of 115 farmers were selected and interviewed by face-to-face interview. They defined adoption as the adoption of soil conservative practice (rock wall); thus, adopters and non-adopters. In their findings, it was discovered that age, education, group membership, and per capita income negatively influenced the ability to manage the rock walls, while age squared and the interaction between age and per capita income positively influenced the management. They asserted that, factors influencing management of rock walls may be different for each farmer or group of farmers depending upon the constraints they faced.

The dependent variable in the logit/probit model is dichotomous and can only assume two outcome values, i.e. adopt or not to adopt. The major shortfall of the probit/logit models is that they do not cater for intermediaries, hence, the need for ordered probit/logit models which are applied to cases of more than two outcomes of an ordinal dependent variable (a dependent variable for which the potential values have a natural ordering, as in poor, fair, good, and excellent adoption).

Application of ordered probit model can be found in the work of Teklewold, Kassie, and Shiferaw (2013) who employed it together with multivariate probit to analyse the factors that facilitate or impede the probability and level of adoption of interrelated sustainable agricultural practices (SAPs) by farm households, using data from multiple plot-level observations in rural Ethiopia. The results show that there is a significant correlation among SAPs, suggesting that adoptions of SAPs are interrelated. The analysis further shows that both the probability and the extent of adoption of SAPs are influenced by many factors such as a household's trust in government support, credit constraints, spouse education, rainfall and plot-level disturbances, household wealth, social capital and networks, labour availability, plot and market access.

Saliu, Ibrahim, and Eniojukan (2016) also employed ordered probit regression to examine the socio-economic determinants of the adoption of improved rice technologies by small scale farmers in Kogi State, Nigeria. Saliu et al. (2016) used multistage random sampling technique to select 120 registered rice farmers with the Kogi State Agricultural Development Project (ADP). The results of the ordered probit model revealed that membership of cooperative, source of fund, and source of labour determined the adoption of rice technologies, while marginal effect on farm size, household size, contact with extension agents favoured the adoption of all the eight most important rice technologies which could be used as a measure towards pleasant disposition to commercial rice farming. For joint adoption of multiple technologies as in the case of this present study, the ordered probit model will not also be appropriate, hence, the need to employ count data models such as Poisson regression, zero inflated Poisson regression and the negative binomial regression models.

Count data models have been applied by many researchers for empirical studies on adoption of improved production techniques. Mensah-Bonsu et al. (2017) estimated Poisson and negative binomial regression models to assess the intensity of land and water management practices among smallholder maize farmers in Ghana, and the factors driving the number of practices adopted. They found farmers' use of fertilizer, non-burning of farmland and ploughing-in of vegetative cover as the practices adopted the most by maize farmers. The findings of Mensah-Bonsu et al. (2017) revealed that farmers who combined three of the land and water management practices have the highest average productivity. Based on their estimations, access to extension contact, credit and farmers' experiences of food shocks are important driving factors that have implications for a comprehensive land and water management policy. However, the regression results for maize yields suggested that the adoption of a high number of the technologies might not necessarily result in better yields.

Also, Abdul-Hanan et al. (2014), investigated the factors that influenced the adoption of Soil and Water Conservation (SWC) techniques in Ghana. This involved 1,530 farm households that were selected from 20 districts across Ghana. They also estimated a Poisson regression model, and concluded that significant policy variables that positively influence the adoption of SWC techniques were credit, farm size, group membership and proximity to an input store. Other studies that previously analysed the adoption of SWC techniques with similar approaches include Boyd et al. (2000), Kato et al. (2011), Olarinde et al. (2012), and Kassa et al. (2013).

Another approach to analysing adoption of improved farm practices is the use of multinomial regression which was applied by Etwire et al. (2013) to study smallholder farmers' adoption of technologies for adaptation to climate change in Northern Ghana. In that study, a total of 320 farmers were selected through a multistage sampling procedure. Adoption in this study was defined as mutually independent strategies such as soil and plant health strategies, improved varieties and breeding strategies, recommended agricultural practices and other introduced practices. The empirical results reveal that agro ecology (locating in guinea savannah or Sudan savannah) and noticing of unpredictable temperatures are factors that have a positive and negative effect on the likelihood of adoption of soil and plant health strategies respectively. Also, receiving agricultural extension service increases the chances of adoption of improved varieties and breeds, agro ecology was found to rather reduce the chances of adoption of these varieties and breeds. Etwire et al. (2013) also found that age of household head and agro ecology were inversely related to the uptake of recommended agricultural practices. Unpredictable temperature was however found to have a direct relationship with adoption. Lastly, women were found to be more likely to adopt other introduced strategies such as planting of trees, irrigation and fire belt establishment. Among others, the authors recommended that farmers cultivate smaller farms for effective management.

However, when the technologies being studied are not mutually exclusive, then the multinomial logit specified by Etwire et al. (2013) becomes limited in explaining adoption, hence the need to apply a better regression model such as multivariate probit (MVP) that can accommodate interdependencies in the technologies.

Some recent studies that employed multivariate probit analysis include Danso-Abbeam and Baiyegunhi (2017) and Ahmed (2015). Danso-Abbeam and Baiyegunhi (2017) employed Multivariate Probit (MVP) and Tobit models to explore smallholder cocoa farmers' adoption decisions of agrochemical inputs in the Ghanaian cocoa industry using farm-level data collected from a sample of 838 farm households in four cocoa producing regions. The result of the study showed that agrochemical management practices are complementary and thus the adoption of an agrochemical input is conditional on the adoption of other inputs. Different household characteristics, household assets, institutional variables, and the perception of soil fertility status and the incidence of pests and diseases influenced the adoption of individual agrochemical inputs. The results also showed that intensity (or extent) of agrochemical adoption (measured as farmers' expenditure on agrochemicals) is also influenced by some socioeconomic and institutional variables such as extension services and farmers' visits to demonstration farms.

Ahmed (2015) also examined the nature of the relationship that exist between two broad categories of intensive and natural resource management, by using fertilizer and certified seeds as input-intensive technologies; and manure and soil conservation as natural resource management practices. The results of the multivariate correlation coefficient indicated that there is positive relationship between improved seed and fertilizer, and between improved seed and soil conservation. There was also negative relationship between adoption of manure and fertilizer, and between manure and improved seeds. The results also indicated that the variables affecting farmers' decisions to adopt a technology differ among technologies. Educational level of the household head, family size, off /non activities, live-stock ownership, distance to the market, plot ownership, slope of the plot and other variables also play significant roles, partly with differing signs across technologies.

Other authors have also employed varied approaches to studying adoption. For instance, the effects of socioeconomic characteristics on adoption level and sources of soil management information were investigated in Owerri Agricultural Zone, South-eastern Nigeria by Onweremadu and Matthews-Njoku (2007). They used structured interviews to collect data which were subjected to percentage, mean and multiple regression analysis.

The result revealed that, arable farming was dominated by relatively young and educated people who can enhance adoption and soil management technological transfer. The results in this study also indicated that, farmers were exposed to a wide range of impersonal sources of soil information and had potentials of disseminating such soil information to neighbouring farmers. The study found age, education, and income to dictate the adoption status in the study area.

Also, Mwangi and Kariuku (2015) reviewed the factors that influence the adoption of new agricultural technologies by smallholder farmers in developing countries. They found the perception of farmers towards a new technology has a key precondition for adoption to occur. They also categorised the factors that influence adoption into human specific factors, economic factors, technological and institutional factors. The review also suggested that, the effect of each of these factors on technology adoption may differ depending on the type of technology. In the view of Mwangi and Kariuku (2015) also, technology adoption by farmers can be enhanced if policy makers and developers of new technologies understand farmers need as well as their ability to adopt technology in order to come up with technology that will suit them.

When measuring the effect or impact of technology adoption, various approaches can be adopted to cater for observed and unobserved biases in the sample. These approaches include Propensity Score Matching (PSM) for observed biases, Heckman's selectivity bias correction measure and treatment effect for unobserved biases. For instance, Anang et al. (2016) addressed self-selection into credit participation using PSM, and found that the mean TE did not differ between credit users and credit constrained farmers. Villano et al. (2015) used cross-sectional farm-level data from 3,164 rice-farming households in the

Philippines, to measure the impact of modern rice technologies on farm productivity while disentangling technology gaps (the distance between production frontiers) from managerial gaps (differences in technical efficiency). To do so, they first found an adequate control group using PSM to mitigate the effect of biases from observable variables. The analysis showed that the adoption of certified seeds has a significant and positive impact on productivity, efficiency and net income in rice farming.

Ibrahim et al. (2012) employed the Heckman two-stage model in estimating the determinants of adoption of improved peanut varieties and its' potential impact on farmers' income in Savelugu/Nanton and Tolon/Kumbungu districts in the northern Region of Ghana. The study used a cross-sectional data from 219 peanut farmers. Adoption in this study was defined as binary (i.e. 1 for adopters and 0 for non-adopters). They found membership in a farmer organisation, number of bicycles owned, importance of early maturity as a varietal characteristic, and farm location as significant factors that influenced the adoption of improved peanut varieties. The study concluded that private assets, social assets and location factors are important variables in explaining adoption decisions.

Azumah, Donkoh, and Ansah (2017) also examined the link between contract farming and adoption of climate change coping and adaptation strategies. This study used cross sectional data from 230 farmers that were selected through a multistage sampling procedure. The data was analysed using instrumental variable regression to correct for endogeneity of contract farming. They found that the major coping and adaptation strategies used by farmers include spraying of farms with chemicals, row planting, mixed farming, mixed cropping and crop rotation. Based on their econometric results, they confirmed that contract farming enhances the adoption of climate change adaptation strategies. The study also found that there is a feedback effect on contract farming, such that farmers adopting more adaptation strategies had higher probabilities to obtain contract offer. They further established that land ownership and extension services exert significant and positive influence on adoption. The authors recommended for improved communication of coping and adaptation strategies to the farmers. A similar study was carried out by Azumah, Donkoh, and Ehiakpor (2016) to determine the factors that influence farmers' participation in contract farming and the effect of participation on farm income. Azumah et al. (2016) also used a sample of 230 farmers in the northern region of Ghana and estimated a treatment effect model. They found that, access to extension services, credit, farm size and off-farm income had significant influence on the participation in contract farming. Their study established generally that farmers who participated in contract farming had higher incomes than their non-participating counterparts. Other factors that significantly influenced farm income were land, labour, weedicides and fertilizers.

Muzari et al. (2012) reviewed studies on the impacts of technology adoption on smallholder agricultural productivity in sub-Saharan Africa. They found that the main factors affecting technology adoption are assets, vulnerability and institutions. They concluded that lack of assets such as land, education or equipment will limit technology adoption. This means that more attention needs to be paid to technologies that require few assets to operate or own. Decision makers also need to recognise that technologies that build on assets which the poor farmers already have are more likely to be adopted. To encourage adoption of new technologies, pro-poor agricultural researchers must look beyond simply boosting productivity. Policy makers were encouraged to emphasise on certain variables which reduce the farmers' vulnerability to loss of income, bad health, natural disasters, and other factors. More so female households in some countries have limited access to institutional credit. Therefore, improving current smallholder credit systems to ensure that a wider spectrum of smallholders is able to access credit, more especially female-headed households is necessary. They concluded finally that, other steps that may be taken to encourage the adoption of agricultural technologies are increasing agricultural productivity, reducing land degradation, reducing the price of fertilizers, offering credit, and waiving some of the taxes levied on input trading businesses.

The review of previous empirical studies provided direction to the selection of variables and the choice of appropriate methodology for this present study. It also enabled the researcher to improve on the shortfalls in previous adoption studies. Specifically, this study examined the socio-economic, institutional, location and technical constraints to the adoption of improved agricultural technologies by rice farmers in northern Ghana which have not been sufficiently captured by literature as stated above. Several of the reviewed studies have often concentrated on smallholder farmers generally. Information on crop specific studies (for example rice) are either scanty or non-existent. Again, these studies failed to explicitly analyse the constraints to adoption and the adoption decision of rice farmers. This provide a literature gap on adoption in northern Ghana, hence the need for this present study.

3.5 The Concept of Efficiency

One of the important tools for economic analysis is the production function pioneered by Wicksteed (1894). A production function defines the technological relationship between the level of inputs and the resulting level of outputs (Zeytoon, 2005). It is purely a technical relation which connects factor inputs and outputs (Koutsoyiannis, 1977). In this case, it describes the laws of proportion, that is, the transformation of factor inputs into products (outputs) at any particular time period. The usefulness of a production function is that it sets the available production technology to the highest level of output that can be obtained under a given technology and this is known as the frontier. But these functions are based on the assumption that every farmer operates on this frontier. However, in practice, each farmer obtains a different level of output even if they were operating under the same technology. Therefore, it is appropriate to measure the extent to which each individual farmer's observed output deviates from the expected average output. This is known as a measure of efficiency (Farrel, 1957; Kumbhakar and Lovell, 2000).

According to Farrel (1957), efficiency can be categorised into technical and allocative efficiencies, the product of which gives rise to economic efficiency. Allocative efficiency is the ability of the firm to use resources (inputs) to a level that their marginal contribution to the total production value is equal to the resource prices. Thus, obtaining maximum output relative to input prices. In this study, the focus was on the technical efficiency of the farmers, hence, the subsequent section explains technical efficiency in detail.

Kumbhakar and Lovell (2000) define technical efficiency in two ways:

1. the ability to reduce input usage in the production of a fixed output; or
2. the ability to produce the maximum output from a fixed input.

In both definitions, the prime aim is to improve productivity. Given these definitions, Debreu (1951) and Farrel (1957) proposed two ways to measure technical efficiency. The first being the input oriented and the second, output oriented. This is jointly known as Debreu-Farrel measure of technical efficiency. Given the production frontier model:

$$y_i = f(x_i\beta)exp\ (v_i).TE\ \dots\dots\dots\dots..(3.11)$$

Where y_i is a scalar output of producer i, x_i is a vector of inputs, β is a vector of technology parameters that must be estimated, TE is the technical efficiency of the farmer, $f(x_i\beta)exp\ (v_i)$ is the stochastic production frontier and v_i is the random error term. From this equation, TE can be defined as;

$$TE_i = \frac{y_i}{f(x_i\beta)\ exp\ (v_i)}\ \dots\dots\dots\dots\dots\dots\dots\dots.(3.12)$$

By this equation, technical efficiency can be defined as the ratio of the observed output to the maximum feasible output in a production environment characterised by random variables, $exp\ (v_i)$. y_i achieves its maximum feasible value of $f(x_i\beta)$ exp (v_i) if and only if TE_i is equal to one. Otherwise, if TE_i is less than one, then this implies that the observed output is not the highest expected output under the given technology. This shortfall in the output is known as technical inefficiency. Okon et al. (2010) stated that there is inefficiency when an observation deviates from the frontier (an efficient technology).

3.5.1 Methods of Measuring or Estimating Efficiency

The most common techniques that are used to estimate efficient frontiers have been the parametric and non-parametric methods. The parametric methods involve the determination of appropriate functional forms that can best represent a given production technology. On the other hand, the non-parametric methods do not require the specification of a functional form.

Empirically, the non-parametric approach has been measured using Data Envelopment Analysis (DEA). DEA is a mathematical programming model that is applied to an observed data and used to estimate both the production frontier and the efficiency scores of individual farmers (Djokoto, 2012; and Coelli et al., 1998). The parametric approaches, on the other hand are subdivided into deterministic and stochastic models. The deterministic models are also termed as 'full frontier' models, which engulf all the observations, identifying the distance between the observed production and the maximum production, defined by the frontier and the available technology, as technical inefficiency. That specification, therefore, assumes that all deviations from the efficient frontier are under the control of the agent.

However, there are some factors that cannot be controlled by the farmers. For instance, the rainfall pattern of a production season. Meanwhile, these factors also have effect on the production of crops and the efficiency of the farmers. Therefore, the assumption by the deterministic approach that all the production shortfalls are due to inefficiency within the farmers control could be a limitation. This limitation is addressed under stochastic production frontier. The stochastic frontier procedure estimates both specification failures and uncontrollable factors independently of the technical inefficiency component by decomposing the error term into two, the technical inefficiency and the random error term.

3.5.1.1 Non-parametric approach

As noted earlier, the non-parametric approach has become synonymous to Data Envelopment Analysis (DEA). The DEA is a body of techniques for analysing production, cost, revenue, and profit data, essentially, without parameterising the technology (Green, 2008). It originates from the same seminal paper presented by Farrell (1957). That is, the approach used by Farrell in measuring efficiency was the non-parametric approach in which no specific functional form was needed to be predefined and the production possibility set was represented by means of a frontier unit-isoquant (that is single-input/output model).

Farrel's method of measuring efficiency was later generalised to the multiple-input/output case and reformulated as a mathematical programming problem by Charnes et al. (1978). The method was later named by Charnes et al. (1981) as Data Envelopment Analysis (Zamorano, 2004).

It was originally referred to as the CCR model, derived from the initials of the co-authors (Charnes, Cooper and Rhodes). The CCR model used constant returns to scale (CRS) concept to measure relative productive efficiencies of decision-making units (DMUs) or firms with multiple inputs and outputs (Lie-Chien and Lih-An, 2005). It assumes *m* inputs, *s* outputs and *n* firms. The CCR of a k^{th} DMU is stated as:

$$max \quad h_k = \frac{\sum_{r=1}^{s} U_r Y_{rk}}{\sum_{i=1}^{m} V_i X_{ik}} \quad for \quad r = 1, 2, \ldots, s \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (3.13)$$

$$s.t. \quad \frac{\sum_{r=1}^{s} U_r Y_{rj}}{\sum_{i=1}^{m} V_i X_{ij}} \leq 1 \quad \text{for } j = 1, 2, \dots, \text{n} \quad \dots\dots\dots\dots\dots..(3.14)$$

$$U_r, V_i > 0; \quad i = 1, 2, \dots, m$$

where h_i is relative efficiency of the k^{th} DMU; Y_{rj} is r^{th} outputs of the j^{th} DMU; X_{ij} is i^{th} inputs of the j^{th} DMU; U_r is a weight of the r^{th} output; and V_i is a weight of the i^{th} input. That is, the relative efficiency score of a firm under the CCR model are the maximised ratio of weighted outputs to weighted inputs subject to a constraint which specifies the given ratio as 1, at most (Charnes et al., 1978).

Banker et al. (1984) revised the CCR model by relaxing the Constant Returns to Scale (CRS) assumption, and adding a convexity restriction which makes the linear programming problem to have three constraints namely, constraining the input to a given maximum quantity, constraining the output to a given minimum quantity and the convexity restriction ($\sum_j^n \lambda_i = 1$). Where λ is a factor used by a firm to weight both inputs and outputs. They referred to the revised model as BCC model which has Variable Returns to scale (VRS) (Lie-Chien and Lih-An, 2005).

The basic objective of the non-parametric approach, specifically the DEA, in measuring productive efficiency is to define a frontier envelopment surface for all sample observations. This surface is determined by those units that lie on the efficient firms. On the other hand, units that do not lie on or that lie below that surface are said to be inefficient and for each unit, an individual inefficiency score is calculated. The model (DEA) does not create room for statistical noise, and therefore can be initially said to be a non-statistical technique under which the inefficiency scores and the envelopment surface (efficiency scores) are calculated rather than estimated.

In summary, the main strengths may be the lack of parameterisation; no need for any distributional assumptions; and no need for any functional specification about the form of the technology and its related problems. The main drawback is that it is shared with the other deterministic frontier estimators. That is, any deviation of an observation from the frontier must be attributed to inefficiency. There is no provision for statistical noise or measurement error in the model, a problem, which is compounded by the absence of a definable set of statistical properties (Greene, 2008).

3.5.1.2 Parametric approach

Unlike the non-parametric approach, the parametric techniques (deterministic and the stochastic frontier approaches) are the most commonly used in measuring efficiency in both cross sectional and panel data. This study relies on cross sectional data, hence the discussion of the deterministic and stochastic frontier in the subsequent sections are done within cross sectional data framework.

3.5.1.2.1 Deterministic frontier analysis

In the purview of a cross-sectional case, a general parametric frontier is stated as:

$$y_i = f(X_i, \beta).TE_i \quad \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots..(3.15)$$

where i is the i^{th} producer, y is a scalar output in the case of single output, X represents *N*1* vector of inputs, β is a vector of technological parameters to be estimated, and TE_i indicates the output-oriented technical efficiency of producer *i* which is defined as the ratio of the observed output to the maximum feasible output as given:

$$TE_i = \frac{y_i}{f(X_i, \beta)} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (3.16)$$

Equation 3.15 can be redefined as:

$$y_i = f(X_i, \beta).\exp(-u_i) \text{ for } u_i \geq 0 \quad \ldots\ldots\ldots\ldots\ldots. (3.17)$$

with u_i as the technical inefficiency for the i^{th} producer which lie within 0 (complete inefficiency) and 1 (complete efficiency). From the equation 3.17, it can be observed that the deterministic frontier analysis does not differentiate between the effects of external shocks (noise) and producer-specific inefficiency. Like other parametric approaches to estimating efficiency, the deterministic production frontier requires specification of the functional form which is mostly done using Cobb-Douglas or the transcendental logarithmic (often referred to as translog) forms. Once the production structure has been parameterized, two techniques are normally applied to either calculate or estimate the vector of technological parameters and to also obtain estimates of u_i and the technical efficiency scores (TE_i) for each farmer. The two techniques are the goal programming and the deterministic econometric techniques.

The goal programming technique uses mathematical programming techniques and limits the possibility of making statistical inference with the estimated parameters. This is not the case of the deterministic econometric approach; hence, it has become the next best alternative. This approach is based on an econometric formulation with which it is possible to estimate rather than 'calculate' the parameters of the frontier functions. Besides, statistical inference based on those estimates will be possible. Specific methods of estimation, such as Modified Ordinary Least Squares, Corrected Ordinary Least Squares and Maximum Likelihood Estimation have been developed in the econometric literature in order to estimate the deterministic-full frontier models (Zamorano, 2004).

However, both the goal programming models and the deterministic econometric approaches assume that all the inefficiencies in production are non-random. This limitation is resolved under the stochastic frontier models used in this study.

3.5.1.2.2 Stochastic production frontier analysis

The stochastic production frontier (SPF) model was independently but simultaneously introduced by Aigner et al. (1977), and Meeusen and van den Broeck (1977). Like the deterministic frontier model, this model allows for technical inefficiency, but also equally importantly acknowledges the likely and unavoidable effects of random shocks on output and therefore, efficiency. Stochastic production function models are credited with the virtue of separating the effects of vagaries of the weather, variations in input performances among others from that of farmer specific characteristics (Kumbhakar and Lovell, 2000). With the stochastic production frontier, the function is stated as:

$$y_i = x_i\beta_i + \varepsilon_i \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..(3.18)$$

where ε_i is a composed error term given as:

$$\varepsilon_i = \nu_i - u_i \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..(3.19)$$

With ν_i being the two-sided or symmetric noise component whilst u_i is the non-negative technical inefficiency component. This implies that the composed error term (ε_i) is asymmetric since $u_i \geq 0$.

From the equation above and given the properties of u_i, if $u_i = 0$ then $\varepsilon_i = \nu_i$, which means that the error term is symmetric and there is no technical inefficiency. However, if $u_i > 0$, then $\varepsilon_i = \nu_i - u_i$, which implies that the composed error term is negatively skewed and there is therefore technical inefficiency. The existence of technical inefficiency or otherwise can be done through log likelihood test from an OLS and stochastic frontier specifications (Kumbhakar and Lovell, 2000).

In estimating the stochastic production frontier, there are two essential objectives, namely to obtain estimates of the technology parameters *(βs),* and to obtain estimates of each producer's technical efficiency. The latter objective will require separation of the noise component (ν_i) from the inefficiency component (u_i). That is, the producer-specific efficiency which is contained in the u_i must be extracted from the composed error term. According to Kumbhakar and Lovell (2000), OLS can only produce consistent estimates of the production technology parameters but not the intercept and estimates of the producer-specific technical efficiency. Therefore, in order to achieve the latter objective, certain distributional assumptions must be made on the two error terms ν_i and u_i, which necessitates the use of a more appropriate method of estimation rather than the OLS.

3.6 Empirical Studies on Technical Efficiency

Following the previous discussion on the concept of efficiency and its measurement, various scholars have empirically estimated efficiency of production using various approaches. Most of the studies on efficiency employed the stochastic frontier analysis which has been found to contain the problem of composed error term.

For example, Awunyo-Vitor et al. (2013) investigated the determinants of technical efficiency in small-scale cowpea production in the Ejura-Sekyedumase Municipality of Ashanti region using a stochastic frontier production function that incorporates inefficiency factors. Using random sampling technique, data for the study was collected from 200 cowpea farmers within the municipality. The study found that small-scale cowpea farmers were not fully technically efficient as the mean efficiency was 66%. Farm size, seed, pesticides and labour were the major input factors that influenced changes in cowpea output. Their results also showed that a farmer's educational level, membership in farmer-based organization and access to extension services significantly influenced their efficiency positively. Based on their findings, they recommended that policies that would encourage cowpea farmers to join farmer-based organisations and provide them with easy access to extension services should be formulated and implemented to the latter, since those variables are the best options that would improve the efficiency of the farmers. This study provided background information on the selection of variables and allowed the researcher to contrast the methodological approaches in estimating technical efficiency.

The study by Audu et al. (2013) focused on the resources used in yam production in Ankpa local government area of Kogi State in Nigeria, and their effects on the output of yam as well as the effects of the farmers' socioeconomic characteristics on their technical efficiency. They randomly selected 140 farmers from whom data were collected for the study. Stochastic frontier Cobb-Douglas production function was selected by the researchers to analyse the data without a test of functional form. Results from their study showed that family labour, hired labour, fertilizers, herbicides, yam stakes and yam setts positively influenced yam output, with family labour, herbicides and yam stakes not being significant. Age, education, household size and access to credit were found to be negatively related to the farmers' technical inefficiency (or to have positive influence on efficiency), while extension visits and sex were found to have positive effects on inefficiency (or to have negative influence on efficiency). The farmers' specific technical efficiencies ranged from 18% to 96% with a mean of 76% implying that no farmer was fully technically efficient. Recommendations made to enhance yam production in the area included production and distribution of farm inputs to the farmers at cheap prices, training of more extension agents so as to increase extension agents and farmers' interaction and to encourage commercial banks to give more loans to the farmers.

Also, Nkegbe (2012) estimated the link between some promoted soil management practices and farmer efficiency using the translog stochastic frontier model with an instrumental variable approach, and a comparative application of the half normal, truncated and gamma distributional assumptions. In effect, he estimated the effect of adoption on technical efficiency. The author used multistage sampling procedure to select a total of 445 farm households in northern Ghana. The author found land, capital, purchased input, labour, purchased input squared, land squared, labour squared, and the combination of land and purchased input to have significant effects on crop production; off-farm income, credit, and practice in the inefficiency model were significant at 1%, 5% and 10% levels respectively. Efficiency scores for the chosen half normal model ranged between 18% and 90% with a mean of 63% and standard deviation of 17%. This study also failed to address the unobservable characteristics of the farmers that may influence the adoption of soil management practices on technical efficiency.

Investigating the technical efficiency of tomato farmers at the Irrigation Company of Upper East Region, Donkoh et al. (2013) used cross sectional data, collected from 100 tomato farmers within the Tono Irrigation Project for the 2007/2008 cropping season. The authors also estimated the Cob-Douglas Stochastic Frontier Model without testing for the appropriateness of the functional form. The respondents for their study were selected using purposive and simple random sampling techniques. Result from their study showed a mean efficiency of 71% with a minimum efficiency of 36% and maximum of 99%. The study also found land, family labour and seed to be significant in determining output, with their expected positive signs. Also, the technical efficiency levels of the farmers were influenced by experience, education and farm size. The authors explained that the significance of these factors in explaining efficiency was consistent with some other previous studies.

Piya et al. (2012) compared the technical efficiency levels of rice farmers in rural and urban areas of Nepal. They estimated a Cobb-Douglas production function and the individual efficiency scores using stochastic frontier analysis. Results from their study suggested average efficiency scores of 74% and 67% for the two locations (Chitwan and Dhadin districts, respectively), indicating that production can be increased by 26% and 33% in the two locations through efficiency improvement with a given technological condition. Their results also showed that land, chemical (fertilizer pesticides and fungicides), seed and labour were all significant in output with their expected positive signs except labour which had negative sign in both locations as well as in the pooled sample. Furthermore, age, education, share of agriculture in household income, sharecropping and degree of commercialization (total sales of crops per year divided by the total crop production per year, multiplied by 100) were found to have significant effects on technical efficiency, though commercialization was only included in the model for Chitwan district.

Narala and Zala (2010) investigated the ttechnical efficiency (TE) of rice farms under irrigated conditions in Central Gujarat using a stochastic production frontier analysis. They also assessed the effect of farm-specific socio-economic factors on TE using regression analysis. Mean TE of the farmers was found to be 72.78%, which indicates that on average, the realized output ccould be raised by 27% in the region with the available technology and resources, without any additional resources. Narala and Zala (2010) found factors such as operational area, experience, education and distance of field from canal structure to be most influential determinants of TE. Number of working family members was also significant, but had a negative relationship with TE. The authors concluded that by adopting good management practices and proper allocation of the existing resources and technology, along with sound extension programmes, the potential that exists for improving the productivity of rice in the state, could be exploited.

Kashiwagi, Kefi, Ksibi, et al. (2013) investigated the effect of the introduction of irrigation technique on the technical efficiency of olive production in a sample of olive-growing farms in Tunisia. They estimated a Cobb-Douglas form of stochastic production frontier function. Results indicate that estimated TE scores vary, ranging from a minimum of 3.0% to a maximum of 91.2% with a mean value of 61.2%. This suggests that olive-growing farms in Tunisia can increase their production on average by 38.8% through more efficient use of technology and inputs. The introduction of irrigation increased productivity, however, the estimated TE of irrigated olive farms varies across farms and they are less efficient than non-irrigated farms. This finding suggests that the introduction of irrigation to non-irrigated farms has the potential to increase production levels, however, the current production of the irrigated farms is far from the "best practice frontier" that realizes maximum possible output. Kashiwagi et al. (2013) also found that aaccumulation of experience and knowledge by farm owners and selection of olive cultivars significantly contribute to improving TE.

Naceur, Sghaier, and Bachta (2011) assessed the technical efficiency (TE) and proposes a measure for irrigation water efficiency (IE) based on the concept of input-specific technical efficiency for a sample of 100 irrigators in Zeuss-Koutine region of Tunisia. Naceur et al. (2011) employed data envelopment analysis (DEA) to quantify TE and IE. A major finding of the study is that the irrigation systems are clearly inefficient. Under constant returns to scale specification, the average TE of the sample was 64%. Implying that output production level could improve by 36%. A similar pattern of scores was shown for IE; although in this case the average IE was even lower (47.8%) indicating that if farmers became more efficient using the technology currently available, the same level of output can be produced using the same level of other inputs but with, on average, 52.2% less water irrigation.

Despite the fact that several studies have been conducted on efficiency of farmers, crop specific studies especially for rice, is limited, with most of these studies adopting the Stochastic Frontier Analysis (SFA) for data analyses. The approaches used by most of these studies including Nkebge (2012), Donkoh, Ayambila and Abdulai (2013) and Oluwatusin

(2011) have been be deficient in addressing estimation biases due to unobserved variables (Greene, 2010). The few that have employed PSM approach with SFA only addressed observed biases.

For example, Abdulai, Zakaria, and Donkoh (2018) examined the adoption of improved rice cultivation technologies on farmers' technical efficiency in the Sagnarigu District of Ghana. They used a stochastic frontier model to estimate the determinants of output and technical inefficiency, while propensity score matching was also used to analyse the average treatment effect (ATE) and the average treatment effect on the treated (ATT). A total of 120 respondents comprising 60 adopters and 60 non-adopters were randomly selected for the study. Abdulai, Zakaria, and Donkoh (2018) found farm size, fertilizer, weedicides and household labour to have positive and significant effect on rice output. They also found that farmers who adopted the rice cultivation techniques were less technically inefficient than those who did not adopt. The ATT was 0.121 which implies that farmers who adopted the rice technologies increased their technical efficiency by about 12% and this was significant at 10% for the PSM with similar results obtained for the nearest neighbour matching. Moreover, the mean technical efficiency estimates for adopters and non-adopters were about 58% and 48% respectively under regression adjustment and inverse-probability weights. The existence of a technical efficiency gap of 10% between adopters and non-adopters of rice technologies emphasized the significant effect of technology adoption on farmer's technical efficiency.

Anang et al. (2016) also conducted a study on the effects of agricultural micro-credit on technical efficiency (TE) of rice farmers in northern Ghana by using a stochastic production frontier. They compared TE of smallholder rice farmers with micro-credit to those without micro-credit by fitting a stochastic frontier production function. They addressed self-selection into micro-credit participation using PSM, and found that the mean TE did not differ between credit users and credit constrained farmers. Credit-participating households had an efficiency score of 63.0% compared to 61.7% for non-participants. They found significant inefficiencies in production and thus a high scope for improving farmers' technical efficiency through better use of available resources. They also found that apart from labour and capital, all the conventional farm inputs had a significant effect on rice production. Anang et al. (2016) also found the determinants of TE to include age, sex, educational status, distance to the nearest market, herd ownership, access to irrigation and farmers' specialisation in rice farming. The limitation of this study is that it failed to account for the effect of unobservable characteristics of credit constraint on technical efficiency, leading to biased estimates (Greene, 2010).

Asante, Wiredu, Martey et al. (2014) examined whether the adoption of NERICA rice varieties introduced and disseminated among rice farmers has had an impact on technical efficiency of smallholder rice producers in Ghana. Their study also explored the effectives of institutional linkages among farmers to improve technical efficiency of smallholder farmers. The Cobb-Douglas stochastic production frontier was used to generate the technical efficiency scores. The estimated technical efficiency scores were regressed on NERICA adoption besides other socio-economic, institutional and farm level covariates, which were hypothesized to affect technical efficiency. Finally, to estimate the impact of adoption of NERICA rice varieties on technical efficiency, propensity score matching and ordinary least squares regression procedure were used to consistently estimate the average treatment effect. Asante et al. (2014) found the adoption rate of NERICA rice to be high at about 68% among the sampled farmers. They further established that the estimated technical efficiency ranged from 12.7% to 93.7% with an average of 69.1%, suggesting that rice farmers in Ghana could increase technical efficiency in rice production by about 31 per cent without necessarily varying the existing input levels. Also, adoption of NERICA rice varieties was found to have a positive and significant impact on technical efficiency of rice producing households in the country, suggesting that the benefits of adoption of the NERICA varieties have been translated into improved technical efficiency.

Asante et al. (2013) also analysed the adoption of yam minisett technology and its impact on the technical efficiency of yam production in the Ashanti and Brong Ahafo regions of Ghana. The study also employed the PSM approach together with the stochastic frontier analysis, and found that the direction of the impact of adoption of the yam minisett technology on the technical efficiency of smallholder farmers depends on the location of the farmer. Their analysis suggested average technical efficiencies of 85.4% and 89.2% with ranges of 27.7% to 99.9% and 29.7% to 97.8% in the Ashanti and Brong Ahafo regions, respectively. Also, their results indicated that land, labour, seed and stake significantly influenced the output of yam. The study found that the adoption of yam minisetts and some socioeconomic factors such as land, age, household size, education, experience and income significantly influence the efficiency of yam farming.

The above studies have highlighted the application of the stochastic frontier model by using different functional forms. What is also clear from the review of previous studies is that they have either ignored the presence of selectivity bias or have failed to address it. This study therefore expands on the previous methodologies and introduced the correction of the effects of unobservable characteristics in efficiency estimation. First, the study followed the approach of Anang et al. (2016), and Villano et al. (2015) to define adequate control group using PSM to account for the effect of biases arising from observable variables. Again, biases stemming out from unobserved variations was tested using a recently developed technique for stochastic frontier analysis (SFA) correcting for sample selection by Greene (2010).

CHAPTER FOUR

METHODOLOGY

4.0 Introduction

This chapter outlines how the study was conducted. It discusses the study area, research design, study population, sampling technique and sample size, data collection instruments and techniques, and analysis.

4.1 The study area

The study was conducted in two out of the three administrative regions of northern Ghana (Northern and Upper East regions). The specific locations are indicated by Figure 4.1.

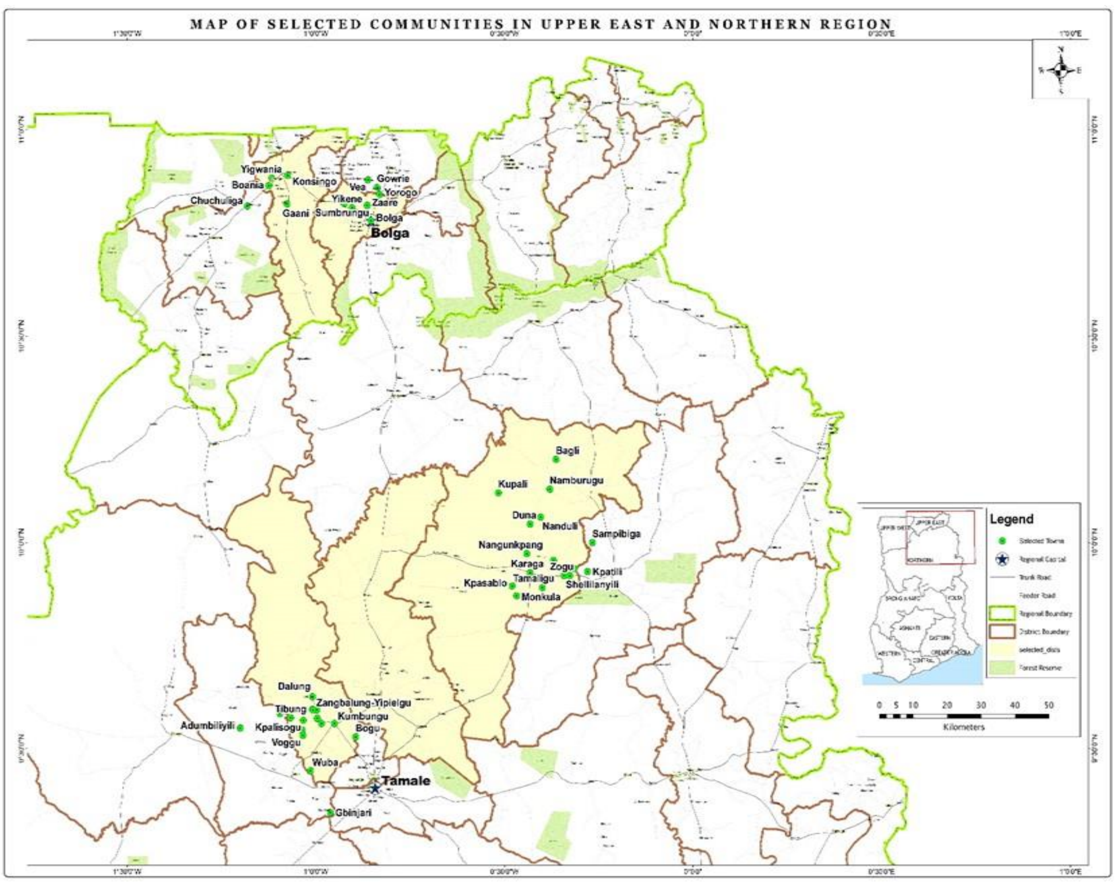

Figure 4. 1: Map of the study area indicating the selected districts and communities

The choice of these two regions was based on the high potential of the regions in rice production and the availability of irrigations schemes for dry season rice production. Two climatic conditions pertain in the northern parts of Ghana. There is a rainy season which begins lightly in April and rises steadily to a peak in August/September and gradually decline by October/November (GSS, 2014). There is also a dry season which occurs between November and April with a peak in February each year (GSS, 2014). This period is also characterised by dry harmattan winds which engulf the northern parts of Ghana. The vegetation of the two regions is generally the Guinea savannah with its characteristic grass and trees. The biodiversity in tree vegetation used to be high, but now it is decreasing due to over exploitation.

The major economic activity of the people is agriculture, which combines crop and animal husbandry. Most part of the two regions is rural, with the agricultural sector employing the largest percentage of the economically active population in the Northern and Upper East regions of Ghana (GSS, 2014). While about 70% of the estimated economically active rural population in the Northern region are employed by the agriculture sector, the case for the Upper East region is about 79% (MoFA, 2016).

Among the several crops grown in the two regions are maize, millet, rice, yam, sorghum, groundnut, cowpea and bambara groundnuts. The region also has a high potential in animal production in Ghana (MoFA, 2016). The most predominant animals found in the area include cattle, sheep, goat, guinea fowls, fowls, and donkeys. While the crops are mainly grown for subsistence, the animals are mainly for cash and are mostly kept as an insurance or in-kind savings for the family. Over the years, the regions have been identified as among the poorest in Ghana, with poverty levels above 40% (GSS, 2014).

The preceding sub-sections provide some background information about the five irrigation schemes where some of the respondents for this study were drawn from.

4.1.1 The Bontanga Irrigation Project

The Bontanga Irrigation Project is a large-scale gravity-fed scheme, and the largest in northern Ghana (Braimah, King, and Sulemana, 2014). It is located at Bontanga in the Kumbungu District of the northern region of Ghana, 34km North West of Tamale, the regional capital of the Northern Region of Ghana. The scheme covers a potential area of 800 hectares. However just about 450 hectares is considered irrigable, of which 240 hectares is used for lowland rice cultivation and the remaining 210 hectares for upland vegetable production (Braimah, King, and Sulemana, 2014). Presently, there are 13 communities that farm within the Bontanga Irrigation Project area (Abdul-Ganiu et al., 2012). These include: Tibung, Kumbungu, Kpalsogu, Dalun, Wuba, Kukuo, Kpong, Saakuba, Yipelgu, Voggu, Kushibo, Zangbalung and Gbugli. The farmer population on the project as at the year 2012 was 525 and they were organized into a cooperative made up of 10 farmer-based organizations (FBOs) (Braimah, King and Sulemana, 2014). The average farm holding size on the project is 0.6 hectares. The main crops cultivated within the project area include rice, maize, onion, pepper, tomato and okro (MoFA, 2011).

4.1.2 The Golinga Irrigation Project

The Golinga Irrigation Project is a medium scale gravity-fed scheme located at Golinga in the Tolon District of the northern region of Ghana (MOFA, 2011). The project is served by the Kornin River. The scheme has a potential coverage of 100 hectares of which only 40 hectares of the land is under cultivation. The vegetables are produced only in the dry season from October to April while rice is produced both in the dry and wet seasons. Presently, there are five communities that farm at the Golinga Irrigation Project's area. These include; Golinga, Gbulahigu, Tunaayili, Galinkpegu, and Naha. The farmer population on the scheme in 2012 was 150 and organized into a cooperative made up of five FBOs (Braimah, King, and Sulemana, 2014). The average farm holding size on the project is 0.2 hectares. There are also seven committees on the project which perform different responsibilities. The farmers on this project cultivate the same crops as those on the Botanga irrigation scheme (Braimah, King, and Sulemana, 2014).

4.1.3 The Libga Irrigation Project

The construction of Libga irrigation project started in 1970 and was completed in 1980. The scheme is located near Savelugu. The project has a gross area of 20ha with all this area developed. The area under irrigation however is about 16ha. The major crops cultivated on the project are rice, cowpea and pepper. The project takes its source from river Perusua. The climate is the Guinea Savannah type.

4.1.4 The Tono Irrigation Project

Tono Irrigation scheme is one of the two irrigation projects under the management of Irrigation Company of Upper Region (ICOUR). The other one is the Vea Irrigation project described in the following sub-section. The scheme is located in the Upper East region and lies between latitude 10^{o} 45' N and longitude 1^{o} W. The project was established by the government of Ghana to promote the production of food crops by smallholder farmers. The construction of the project started in 1975 and was completed in 1985. The project lies in the Guinea Savannah ecological zone of Ghana. It has a potential area of about

3,840.00Ha with a developed area of about 2,490.00Ha (the developed area is the same as the irrigable area). The source of water is from river Tono.

4.1.5 The Vea Irrigation Scheme

According to the official website of the MoFA, the Vea Irrigation scheme is one of the two irrigation projects under the management of Irrigation Company of Upper Region (ICOUR) (MoFA, 2017). The scheme is located in the Upper East region of Ghana and lies between latitude 10^{o} 45' N and longitude 1^{o} W. The project is situated at Vea which is near Bolgatanga. The construction of the Vea project was started in 1965 and completed in 1980. It lies in the Guinea Savannah ecological zone of Ghana. It has a potential area of about 1197Ha and the area developed is about 850ha with an irrigable area of about 468Ha.

4.2 The Research Design

According to Creswell (2009), research designs are the plans and procedures for research that span the decisions from broad assumptions to detailed methods of data collection and analysis. The study adopted the mixed research design (i.e. quasi-experimental research design). The mixed research design is a combination of both qualitative and quantitative methods of data collection and analyses. The quantitative data collection method involved a survey among cross section of farmers while the qualitative data collection methods included focus group discussion and observation. The choice of cross-sectional data over panel or time series data was based on the availability of information for the purpose of analysis at the time of the study. Also, the researcher could not collect information on the same respondents over time, to consider panel or time series modelling. Moreover, the implementation of the sample selection framework in stochastic frontier analysis cannot apply time series or panel data using the LIMDEP 11 or NLOGIT 6 software which is capable of executing that model.

4.3 Population and sample size for the study

Rice farmers in the Guinea Savannah ecological zone constituted the population *(N)* for this study. Rice farmers of the major irrigation schemes as well as those located in areas of vast natural rice valleys were considered. The Ghana Living Standard Survey (GLSS) round 6 (2014) puts the number of households in the Guinea Savannah zone who produce rice at 296,489. However, the entire population of rice farmers could not be surveyed due to financial and time constraints. Hence, the need for sample size determination.

The determination of the sample size follows Slovin's (1960) formular used to calculate sample size when little information is available for the population (Ryan, 2013; and Ariola, 2006). This was applied as follows:

$$n = \frac{N}{1+Ne^2} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4.1)$$

Where *n* is the sample size, *e* is the margin of error (which is 0.05 with confidence level of 95%). N is the population of rice farmers, which is 296,489 for this study. By substitution, the sample size *(n)* is computed as 400. The sample size was however adjusted to 543 to cater for some design effect that might have arisen. Of the 543 questionnaires returned, 223 (representing about 41%) were sole irrigation farmers while the remaining 320 (representing about 59%) produced solely under rain fed conditions. About 68% of the respondents were from the Northern region. The rest of the 32% of the respondents were from the Upper East region. The proportion of the sample assigned to each region was based on the density of rice production points in the two regions, with the northern region being dominant in the production of the commodity.

4.4 Sampling procedure

Data used for adoption studies are generally collected from cross-sectional sample of farmers within the target communities. For this study, multistage sampling method was adopted to select the respondents from rice growing communities in the two regions for the study. First, the Northern and Upper East regions were selected because of their high contributions to the national rice output. Together, the two regions alone contribute about 45.89% (27.54% and 18.35% respectively for northern and upper east region) of the national paddy rice (MoFA SRID, 2017). Also, productivity of rice is lower in the two regions (2.2MT/Ha and 2.4MT/Ha respectively for northern and upper east region) compared to the national average of about 3MT/Ha (MoFA, 2018). Again, the regions have vast natural lowlands suitable for rice production. The two regions are also blessed with irrigations schemes that have produced rice over the years. Farmers from all five (5) major irrigations schemes in the two regions (Tono and Vea in the Upper East region, Libga, Golinga and Bontanga in the Northern region) were also considered for this study.

In the second stage, simple random sampling through balloting was used to select 5 districts in each of the two regions. Again, simple random was used to select 4-7 communities (depending on the size of the irrigation catchment area) in each of the selected districts. In all, a total of 62 farm communities were selected for this study. In the third stage, stratified sampling method was used to group the farmers in the selected communities into two strata; those who engaged in irrigation farming and those who engage in rainfed rice production.

These two groups are homogenous within groups but heterogonous to each other. In each of the two strata, simple random sampling was again used to select a number of farmers as the final respondents for the study.

In this study, three group of farmers were eligible for sampling irrespective of whether they were irrigation farmers or non-irrigation farmers. These included participants in demonstrations. This group included farmers who hosted demonstrations of projects supported largely by IFDC FtF USAID-Ghana ATT project, ADVANCE II project, SARI and IITA researchers. The second group of farmers are the neighbours and/or participants in field days. This group included rice farmers who attended field days on the technologies under consideration. The third group of farmers are the non-participants or the reference farmers. These are farmers who did not host any technology demonstration or attended any field day.

4.5 Data type and collection instruments

This study used cross sectional primary data. A questionnaire was designed to collect primary data from rice farmers. The questionnaire included questions on the socio-economic and demographic information of the respondents, technology application and adoption characteristics of rice farmers as well as the level and costs of inputs used for production and the output levels of the farmers. Some focus group discussions were also organised to validate some of the responses from farmers for qualitative analyses. Again, interview guides and checklists were developed and used to collect data from NGOs and sector actors who are involved in agricultural technology transfer and the rice value chain.

Pretesting of the questionnaire was conducted using 20 rice farmers (10 irrigation and 10 rainfed). A test for consistency and reliability using Cronbach coefficient alpha [1]test produced alpha value of 0.807 (see appendix 1). DeVellis (2012) George and Mallery (2003), and Kline (2000) consider a Cronbach alpha value between 0.8 and 0.9 to be good and acceptable.

The data was collected by ten (10) trained research assistants and supervised by the researcher. The research assistants were undergraduate students from the Faculty of Agribusiness and Communication Sciences, University for Development Studies. The students were all fluent in the English language and the local dialects of the participating communities/districts. The data was collected between January and March 2017. It covered information related to the 2016 production season of the rice farmers which ended technically in December 2016.

4.6 Data analyses

Both qualitative and quantitative approaches were employed to analyse the data. The results are presented in tables and figures. The data was processed and analysed by using MS excel, LIMDEP 11 and STATA 14 econometric software. The various models estimated to address each objective are explained immediately below.

4.6.1 Chi squared test (X^2) and Kendall's coefficient of concordance

This section describes the analysis of the various agricultural technology transfer approaches accessed by the farmers, as well as the farmers' perceptions about the

[1] Reliability can be expressed in terms of stability, equivalence, and consistency. Consistency check, which is commonly expressed in the form of Cronbach Coefficient Alpha (Cronbach, 1951), is a popular method.

effectiveness of each of the approaches. These were analysed using Chi squared distribution test (X^2) and Kendall's coefficient of concordance. The effectiveness of the approaches as well as the perceptions of the respondents were measured on Likert scale.

4.6.1.1 Chi squared analysis

Chi squared (X^2) test is any statistical hypothesis test in which the sampling distribution of the test statistic is a chi-square distribution when the null hypothesis is true. X^2 tests are often constructed from a sum of squared errors, or through the sample variance (Bagdonavicius and Nikulin, 2011). The Chi Square statistic is commonly used for testing relationships between categorical variables. In this study, the X^2 was used to test the distribution of the agricultural technology transfer approaches which in themselves, where categorical. The purpose was to test the assumption that the probability value of the estimated Chi square is greater than 0.1 at 10% significant level. The X^2 was estimated with the following assumptions:

Given that $X_1, ..., X_n$ are i.i.d. $N(\mu, \sigma^2)$ random variables, then:

$$\sum_{i=1}^{n}(X_i - X^*)^2 \sim \sigma^2 X_{n-1}^2 \text{ ……………………….. (4.1)}$$

Where:

$$X^* = \frac{1}{n}\sum_{i=1}^{n} X_i \text{ ……………………………….. (4.2)}$$

4.6.1.2 Kendall's coefficient of concordance

Kendall's *W*-test (also known as Kendall's coefficient of concordance) is a non-parametric statistic (Kendal and Babington Smith, 1939; Corder and Foreman, 2009). It is a normalization of the statistic of the Friedman test, and can be used for assessing agreement among raters. Kendall's coefficient of concordance (*W)* ranges from 0 (no agreement) to 1 (complete agreement).

In this study, the farmers were asked to rank a list of agricultural technology transfer methods or approaches, from the most important to the least important. Kendall's *W* was then calculated from these data. If the test statistic *W*, was 1, then all the survey respondents had been unanimous, and each respondent had assigned the same order to the list of approaches presented. If *W* was 0, then there was no overall trend of agreement among the respondents, and their responses may be regarded as essentially random. Intermediate values of *W* indicate a greater or lesser degree of unanimity among the various responses by the farmers.

While tests using the standard Pearson correlation coefficient assume normally distributed values and compare two sequences of outcomes at a time, Kendall's *W* makes no assumptions regarding the nature of the probability distribution and can handle any number of distinct outcomes. *W* is linearly related to the mean value of the Spearman's rank correlation coefficients between all pairs of the rankings over which it is calculated. The null hypothesis of this test would be that there is independence of the rankings produced by all famers. This is a one-tailed since it only recognises positive associations between vectors of ranks. Basically, the Kendall’s statistic can be computed as:

$$S = \sum_{i=1}^{n}(R_i - R)^2 \text{ ………………………….. (4.3)}$$

S is the sum of squares statistic over the row sums of ranks. Following these, the Kendall’s *W* statistic can be obtained as (Kendal and Babington Smith, 1939):

$$W = \frac{12S}{p^2(n^3-n)-pT} \text{ ………………………….. (4.4)}$$

Where n is the number of objects, p the number of judges. T is a correction factor for tied ranks. Kendall's W statistic is an estimate of the variance of the row sums of ranks R_i divided by the maximum possible value the variance can take; this occurs when all respondents are in total agreement; hence $0 \leq W \leq 1$.

Legendre (2005) discussed a variant of the W statistic which accommodates ties in the rankings and also describes methods of making significance tests based on W. Legendre (2005) compared through simulation the Friedman test and its permutation version. Unfortunately, the simulation study of Legendre was very limited because it considered neither the copula aspect nor the F test. Kendall W is a rank-based correlation measure, and therefore it is not affected by the marginal distributions of the underlying variables, but only by the copula of the multivariate distribution.

The Kendall concordance statistic (*W)* is similar to Spearman rank (nonparametric correlation between two variables) except that it expresses the relationship between multiple cases, which is why it was considered for this study.

Various agricultural technology transfer methods were provided to the individual respondents to rank based on their accessibility and effectiveness. Specifically, 11 approaches were provided and the respondents ranked them from 1 to 11. The higher the rank assigned, the lesser the accessibility or effectiveness of the technology transfer approach. The level of agreement of the respondents on the rankings were tested using the Chi square statistic.

4.6.3 Factors influencing the adoption of improved agricultural technologies

Multivariate probit regression (MVP) was used to estimate the factors that influence the adoption of improved agricultural technologies for rice production. To analyse the intensity[2] of adoption of improved agricultural technologies for rice production, zero inflated Poisson regression, Negative binomial regression and poison regression were estimated. Statisticians and econometricians view the MVP model as a generalisation of the probit model used to estimate several correlated binary outcomes simultaneously. Generally, a multivariate model extends to more than two outcome variables just by adding equations (Greene, 2003).

For the purpose of analysis, the researcher selected seven (7) most promoted and applied improved rice production techniques (i.e. nursery establishment, harrowing, spacing, line planting, use of urea briquette, bunding and irrigation) that had almost the same number of adopters as well as non-adopters. [3]The other ten (10) technologies had very few adopters with less than 6% adoption rate. To understand the reasons for the low adoption levels among farmers for the 10 technologies, the researcher contacted MoFA and agricultural NGOs in the regions who revealed that those technologies were not promoted. However, all seventeen identified technologies were modelled in the case of the count data models for joint adoption.

[2] Adoption intensity is the count of the number of improved agricultural technologies adopted by each farmer. It is a sum of 7 for MVP and 17 for the count data models.

[3] To determine the choice of model, the following hypotheses were set: H_o: the error terms across the seven adoption decisions are not correlated; H_A: there is mutual interdependence among the improved agricultural technologies. First, the likelihood ratio test of the independence of the error terms was conducted. This was significantly different from zero at 1% *(Chi^2 (21) = 731.941; Prob > Chi^2 = 0.0000)*, thereby, allowing us to reject the null hypothesis that the error terms across the seven adoption decisions are not correlated. Therefore, the alternate hypothesis of mutual interdependence among the improved agricultural technologies was accepted. The results therefore supported the use of a multivariate probit model applied in this study as a heptavariate model.

Neglecting the inter-relationships among the improved practices may result in bias estimates of factors influencing adoption of these improved technologies (Wu & Babcock, 1998). To account for such interdependent relationship, MVP regression approach was adopted to jointly analyse the factors affecting the probability of adopting each improved rice production technique.

The MVP estimation technique considers the correlation in the error terms by jointly modelling the effects of a set of covariates on each of the improved agricultural technologies and estimates a set of binary probit models. It allows the relationship between the adoption of different improved production practices to be established, as well as potential correlations between unobserved disturbances (Ahmed, 2015; Kassie *et al.*, 2009). Univariate models such as probit and logit ignore the correlation in the error terms of the adoption equation. Application of such models is therefore inappropriate when adoption practices are interrelated (Belderbos et al., 2004). Failure to account for such unobserved factors and the interdependent relationship of adoption decisions on different technological practices may provide inefficient and bias estimates (Greene, 2008).

Following Danso-Abbeam and Baiyegunhi (2017), as in Kassie et al. (2013) and Mulwa et al. (2017), we formulated a MVP model with the seven sets of binary dependent variables (i.e. nursery establishment, harrowing, spacing, line planting, use of urea briquette, bunding and irrigation), such that:

$$Y_{ik}^{*} = \beta_k X_{ik} + \alpha_k A_{ik} + \varepsilon_k \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(4.5)}$$

(k = nursery establishment (N), harrowing (H), spacing (S), line planting (L), use of urea briquette (U), irrigation (I) and bunding (B)).

$$Y_{ik} = 1 \; if \; Y_{ik}^{*} > \; 0 \; and \; otherwise \; \ldots\ldots\ldots\ldots\ldots\ldots (4.6)$$

Where Y_{ik}^{*} is a latent variable which captures the observed and unobserved preferences associated with the k^{th} improved agricultural technology, and Y_{ik} represents the binary dependent variables. X_{ik} represents the observed household and farm-specific characteristics, as well as institutional variables. A_{ik} represents plot characteristics to account for unobserved heterogeneity. β_k and α_k are parameters to be estimated. ε_k represents the multivariate normally distributed stochastic error term (Wooldridge, 2003). In our multivariate probit framework, the error terms jointly follow a multivariate normal distribution with zero conditional mean. The variance is normalised to unity, where $(\mu_N, \mu_H, \mu_S, \mu_L, \mu_B, \mu_I, \mu_B) \approx$ MVN (0, Ω) and the symmetric variance covariance matrix Ω is specified as:

$$\Omega = \begin{bmatrix} 1 & \rho NH & . & \rho NB \\ \rho HN & 1 & . & . \\ . & . & 1 & IB \\ \rho IN & . & BI & 1 \end{bmatrix} \pm \quad \ldots\ldots\ldots\ldots\ldots\ldots (4.7)$$

ρ is the pairwise correlation coefficient of the error terms with regards to any two of the estimated adoption equations in the model. The correlation between the stochastic components of different improved technologies adopted is represented by the off-diagonal elements (e.g. ρNH, ρNH) in the variance-covariance matrix (Danso-Abbeam and Baiyegunhi, 2017). The correlation is based on the principle that adoption of a particular improved practice may depend on another (complementarity or positive correlation) or may be influenced by an available set of substitutes (negative correlation) (Khanna, 2001).

The diagnosis of the MVP model was based on log likelihood test of the covariance error terms. The significance of the test meant that the estimation of MVP model was appropriate.

4.6.3.1 Analysing the intensity of adoption of farmers

Technology adoption or selection can be modelled using a multinomial Logit or Probit specification. Here, the dependent variable is a categorical, taking a different value according to the portfolio selected. Count data models can also be used to model technology selection where the dependent variable is the sum of the number of improved agricultural technologies adopted or selected. Count data models do offer some useful merits for analysing the adoption of multiple technologies.

Count data models focus on adoption intensity. The use of count data models also allows one to avoid making strong assumptions about relationships among technologies being investigated, as no arbitrary aggregation of techniques is assumed (Sharma et al., 2010).

The existing count data literature on technology adoption typically employs parametric specifications such as the Poisson model or the Negative Binomial. The number of technologies adopted (in this case, improved rice production technologies) is the dependent variable and a set of farm level and socio-economic characteristics are explanatory variables.

The choice of a particular model is based on a diagnostic test. Model specification was first tested by using the deviance and Pearson goodness of fit tests, the Likelihood Ratio (LR) test of alpha (α) =0, and the performance of Vuong test of Zero Inflated Poisson (ZIP) versus standard Poisson regression. AIC and BIC were also computed to aid in the selection of the right model. See section 5.3.2 (Table 5.11) for the model specification test results. Based on the result, the ZIP model estimation is preferred to the Poisson and the NB model, and therefore was considered for further analysis and discussion. All seventeen identified rice production technologies were modeled for adoption intensity. The results of the Negative Binomial regression, Poisson regression and the zero inflated Poisson regression are presented side by side in Table 5.11 for comparison.

Negative Binomial regression model

The negative binomial (NB) regression model as specified by Agresti (1996, 2002) is as follows:

$$P(Y = y|X_1, X_2, X_3, k) = \frac{\Gamma(y+k)}{\Gamma(k)\Gamma(y+1)}\left(\frac{k}{k+\mu}\right)^k\left(\frac{\mu}{k+\mu}\right)^y \qquad y = 0,1,2,\ldots \text{ (4.8)}$$

Where $E(Y) = \mu$ and $var(Y) = \mu + (\mu^2/k)$ are the mean and variance of the NB distribution respectively; and k^{-1} denotes the dispersion parameter. The specification reduces to Poisson regression in the limit as $k^{-1} \rightarrow 0$, and display overdispersion when $k^{-1} > 0$.

The link function: g(μ) = log(μ). The systematic component is specified as:

$$\boldsymbol{g(\mu) = log(\mu) = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3}$$

$$\Rightarrow \quad \boldsymbol{\mu} = \boldsymbol{e^{\alpha+\beta_1 X_1+\beta_2 X_2+\beta_3 X_3}} = \boldsymbol{e^{x'\beta}} \quad (\boldsymbol{x'} = [\mathbf{1} \quad \boldsymbol{X_1} \quad \boldsymbol{X_2} \quad \boldsymbol{X_3}])\ldots \text{ (4.9)}$$

Goodness-of-Fit based on Pearson Residuals for the NB model is obtained with:

$$e_i = \frac{Y_i - \hat{\mu}_i}{\sqrt{V(Y_i)}} = \frac{Y_i - \hat{\mu}_i}{\sqrt{\hat{\mu}_i + \hat{\mu}_i^2/\hat{k}}} \qquad X^2 = \sum e_i^2 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{ (4.10)}$$

The Poisson regression model

According to Greene (1997), the theoretical Poisson regression is represented by the basic Equation:

$$P_r\,(Y=y) = \frac{e^{-\lambda}\lambda^{y}}{y!}, \qquad y = 0, 1, 2 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(4.11)}$$

The parameter λ is assumed to be log-linearly related to regressors X_i. Therefore,

$$ln\ (\lambda) = \beta^{1}x_i \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(4.12)}$$

The log-likelihood function is given by the Equation:

$$ln\ L = \textstyle\sum_{i=1,2,\ldots.n} [-\lambda_i + y_i\,\beta^{1}x_i - \quad lny_i!] \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(4.11)}$$

The expected number of adopted technologies per farmer is given by the Equation:

$$E[y_i I x_i] = var\ [y_i I x_i] = exp\ [x_i\beta^{1} + \mu_i] \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(4.12)}$$

Where, β is a $1 \times k$ vector of parameters; X is a $k \times 1$ vector with the values of k independent variables in the i^{th} observation and n is the number of observations. The equation can also be expressed as:

$$E\ [Y_i] = exp^{\beta_1 x_{1i}} exp^{\beta_2 x_{2i}} \ldots \ldots\ldots exp^{\beta_k x_{ki}} = exp\ [\beta_i X_{jn}]\ C_i \ \ldots \text{(4.13)}$$

Where, j can take any value from 1 to k and identifies a specific explanatory variable and C_i is a constant representing the product of the remaining exponential terms in Equation (5.13). For dichotomous explanatory variables, if

$$X_{ji} = 0,\ E[Y_i] = C_i \text{ and when } X_{ji} = 1,\ E[Y_i] = B_j C_i \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(4.14)}$$

Therefore, 100 x (exp^{β_j} - 1) calculates the percentage change on $E(Y)$ when x_j goes from zero to one, for all observations (i). In general, for independent variables that take several integer values, the marginal change in the expected level of adopted improved technologies when x_j goes from x_{j1} to x_{j2} can be calculated as:

$$\frac{dy}{dx} = \frac{exp^{\beta\,\text{jxj2}} - exp^{\beta\text{jxji}}}{exp^{\beta\text{jxji}}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(4.15)}$$

In this study, seventeen improved technologies were modelled. Based on the theoretical framework, the empirical model examined the farmers' characteristics assumed to influence their adoption of improved technologies decisions.

The covariates include rice farmers' characteristics such as: location, extension methods, education, experience in rice production, FBO membership, receiving trainings, credit access, farm size, household size, sex, and age of the farmer.

Zero Inflated Poisson (ZIP) model

A zero-inflated model is a statistical model based on a zero-inflated probability distribution, i.e. a distribution that allows for frequent zero-valued observations. In other words, the ZIP regression is used to model count data that has a lot of zero counts (Cameron, and Trivedi, 2009). The first zero-inflated model is the zero-inflated Poisson model, which concerns a random event containing excess zero-count data in unit time *(*Lambert, 1992). For example, the number of improved agricultural technologies adopted by rice farmers would be zero-inflated by those farmers who have not adopted any of the identified improved technologies.

Also, the excess zeros are generated by a separate process from the count values and that the excess zeros can be modeled independently. Thus, the ZIP model has two parts, a Poisson count model (see Table 5.12) and the logit model for predicting excess zeros (see Table 5.13). The two model components are described as follows:

$$P_r(y_i = 0) = \pi + (1-\pi)e^{-\lambda} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(4.16)}$$

$$P_r(y_i = h_i) = (1-\pi)\frac{\lambda^{h_i} e^{-\lambda}}{h_i!}, h_i > 1 \quad \ldots\ldots\ldots\ldots\ldots\ldots \text{(4.17)}$$

where the outcome variable y_i has any non-negative integer value, h_i is the expected Poisson count for the i^{th} individual; π is the probability of extra zeros. The mean is $(1-\pi)\lambda$ and the variance is $\lambda(1-\pi)(1+\pi\lambda)$. The methods of moments estimators are given by:

$$\lambda_{mo} = \frac{s^2+m^2}{m} - 1, \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(4.18)}$$

$$\pi_{mo} = \frac{s^2-m}{s^2+m^2-m}, \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(4.19)}$$

Where *m is* the sample mean and s^2 is the sample variance.

The maximum likelihood estimator (Johnson, Kotz, Kemp, 1992) can be found by solving the following equation:

$$X\left(1 - e^{-\lambda_{ml}}\right) = \lambda_{ml}\left(1 - \frac{n_o}{n}\right) \quad \ldots\ldots\ldots\ldots\ldots\ldots \text{(4.20)}$$

Where X is the sample mean, and $\frac{n_o}{n}$ is the observed proportion of zeros.

This can be solved by iteration (Böhning et al., 1999), and the maximum likelihood estimator for π is given by:

$$\pi_{ml} = 1 - \frac{X}{\lambda_{ml}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(4.21)}$$

4.6.4 The Propensity Score Matching (PSM) approach

To determine the technical efficiency of rice farmers in northern Ghana, the study employed a combination of a recently developed stochastic production frontier model to control for biases arising from both observed and non-observable variables. First, the study followed the approach of Anang et al. (2016), and Villano et al. (2015) to define adequate control group using propensity score matching (PSM) to account for the effect of biases arising from observable variables. Again, biases stemming out from unobserved variables was tested using a recently developed technique for stochastic frontier analysis (SFA) correcting for sample selection by Greene (2010).

To control for biases resulting from observables, PSM was used to create a suitable counterfactual dataset. The use of PSM made it possible to match irrigation farmers (*the selection variable)* and rain fed farmers based on observed time-invariant characteristics so that both groups were as similar as possible except for adoption of irrigation. Recent applications of PSM in agriculture include Anang et al. (2016), Villano et al. (2015), Bravo-Ureta et al. (2011), Cavatassi et al. (2011), Rejesus et al. (2011), and Wu et al. (2010). *(See literature review in section 3.6).*

Two main steps were involved in in the estimation of TE in this study. In the first step, propensity scores for all observations were calculated using a probit model. The essence of the propensity scores was to account for sample selection bias due to unobservable differences that may have occurred between the treatment and control groups (Dehejia and Wahba, 2002).

These scores represented the probability of being an irrigation farmer, considering both irrigation and rain fed farmers, based on a set of covariates. The propensity scores (PSs) were then used to match irrigation and rain fed farms falling within a 'common support' area whereby observations from irrigation farmers with a PS smaller than the minimum or larger than the maximum for the rain fed group are removed from the sample (Caliendo and Kopeinig, 2008).

To ensure that the samples within the common support area have the same distribution of observable characteristics, regardless of whether the farmer has adopted the technology or not, it is necessary to test for the 'balancing property' (Becker and Ichino, 2002). Once appropriately matched samples are identified, and assuming that there are no biases from unobservables, the impact of an intervention/adoption is often measured as the average treatment effect on the treated or ATET (Khandker et al., 2010). The ATET is the average impact of the treatment on those individuals who participated and, again assuming no selection bias, can be calculated as (Winters et al., 2010):

$$ATET = E(Y_1|D = 1) - E(Y_0|D=0) \ldots\ldots\ldots\ldots\ldots (4.22)$$

Where Y_1 and Y_0 are the average values of the indicator in question, e.g. output, for irrigation and rain fed farmers, respectively, and D is a dummy variable equal to 1 if the farmer is irrigation farmer, and 0 if the farmer is a rain fed farmer.

4.6.5 The Stochastic Frontier Model with Sample Selection

Stochastic Production Frontier (SPF) models have been used widely in many areas, including agriculture, to model input–output relationships and to measure the TE of farmers (Bravo-Ureta et al., 2007). These methods have also been used to compare the performance of farmers under different technological interventions. For example, the method has been used to examine the impact of technology adoption on output and technical efficiency (TE) of rice farm (Villano et al., 2015).

The limitation of most studies that have used stochastic production frontiers (SPFs) to compare the TE of adopters versus non-adopters is the failure to account for selectivity bias arising from both observable and unobservable variables in a manner that is compatible with the nonlinear nature of the SFM.

For example, following Heckman's (1979) methodology to account for selection bias, several attempts have been made to address sample selection in a stochastic frontier framework. Sipilainen and Oude Lansink (2005) added an inverse Mill's ratio (IMR) to the deterministic part of the frontier function to examine possible sample selection bias in the analysis of organic and conventional farms. A similar approach was implemented by Solıs et al. (2007) when analysing farmers with different levels of adoption of soil conservation practices in Central America. However, this procedure has proven unsuitable for nonlinear models such as the SPF (Greene, 2010).

In recent years, alternative strategies have been proposed to deal with this problem including the one by Kumbhakar et al. (2009) who developed a model where the selection mechanism is assumed to operate through the one-sided error in the frontier, and then used their model to evaluate the performance of organic versus conventional dairy farming in Finland. Lai et al. (2009) studied wage determination employing a copula function and assumed that selection is correlated with the composed error in the frontier. These two models require computationally demanding log likelihood functions.

This study adopts the framework developed by Greene (2010) who extended Heckman's approach to consider sample selection in a stochastic frontier framework assuming that the unobserved characteristics in the selection equation are correlated with the noise in the stochastic frontier. The model introduced by Greene (2010) and used by this study is expressed succinctly with the following three blocks of equations:[4]

Sample selection: $d_i = 1[\propto^1 z_i + w_i > 0], w_i \sim N(0,1)$ ……. (4.23)

Stochastic frontier model: $y_i = \beta^1 x_i + \varepsilon_i$ ………………………….. (4.224)

(y_i, x_i) were observed only when $d_i = 1$. The error structure was specified as:

$\varepsilon_i = v_i - u_i$ ………………………………………………………... (4.25)

$u_i = |\sigma_u U_i| = \sigma_u |U_i| where\ U_i \sim N(0,1)$ ………………………………... (4.26)

$v_i = \sigma_v V_i\ where\ V_i \sim N(0,1)$ …………………………………………….. (4.27)

$(w_i v_i) \sim N_2[(0,0), (1, \rho\sigma_v, \sigma_v^2)]$

- *d* was a binary variable, specified as 1 for adopters (irrigation farmers), and 0 for non-adopters (rainfed farmers);
- *z* was a vector of explanatory variables included in the (binary) sample selection model;
- w_i was the unobservable error term;
- *y* is output for the rice farmers;
- *x* is a vector of inputs in the production frontier; and
- ε is the composite error term.

The coefficients $\propto$ and β were the parameters estimated, while the elements in the error structure correspond to those typically included in the stochastic frontier formulation. In this model, sample selection arose because the noise in the stochastic frontier, v_i, was correlated with unobserved characteristics in the sample selection equation, w_i. The

[4] The model was estimated directly with the help of LIMDEP 11 Software.

selectivity variable ρ, was statistically significant, evidence that selectivity bias in unobservable was present justifying the use of the SFA correcting for sample selection.

4.7 Conceptual framework for adoption of improved agricultural technologies

Moving away from the ideal situation of maximum utility theory creates constraints on the adoption of even profitable technologies. In this section, the study conceptualizes the factors that affect the adoption of improved agricultural technologies and technical efficiency among rice farmers in northern Ghana (see Figure 4.2). Literature on agriculture highlights two major drivers of successful agricultural technology adoption in developing countries: (i) the availability and affordability of technologies; and (ii) farmer expectations that adoption will remain profitable—both of which determine the extent to which farmers are risk averse (Foster and Rosenzweig, 2010; Carletto et al, 2007).

A number of factors drive the above expectations, ranging from availability and size of land, family labour, availability and costs of hired labour, prices and profitability of agricultural enterprises, government subsidy, and other factors such as institutional, location, technical and socioeconomic drivers of technology adoption. The conceptual framework presented here highlights the various pathways through which different factors influence rice farmers' decisions to adopt agricultural technologies. These variables were expected to have positive and direct relationship with adoption of improved rice production technologies by farmers in northern Ghana, which eventually could lead to improved efficiency and output of rice.

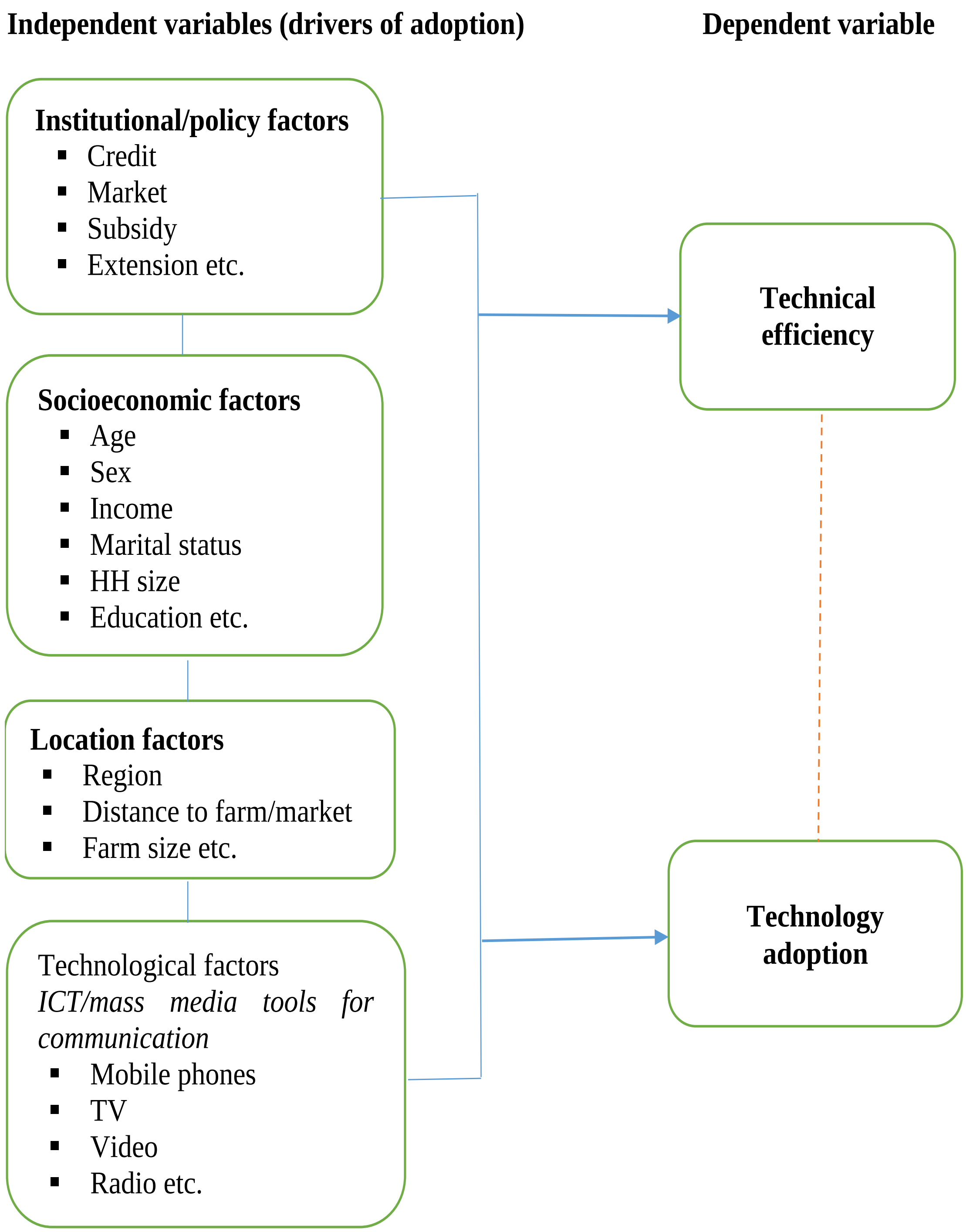

Figure 4. 2: Conceptual framework
Source: Researcher's construct (2018)

4.8 Theoretical framework

In this section, the study presents the theoretical framework for adoption of improved technologies as it pertains to this present study. The economic effects of the adoption of improved technologies is also discussed in section 4.8.1. This study aligns with the random utility theory similar to previous studies on agricultural technology adoption behaviour, to explain adoption decision where the utility of a rice farmer is specified as a linear function of the household socioeconomic, technical, location and farm-specific characteristics as well as a stochastic component (Marenya and Barret, 2007). Famers will adopt an improved agricultural technology or a combination of technologies that can provide maximum satisfaction to them.

The probability of choosing a particular improved technology or a combination of the technologies is equal to the probability that the utility of that particular alternative is greater than or at worse, equal to the utilities of all competing alternatives in the set of choices. In order to maximise the utility U_{ij}, *an* i^{th} rice farmer will compare alternatives technologies and combinations. Conversely, an i^{th} rice farmer will choose a technology *j*, over any alternative technology, *k*, if $U_{ij} > U_{ik}, k \neq j$.

Rice farmers' choice of different interrelated improved technologies is modelled using a multivariate probit model (MVP) which allows for modelling binary choice outcomes together that are correlated. Also, the factors that influence the extent of combinations of improved rice production technologies was modelled using zero inflated Poisson regression (ZIP) which is used when there are excess zeros in the observation.

4.8.1 The economic effects of adoption of improve rice production technologies.

The economic benefits of adopting improved rice production technologies by famers can be enormous. Adisa et al. (2019) examined the benefits of adoption of improved rice technologies among small–scale rice farmers in Kogi State, Nigeria, and found that about 98.6% of the adopting farmers had increased output, 91.5% had acquired new skills in production, with another 85.5% and 72.2% of the respondents reporting increased incomes and farm sizes respectively.

The improved technologies disseminated were rice production facilities, rice farming inputs, and field preparation methods. Donkor et al. (2016) employed the endogenous switching regression and propensity score matching methods to analyse the impact of row-planting technology on rice productivity using 470 rice farms in northern Ghana. The empirical findings showed that the adoption of row-planting technology exerted greater positive impact on rice yields of smallholder farmers, which has positive effect on profitability. In addition, rice yields of adopters and non-adopters were driven by farm inputs, socioeconomic, institutional and technological factors. Donkor et al. (2016) suggested that achieving self-sufficiency in rice and rural economic transformation in sub-Saharan Africa required promotion of agricultural technologies including row-planting.

Wani et al. (2013) also estimated the extent of adoption of an improved rice seed technology in the Kashmir valley and the impact of adoption on the economic and the livelihood security of adopters of this technology. They found that by adopting improved technology, both gross returns and net returns had increased considerably, while the cost of production decreased. The study established that adoption of new technology had provided better economic and livelihood security at the household level in the study area.

By presenting statistics obtained through economic surplus model, Wani et al. (2013) presented a strong case for higher investments in research and development (R&D), extension services delivery and dissemination of improved technology in the Kashmir valley.

Devi and Ponnarasi (2009) studied the economics and the farmer's adoption behaviour of the system of rice intensification (SRI). They found that the adoption of SRI technique would help increase rice production without increasing the area under cultivation. The net return has been found higher in SRI (Rs27009) than the conventional method (Rs 14499). The cost of production per metric tonne of paddy was lower in SRI (Rs 3937) than the conventional method (Rs 7404) of rice cultivation. The cost of production is almost double in the conventional method because of low productivity of rice in this method. The measures of returns over different costs, namely, farm business income, family labour income, net income, and farm investment income are comparatively higher in the SRI than conventional method of rice cultivation. The increased productivity and net profit would attract the farmers, and saving in water-use for rice cultivation is an important advantage for efficient water management.

From the above discussions, it is evident that while numerous studies have been conducted on the economic effects of adopting improved rice production technologies, majority do not relate to Ghana. It is also important to note that findings from these studies are far from being general conclusion since differences exist in terms of agro-ecological zones and technologies as well as socio-economic setting under which production takes place. In Ghana for instance, attention is focused on understanding the factors influencing the adoption of improved rice production technologies while the effects of these techniques on technical efficiency and rice output are given little attention. This study therefore adds to the existing literature on adoption by way of examining the factors that influence adoption and how adoption influence technical efficiency and output of rice farmers in northern Ghana.

4.9 Definition variables

Table 4.1 provides a summary of contextualised definitions for the variables used in this study. In all, there are twenty-six (26) variables out of which two (2) are the main dependent variables. Column one presents the variable name. Column two indicates the definition of the variable in the context of this study and how the variable is measured. Column three indicates the expected sign/direction of the variable in the various models and defines the a priori expectation.

Table 4. 1: Definition of variables

Variable	Definition/ measurement	Expected sign
Adoption Intensity	Number of improved agricultural technologies adopted (from 1 to 7)	+
Output	Natural log of rice output (measured in kg)	+
Age	The total number of years from birth of a farmer.	+
Sex	Dummy: 1 for male, 0 if otherwise	+
HH head	Dummy: 1 for household head, 0 if otherwise	+
Education	Number of years spent in formal schooling.	+
Commercial	Dummy: 1 if farmer produces for commercial purpose, 0 if otherwise	+
Experience	The total number of years a farmer has been cultivating rice.	+
Region (location)	Dummy: 1 for a farmer in northern region, 0 for a farmer in upper east region	+/-
FBO	Dummy: 1 for if the farmer belongs to a farmer group, 0 if otherwise	+
Research	Dummy: 1 for access to research service in the last season, 0 if otherwise	+
Credit	Dummy: 1 for access to credit in the last growing season, 0 if otherwise.	+
Training	Dummy: 1 if farmer had access to trainings last season, 0 if otherwise.	-/+
CC perception	Dummy: 1 for farmers who perceived that rainfall was reducing but with rising temperatures, 0 if otherwise	+/-
HH size	Total number of people in housing unit that feed from the same source	+/-
Farm size	Natural log of farm size (measured in the total hectares of land under rice production)	+
Herbicides	Natural log of quantity of herbicides (measured in litres) used	+
Fertilizer	Natural log of total quantity of fertilizer (measured in kg)	+
Seed	Natural log of quantity of improved seed (measured in kg)	+
Labour	Natural log of total number of persons available that worked on the farmers field during the farming season)	-
HH ext. method	Dummy: 1 for a farmer who accessed information via HH extension method, 0 if otherwise	+
Demos	Dummy: 1 for a farmer who accessed information via farmer led field technology demonstration method, 0 if otherwise	+
TV	Dummy: 1 for a farmer who accessed information via TV, 0 if otherwise	+
Radio	Dummy: 1 for a farmer who accessed information via radio, 0 if otherwise	+
Video	Dummy: 1 for a farmer who accessed information via video, 0 if otherwise	+
Mobile phone	Dummy: 1 for a farmer who accessed information via mobile phone, 0 if otherwise	+

CHAPTER FIVE

RESULTS AND DISCUSSIONS

5.0 Introduction

This chapter presents and discusses the results of the study. Section 5.1 discusses the summary statistics of the variables that are contained in the various models. Section 5.2 to 5.4 offer presentation of the estimated models to address the objectives of the study.

5.1 Summary statistics of variables

Tables 5.1. and 5.2 provide summary statistics for the variables. Table 5.1 presents the statistics for the unmatched sample, while Table 5.2 presents the summary statistics for the matched sample.[5] Each of the tables is partitioned by columns indicating the statistics for the pooled result, irrigated farms, and rain fed farms in columns 2, 3, and 4 respectively. Column 4 of each of the tables presents the result of *t*-test conducted to ascertain whether there is significant difference among the variables of the two regimes of data (i.e. rain fed and irrigated farms).

While reference will be made to the two tables to discuss this section, emphasis will be placed on the matched group because that was used to model the sample selection framework in the stochastic production frontier. Meanwhile, the results from the matched and unmatched samples do not show much difference in the summary statistics.

[5] The unmatched sample constitute the original data set containing 543 observations. The matched sample (538 observations) was obtained after implementing the PSM to address observable errors.

Table 5. 1: Descriptive statistics - unmatched sample

Variable	Pooled Mean	Pooled Std. Dev.	Irrigated farms Mean	Irrigated farms Std. Dev.	Rain fed farms Mean	Rain fed farms Std. Dev.	‡Test of means
Age	38.51	10.67	40.29	11.92	37.27	9.52	3.277***
Sex	0.83	0.37	0.87	0.34	0.81	0.39	1.723*
HH head	0.58	0.50	0.60	0.49	0.56	0.5	0.786
Education	4.05	5.14	3.86	5.52	4.18	4.86	-0.701
Commercial	0.65	0.48	0.64	0.48	0.66	0.48	-0.435
Experience	11.72	7.66	12.48	8.16	11.19	7.26	1.936*
Region	0.68	0.47	0.84	0.37	0.57	0.5	6.901***
FBO	0.64	0.48	0.58	0.5	0.68	0.47	-2.306***
Extension	0.55	0.5	0.43	0.5	0.63	0.48	-4.896*
Credit	0.12	0.32	0.07	0.26	0.15	0.36	-2.797***
Training	0.71	0.45	0.91	0.29	0.58	0.5	9.106***
CC perception	0.66	0.47	0.86	0.35	0.53	0.5	8.537***
HH size	9.35	6.23	9.28	6.65	9.4	5.92	-0.216
Farm size	2.42	3.62	1.29	1.00	3.21	4.48	-6.277***
Output	31.22	47.07	21.98	16.02	37.65	59.03	-3.865***
Herbicide	3.27	8.62	2.28	1.33	3.95	11.13	-2.231***
Fertilizer	6.37	37.73	3.47	6.26	8.4	48.79	-1.5
Seed	55.15	108.42	15.93	26.16	82.48	132.93	-7.375***
Labour	16.8	16.32	25.16	17.86	10.97	12.13	11.029***
Adoption Int.[6]	3.52	2.35	5.58	1.55	2.08	1.65	24.926***
Obs	***543***		***223***		***330***		

‡A t-test is used to determine if the sample means are significantly different between the irrigated and rain fed farms.

*, **, and *** represent 10%, 5%, and 1% level of significance respectively.

Source: Analysis of field data, 2017

[6] Adoption intensity is a summation of the all the improved technologies adopted by a farmer (excluding irrigation). See the MV Probit regression in Table 5.9. Irrigation is excluded because of the partitioning of the result for irrigated and the rain fed farms.

Table 5. 2: Descriptive statistics - matched sample

Variable	Pooled		Irrigated farms		Rain fed farms		‡Test of means
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	
Age	38.43	10.66	40.29	11.92	37.12	9.47	3.425***
Sex	0.83	0.38	0.87	0.34	0.81	0.4	1.804*
HH head	0.57	0.5	0.60	0.49	0.56	0.5	0.87
Education	4.04	5.13	3.86	5.52	4.17	4.84	-0.692
Commercial	0.65	0.48	0.64	0.48	0.65	0.48	-0.304
Experience	11.73	7.68	12.48	8.16	11.19	7.28	1.931*
Region	0.68	0.47	0.84	0.37	0.57	0.50	6.821***
FBO	0.64	0.48	0.58	0.50	0.68	0.47	-2.328***
Extension	0.54	0.50	0.43	0.50	0.63	0.48	-4.735**
Credit	0.12	0.32	0.07	0.26	0.15	0.36	-2.767***
Training	0.72	0.45	0.91	0.29	0.58	0.49	8.866***
CC perception	0.67	0.47	0.86	0.35	0.53	0.50	8.311***
HH size	9.33	6.24	9.28	6.65	9.37	5.94	-0.163
Farm size	2.41	3.64	1.29	1.00	3.20	4.51	-6.21***
Output	31.07	47.19	21.98	16.02	37.5	59.39	-3.804***
Herbicide	3.26	8.66	2.28	1.33	3.96	11.21	-2.221***
Fertilizer	6.39	37.9	3.47	6.26	8.45	49.17	-1.505
Seed	54.88	108.38	15.93	26.16	82.46	133.28	-7.353***
Labour	16.87	16.37	25.16	17.86	11.00	12.21	10.92***
Adoption Int.	3.53	2.36	5.58	1.55	2.08	1.65	24.906***
Obs	***538***		***223***		***315***		

‡A t-test is used to determine if the sample means are significantly different between the irrigated and rain fed farms.

*, **, and *** represent 10%, 5%, and 1% level of significance respectively.

Source: Analysis of field data, 2017

The unmatched sample contains 543 observations, out of which 223 are irrigation farmers. The remaining 320 are rain fed. The matched sample contains 538 observations, made up of 223 irrigation farmers and 315 for rain fed. The matching process eliminated only five observations which incidentally came from the rain fed group.

T-test was performed to compare the mean values of the variables for the irrigated farms to that of the rain fed farms. For the samples of the two systems (i.e. matched and unmatched), the same set of 15 variables were statistically significant. The significant variables are as follows: age, sex, experience, location (region), FBO membership, extension, credit, and training. The rest are perception of climate change, farm size, output, herbicides, seeds, labour and adoption intensity. The variables that were not significant include household headship, education, commercialisation and fertilizer.

From Table 5.2, the average age of a rice farmer in the study area is 38.43 years. The mean age for the irrigation farmers was about 40 years, while that of the rain fed farmers was about 37 years. Azumah et al. (2017) also found the average age of farmers in the northern region of Ghana to be 39.7 years. These indicate a relatively youthful age for rice farmers in the study area as MoFA (2013) reports the average age of farmers to be 55 years in Ghana. The finding is good for agricultural development in Northern Ghana considering that agricultural activities around the area involve much labour as mechanisation is still a challenge.

Males were still found to be dominant in the production of rice. In the pooled sample, 83% of the respondents were male. Specifically, the percentages of male respondents for the irrigated and rain fed farmers were 87 and 81 respectively. This finding does not however suggest that females were least involved in rice production. Focus group discussions conducted with female and male rice farmers in the two regions revealed that the activities in rice production appeared led by the males because they own the lands on which production activities are carried out. In most cases, the females provided labour for transplanting, weeding and harvesting. Females are also mainly responsible for value addition such as parboiling and processing of rice for onward sale in local markets.

Also, 60% of the irrigation farmers were found to be household heads, as against 56% for their counterpart rain fed farmers. On the average, a farmer had up to only 4.04 years of formal education. This was slightly higher for rain fed farmers (4.27 years) compared with (3.86 years) for irrigation farmers. This finding indicates a low level of formal education among farm workers in the northern part of Ghana. While the national average for the population of 15 years who had ever attended school in Ghana currently stands at 85.3%, the regional figures for the Northern and Upper East regions of Ghana are 55.7% and 59.4% respectively, placing the two regions as the worst performing regions when it comes to formal education in Ghana (GSS, 2014).

On the average, 65% of the farmers were commercially oriented. Also, 35% of the respondents produced solely for subsistent purpose. This finding is in line with the current government policies for the rice sector that view rice as a commercial crop. Indeed, the present Feed the Future USAID Ghana interventions, and the previous Millennium Development Authority's (MiDA) Commercial Development of Farmer Based Organisations, and the Rice Sector Support projects, which have been dominant in the study area, named rice as a commercial crop and sought to commercialize the rice sector of Ghana by introducing the value chain concept.

Irrigation farmers were also found to have more experience in rice production (12.48 years) compared with their rain fed counterparts (11.19 years). This finding shows that the rice farmers in the study area were very experienced as they possessed up to a decade of knowledge in the production systems of rice.

About 68% of the respondents were from the Northern region. The rest of the 32% of the respondents were for the Upper East region of Ghana. The proportion of the sample assigned to each region was based on the density of rice production points in the two regions.

The result from Table 5.3 also reveals that 64% of the farmers were members of farmer groups. Surprisingly, there was a 10-percentage difference in terms of group membership between the irrigation and rain fed farmers. While 68% of the rain fed farmers belonged to farmer-based organisations, only 58% of the irrigation farmers were in a farmer association.

Access to agricultural extension service was also relatively low (43%) among the irrigation farmers as compared with 63% for the rain fed farmers. The poor agricultural extension system in Ghana could be attributed to the low investment by the government in the agriculture sector lately. Agriculture extension agents from the agriculture training colleges and universities in Ghana are no more automatically recruited into the Ministry of Food and Agriculture to provide extension services to farmers like it used to be in the 1980s and 1990s. This has widened the agriculture extension agent farmer ratio to about 1:3000 (GSS, 2014), leaving industry players in the NGO sector to provide trainings on improved technologies to farmers in the area. There appear also to be some level of incoordination among various NGOs in delivering services. This could result in transmitting several conflicting information to the same farmers.

Just about 12% of the farmers had access to production credit in the previous season. Credit access among the rain fed farmers was relatively high (about 15%), compared with that of their counterpart irrigation farmers (about 7%). Perhaps, this was due to the relative larger farmer sizes owned by the rainfed farmers (see Table 5.1) which required higher investments to manage. This is an indication of low level of financing for agricultural activities in the area. Climate change is now evident in the area, making investments into the agricultural sector riskier than ever, a possible justification by financial institutions to shy away from funding production activities of rice farmers in the area.

The results from Table 5.2 also reveal that about 72% of the farmers had received training on improved agricultural technologies for rice production the previous season. Fewer rain fed farmers (58%) received training as compared with their counterpart irrigation farmers (91%), an indication that the projects that are leading in the development of the rice sector in northern Ghana were paying more attention to irrigation farmers and intensification systems.

Majority (67%) of the farmers perceived the situation of climate change to be worsening in the area. There was a general consensus among the rice farmers that temperature in the area was increasing, with corresponding low levels of rainfall. The perception was particularly higher among the irrigation farmers (86%) compared to e rain fed farmers (53%).

The average household size was found to be 9, indicating that household sizes in the study area were relatively high compared with Ghana's national average of 4.0 (GSS, 2014). The study also found the average land holding per rice farmer in the study area to be 2.41 acres (translating into 0.96 hectares). Rain fed farmers had higher farm sizes (3.2 acres per farmers) than their counterpart irrigation farmers (1.29 acres per farmer). This translates to 1.28 Ha and 0.52 Ha for rainfed and irrigation farmers respectively. This indicates that average land holding for rice production was low in the area. Generally, average farm sizes for crop production is supposed to reduce with Ghana's current increasing trend in population growth.

The average output of rice was also reported to be 31.07 bags[7], which translates into an average yield of 12.89 bags/acre (0.52 MT/Ha). The output for irrigated farms was 21.98 bags, translating into about 17bags/acre (0.68 MT/Ha). The reported output for the rain fed farms is 37.5 bags, translating into about 11.7 bags/acre (0.47 MT/Ha). While the achievable yield of rice is projected to about 6.0 MT/Ha, current national average yield of the commodity is about 2.75 MT/Ha, with the Northern and Upper East regions recording lower yields than the national average (MoFA SRID, 2016), corroborating with our present finding. This can be attributed to many factors including low investment in the agricultural sector. Ragasa et al. (2013), also found low level of technology adoption (i.e. fertilizer and improved seeds) by rice farmers as being the main factor that accounts for the low levels of productivity among the farmers in the study area.

[7] A bag of rice is standardised at 100kg (0.1MT). Yield is calculated from Table 5.2 as output ÷ farm size

Average herbicide usage was also found to be 3.26 litres per farmer (translating into about 1.35 litres/acre). Average herbicide usage among the irrigation farmers was reported to be 2.28 litres (about 1.77 litres/acre), and 3.96 litres (1.24 litres/acre) for the rain fed farmers.

The study also revealed low level of fertilizer usage among rice farmers in the study area. Table 5.2 reveals that on the average, a farmer applied 6.39 bags [8]of fertilizer on their rice farm (translating into 2.65 bags/acre). Irrigation farmers applied about 3.47 bags, which translates into about 2.70 bags/acre. Rain fed farmers on the other hand used about 8.45 bags of chemical fertilizer on their rice farms, translating into an average of 2.64 bags/acre. This finding indicates a low usage of fertilizer among the rice farmers, corroborating with Ragasa et al (2013) who made similar finding of low usage of fertilizer among farmers in northern Ghana. Farmers admitted in various focus group discussions held at the Botanga and Tono irrigation schemes that there were some fertilizers supplied to them under the government of Ghana fertilizer subsidy programme. However, the quantity allocated per farmer was insufficient. They mentioned also that the discounted prices were still expensive for them to bear, resulting in low fertilizer usage. Farmers also complained about the longer distances they had to cover to buy fertilizers. They explained that the distances covered added to the cost of fertilizer because they had to pay for transportation services.

Table 5.2 also reveals that an average rice farmer in the study area used 55kg of seed on their rice farm. This translates into 23kg of rice seed usage per acre. Farmers under irrigation schemes used 15.93kg as against 82.46kg for their counterpart rain fed farmers. These translate into 12.35kg/acre and 25.77kg/acre respectively for irrigation and rain fed

[8] A standard bag of fertilizer in the study area, regardless of the formulation, weighs 50kg

farmers. Savannah Agricultural Research Institute (SARI undated) as in Ragasa et al. (2013) recommends that rice plots be planted in rows or lines. For transplanting, the recommended planting density is 35–45 kg/Ha, at a spacing of 20 cm x 20 cm at two plants per hill (20 x 25 cm based on SARI report), with transplanting taking place 21–28 days after seeding. For direct seeding, the recommended planting density is 45 kg/Ha for dibbling or drilling and 100 kg/Ha for broadcasting. Transplanting is recommended for more reliable plant stand, but moisture conditions must allow for transplanting. In the north, dibbling or drilling in lines or rows is recommended over broadcasting (SARI undated). Based on the submission by Ragasa et al. (2013), and SARI (undated), the study found that rice farmers in the study area were using up to the recommended seed rate per unit area, except for broadcasting.

The average distributions of labour usage among the irrigation and rain fed farmers were 25 and 11 workers respectively. [9]This indicates that there was a higher usage of labour among the irrigation farmers than the rain fed farmers. Similarly, irrigation farmers were found to be adopting more improved rice production technologies (5.58) as compared to the rain fed farmers who on the average, were adopting two (2) out to the seven (7) critical improved technologies identified.

[9] The labour distribution per acre is 20.1 and 3.4 workers respectively for irrigation and rainfed regimes based on computation using data from Table 5.1.

5.2 Agricultural technology transfer methods and their perceived effectiveness

This section of the thesis looks at the main sources of information about improved agricultural technologies and the various agricultural technology transfer methods that are employed by stakeholders of the agricultural extension delivery system in the study area. The study employs Kendall's *W*-test to rank the various sources of information on improved agricultural technologies to the farmers, as well as the agricultural technologies transfer methods that are available in the study area.

5.2.1 Sources of information on improved agricultural technologies

The results from Table 5.3 reveal that about 92% of the respondents received information on improved production techniques from colleague farmers, corroborating with Nakano et al. (2018). About 78% of the respondents received information from research institutions such as SARI and IITA. This revelation was not surprising as IITA and SARI continue to maintain research stations and experimental sites in the study area. Researchers from these institutions usually use lead-farmers who maintain and manage various experiments set out by the researchers. Field days are organised by these researchers during which they communicate relevant technologies to the farmers who attend.

Also, majority of the farmers received information from NGOs such as IFDC Ghana and the Advance II project, as well as through mass media mechanisms such as radio, television sets and via mobile phones. The least source of information to the farmers was found to be via government extension agents, mostly from the Ministry of Food and Agriculture; and also, through other bodies such as produce aggregators. The deterioration of the public agricultural extension system in Ghana coupled with reduced government funding for the sector has led to poor farmer access to public extension staff, which currently stands at about five million smallholder farmers to 3500 agricultural extension agents in Ghana (McNamara et al., 2014).

Table 5. 3: Main source of information on improved agricultural technologies

Source of information*	Freq. (Yes)	Percent
Colleague farmers	502	92.4
Researchers (e.g. SARI)	423	77.9
NGOs (e.g. IFDC)	420	77.3
Media (radio, TV, mobile phone etc.)	411	75.7
MoFA extension agents	283	52.1
Others (e.g. produce aggregators)	283	52.1
N=543		

*This was multiple response, so farmers were allowed to choose as many options as applied to them

Source: Analysis of field data, 2017

Results of the Kendall's *W*-test of the main sources of information to farmers on improved agricultural technologies in the study area as shown by Table 5.4, reveal a low concordance strength *(W)* of 0.185. This was however significant at 1%, thereby allowing us to reject the null hypothesis that there was no agreement among the raters.

Table 5. 4: Results of Kendall's W test of main source of information on improved agricultural technologies to rice farmers

Source of information	Mean Rank	Std. Dev.	Min	Max	Ranking
NGOs (e.g. IFDC)	2.73	1.750	1	6	1st
Colleague farmers	2.91	1.285	1	6	2nd
Researchers (e.g. SARI)	3.08	1.645	1	6	3rd
MoFA extension agents	3.56	2.143	1	6	4th
Media (radio, TV, mobile phone etc.)	3.9	1.570	1	6	5th
Others (e.g. produce aggregators)	4.83	1.260	1	6	6th
N	543				
Kendall's W[a]	0.185***				
Chi-Square	502.384				
df	5				

*Note: The ranking was done from 1 – 6, 1 being the most important, and 6 being the least important ranking

[a.] Kendall's Coefficient of Concordance. *** represents 1% level of significance

Source: Analysis of field data, 2017

NGOs came first in terms of ranking as the main source of information to rice farmers in the study area with a mean rank of 2.73. This was followed by information from colleague farmers with a mean rank of 2.91. Research institutions, MoFA Extension Agents, and the Mass media came third, fourth and fifth respectively with mean ranks of 3.08, 3.56, and 3.90 respectively. Other sources of information such as those from produce aggregators who normally engage rice framers on contractual basis came last with a mean ranking of 4.83. The activities of produce aggregators and market queens in the rice sector have seen steady improvements in the study area during the past few years, with much investment coming in from the aggregators in the form of production capital and supply of rice varieties of interest to rice farmers who are engaged by these aggregators on contractual basis. Buadi et al. (2013) found that aside the critical role of the NGOs in the trainings of farmers and transferring critical agricultural technologies for improved production, they were also involved in information support services to the farmers, input supply, credit provision, as well as the monitoring and evaluation of extension activities. The farmers generally perceived the services of the NGOs to be relevant to their operations and leading to improvements in their incomes and welfare.

A study of the information needs and information seeking behaviour of rural dwellers in Nigeria indicated agricultural information as one of their needs (Momodu, 2002). Farmers will often times, require information on 'where to purchase fertilizers', 'how to use them', information on pesticides, herbicides, storage, and improved varieties of crops. Momodu (2002), noted that this information can be made available to farmers via ICT tools such as mobile phones and radio which are able to transmit information in real time. Alemna and Sam (2006), however noted a negative effect in the use of ICTs in the rural areas of Ghana because literacy rates are very low. The situation gets worse when it comes to computer literacy. There are fewer computer-literate personnel in the rural areas. On the other hand, if farmers are to make good use of ICT, the staff who advise and train farmers need to have more knowledge and skills in ICT. However, with the improvements in the literacy rate of Ghanaians in recent years (GSS, 2014), the use of ICT tools for information dissemination to farmers could increase. NGOs such as IFDC Ghana, and farm radio international are already employing ICT mechanisms such as mobile phones, video and radio programmes to reach out to millions of Ghanaian farmers in the study area.

5.2.2 Agricultural technology transfer methods in northern Ghana

This section discusses various agricultural technology methods that are being used to transmit information to farmers in the study area. The study identified four main agricultural technology transfer methods namely: the household method, the mass media method, the school approach, and the farmer-to-farmer method. To assess the agreement among raters, the Kendall's *W*- test was employed to rank the main agricultural technology transfer methods in the study area (See Table 5.5). The strength of concordance *(W)* was estimated to be 0.45 and significant at 1%, an indication that the null hypothesis that there was no agreement among the raters could be rejected.

Table 5. 5: Results of Kendall's W test of main agricultural technology transfer methods

Technology transfer method/approach		Mean Rank	Std. Dev.	Min	Max	Ranking
Farmer-Famer		2.8	2.008	1	10	1st
Household		3.95	2.484	1	10	3rd
School	Demonstration	3.04	1.864	1	10	2nd
	Lecture	6.19	2.494	1	11	5th
Mass media	Radio	4.32	2.800	1	10	4th
	Mobile phone	6.43	2.509	1	10	6th
	Video screening	6.88	2.460	1	10	7th
	TV programmes	7.03	2.307	1	11	8th
	Drama	7.68	2.053	1	11	9th
	Posters	8.59	1.885	1	10	10th
	Newspaper	9.1	1.913	1	11	11th
N		543				
Kendall's W^a		0.450***				
Chi-Square		1258.622				
df		10				

*Note: The ranking was done from 1 – 11, 1 being the most important, and 11 being the least important ranking.
The mean is measured on a 5-point Likert scale. 5 being most effective and 1 being least effective
[a] Kendall's Coefficient of Concordance, *** represents 1% level of significance
Source: Analysis of field data, 2017

The results from Table 5.5 show that farmer-to-farmer extension approach *(where information is passed on from one farmer to the other in the same community or farm area)* was the main extension or agricultural transfer method in the study area, corroborating with Nakano et al. (2018). This approach was ranked first by the farmers with a mean rank of 2.8. Out of the two technology transfer methods under the school approach, the farmer led technology demonstration method came second with a mean rank of 3.04. The lecture method *(mostly done through classroom trainings)* was ranked fifth with mean rank of 6.19. The household or individual extension method came third with a mean rank of 3.95. By this method, farmers get to know about information from household members who have come in contact with such technologies either by learning from colleague farmers or other extension systems. According to Aremu, Kol, Gana, and Adelere (2015), radio is one of the fastest and most powerful instruments of communicating with the masses of rural people and farmers. They noted also that radio was useful in reporting news, such as announcement of meetings, and disseminating new skills, production techniques or new methods of production in agriculture that will ultimately improve the living standards of rice farmers. Although radio placed fourth (with mean rank of 4.32), it was found to be the most prominent agricultural technology transfer method among all the identified mass media extension methods.

Electronic and mass media mechanisms are strong platforms for the dissemination of knowledge, skills and improved technologies to rice farmers. Such media play influential roles in providing extension services, especially in view of the public extension agencies' ineffectiveness in providing the much-needed agricultural extension services to farmers (Baloch and Thapa, 2017). Despite the development of technology and ICT as well as the mass media in Ghana in recent years, their use in disseminating agricultural information is still low, especially in the study area (Etwire et al., 2017). Majority of the mass media/ICT approaches to agricultural extension were ranked least by the farmers as being dominantly used by change agents to disseminate information on improved technologies. Out of all the mass media methods, newspaper and poster were the least ranked with eleventh and tenth positions respectively. TV and drama came eighth and ninth with mean ranks of 7.03 and 7.63 respectively. Surprisingly, the use of mobile phones and videos for extension came sixth and seventh with mean ranks of 6.43 and 6.88 respectively, diverging from the finding of Fu and Akter (2016). Video screening has recently been used by many projects including the Feed the Future USAID-Ghana Agriculture Technology Transfer project to train thousands of farmers in the northern regions of Ghana because of its low cost and ability to transfer information to many farmers at the same time and at their comfort (Bentley, Chowdhury and David, 2015).

5.2.3 Effectiveness of agricultural technology transfer methods in northern Ghana

In section 5.2.2, the various agricultural technology transfer methods that are being used to transfer information to rice farmers in Northern Ghana were discussed. This section presents the perceived effectiveness of rice farmers about the various technology transfer methods in terms of influencing the adoption of improved rice production technologies. The perception of the farmers was measured on a 5-point Likert scale, 5 being most effective and 1 being the least effective. The computed mean values shown in Table 5.7 indicate the weight of the perception by the farmers about a particular technology transfer method.

All the extension methods except newspaper, mobile phone, TV and Posters had more than a 50% perception index (2.5 mean value and above) of influencing rice farmers to adopt improved production techniques. The extension method that was most perceived by farmers to influence adoption was demonstration (with mean value of 4.51). According to Aremu et al. (2015), and Anandajayasekeram et al. (2008), it is possible to reach large numbers of farmers within a short time at minimal cost and with great impact, using the demonstration method. The disadvantages of the approach however, is that some farmers who attend the demonstrations may not be decision-makers in their homes and so considerable time is needed before such farmers who attend demonstrations become influential in their homes or society. The farmer-to-farmer extension method was also perceived to have very high impact on adoption of improved rice production technologies (mean of 4.47). By this method, there is the provision of training by farmers to other farmers, usually, through the creation of a structure of farmer promoters and farmer trainers (Simpson et al., 2015; Scarborough et al., 1997).

Household extension method, class room lecture approach, and Radio came third, fourth, and fifth with mean values of 3.59, 3.45 and 3.38 respectively. Although farmers perceived TV, video, drama, and posters to influence adoption, they had low perception index of less than 3.0, meaning they were less effective as compared to the others. The household or individual extension method is most effective for activities undertaken by or within the full control of the individual farmer or household. In this regard, discussion with the whole family highlights more problems, and more experience is brought to the discussion (Anandajayasekeram et al., 2008). However, the household or individual extension method is characterised by high cost in terms of time and transportation. Only a few farmers may actually be visited. Also, the area covered is small since all the effort is concentrated on a few farmers or households per given time.

Table 5. 6: Perceived effectiveness of the technology transfer methods in terms of influencing adoption

Method	Mean	Std. Dev.	Ranking
Demonstration	4.51	0.962	1st
Farmer-Farmer	4.47	1.069	2nd
Household	3.59	1.433	3rd
Lectures	3.45	1.429	4th
Radio	3.38	1.574	5th
Video	2.91	1.689	6th
Drama	2.58	1.561	7th
TV	2.39	1.496	8th
Posters	2.21	1.324	9th
Newspaper	1.74	1.136	10th
Mobile phone	1.50	1.010	11th

*Note: *N*=543. The mean is measured on a 5-point Likert scale. 5 being most effective and 1 being least effective

Source: Analysis of field data, 2017

5.3 Adoption of improved agricultural technologies by rice farmers

This section discusses the results from the multivariate probit and adoption intensity models. First, the nature of the relationship between the improved rice production technologies is discussed. Secondly, the results from the individual probit equations to allow for comparison is presented. Finally, the results of the determinants of adoption intensity by comparing the parameter estimates of Poisson and negative binomial regression models are presented. In Table 5.7, the improved agricultural technologies and the frequency of farmers' adoption and practice these technologies are also presented. The results reveal that about 59% of the respondents practiced nursery. This was followed by proper spacing of rice plants (about 53%) and line planting (about 52%). Also, about 51%

of the farmers adopted bunding. The technologies with adoption rates below the midpoint of 50% were harrowing, irrigation and urea briquette with adoption rates of 43.65%, 41.07%, and 34.81% respectively.

Table 5. 7: Practice of improved agricultural technologies among rice farmers

Improved technology*	Freq. (No. of farmers practicing)	%
Nursery	321	59.12
Harrowing	237	43.65
Line planting	281	51.75
Spacing	287	52.85
Urea briquette	189	34.81
Irrigation	223	41.07
Bunding	276	50.83
N=543		

*Multiple responses

Source: Analysis of field data, 2017

5.3.1 The relationships among the improved agricultural technologies – pairwise correlations

Table 5.8 presents the results of the correlation matrix from the multivariate regression. The likelihood ratio test *(Chi^2 (21) = 731.941; Prob > Chi^2 = 0.0000)* of the independence of the error terms is significantly different from zero at 1%, thereby, allowing us to reject the null hypothesis that the error terms across the seven adoption decisions are correlated. The alternate hypothesis of mutual interdependence among the improved agricultural technologies was therefore adopted. The results therefore support the use of a multivariate probit model applied in this study as a heptavariate model.

The results also indicate that the joint probability of adopting all the improved technologies is 11.1%, while the joint probability using none of the improved technologies is 11.2%. From the linear predictions, the probability of a rice farmer adopting nursery, harrowing, spacing, and line planting are 34.8%, -22.7%, 11.5%, and 5.8% respectively. The probability of adopting urea briquette, irrigation, and bunding are -60.2%, 24.9%, and 3.1% respectively. All the pairwise coefficients were positively correlated, indicating complementarity among the improved rice production technologies. The relationship among all the complementary technologies were significant except for harrowing and nursery, harrowing and spacing, harrowing and line planting, and harrowing and urea briquette. The highest positive correlation was between spacing and line planting (97.5%), while the lowest was between harrowing and nursery (3.4%). As farmers adopt the complete package of improved rice production technologies, they may be able to maximise their impact of the technologies for improved output.

Table 5. 8: Correlation matrix of the technologies from the multivariate probit model

	Nursery	Harrowing	Spacing	Line planting	Urea briquette	Irrigation	Bunding
Nursery	1						
Har	0.034 (0.092)	1					
Spa	0.686 (0.053)^c	0.127 (0.088)	1				
Line	0.671 (0.051)^c	0.062 (0.087)	0.975 (0.009)^c	1			
Ure	0.665 (0.067)^c	0.057 (0.089)	0.693 (0.055)^c	0.668 (0.058)^c	1		
Irrig	0.798 (0.042)^c	0.219 (0.089)^b	0.590 (0.060)^c	0.539 (0.062)^c	0.491 (0.074)^c	1	
Bun	0.462 (0.074)^c	0.226 (0.082)^c	0.529 (0.062)^c	0.473 (0.068)^c	0.391 (0.072)^c	0.578 (0.057)^c	1
Line pred the	*0.348*	*-0.227*	*0.115*	*0.058*	*-0.602*	*0.249*	*0.031*
Join … uccess)				0.111			
Join … ailure)				0.112			
Log				-1301.0687			
Wal				757.66^c			

Likel … of $Rho_{ij} = 0$. Chi^2 (21) = 731.941 Prob > Chi^2 = 0.0000

^{a}, ^{b}, a … .0%, 5%, and 1% level of significance respectively.

Sourc … field data, 2017

5.3.2 Determinants of adoption of improved rice production technologies

This section presents the factors which influence the adoption of improved agricultural technologies by rice farmers. The parameter estimates of the multivariate probit model which account for the determinants of adoption of each of the seven identified technologies is presented first. Secondly, the results of zero inflated poison (ZIP) regression, negative binomial, and normal Poisson regression models which cater for the determinants of adoption intensity of the various technologies are also presented.

5.3.2.1 Parameter estimates: multivariate probit model

Several factors can influence rice farmers' decision to adopt one particular technology or the other. This sub-section identifies the variables which determine the adoption of improved agricultural technologies using multivariate probit (see Table 5.9). The model contained seven dependent variables (improved technologies) and seventeen explanatory variables, of which twelve were dummies and five continuous. Variables such as "other sources of information" to farmers, and some socioeconomic variables were dropped because they were extremely skewed, meaning there was very low number of respondents subscribing to those variables making them impossible to be modelled. The location variable (Region) showed a significant and negative relationship with rice farmers' decision to adopt harrowing, spacing, line planting, urea briquette, and bunding. This means that farmers in the Upper East region had a higher probability of adopting these technologies than their counterparts in the northern region. Expert interview with a technical staff at IFDC Ghana (originators of the Urea Deep Placement (UDP) technology) revealed that, IFDC had started the dissemination of the technology in the Upper East region before the northern region, under the USAID Ghana Agriculture Technology

Transfer project. Perhaps, the reason for the early adoption in the Upper East region. The technologies have also been established in Table 5.8 to be complementary, meaning the promotion and adoption of the UDP technology was contingent on the adoption of the others. Besides, the UDP technology has complementary elements that include line planting, proper spacing, proper leveling with accompanying water conservation mechanisms which is better achieved with bunding.

Communicating improved agricultural technologies to farmers is critical, and influences the adoption of these technologies. Four agricultural extension approaches/methods were modeled. Household extension method was significant and negatively related to the decision to adopt nursery, spacing, line planting, urea briquette, irrigation and bunding. This means that household extension method was less effective in influencing farmers' decision to adopt these technologies. This is understandable as the household extension method may not be able to promote cross learning and experience-sharing among farmers from different homes and backgrounds. Demonstration was not significant for two of the technologies (nursery and irrigation) but was significant with positive relationship for harrowing, spacing, line planting, urea briquette, and bunding. Perhaps, these technologies were considered technical by the farmers, hence their participation in demonstrations to acquaint themselves with the processes involved in carrying out these activities.

TV also had positive and significant relationship with nursery establishment, line planting, urea briquette and bunding, meaning, farmers with access to TV had a higher probability of adopting these technologies. Radio and video had significant relationship with the adoption of nursery, spacing, line planting, urea briquette, irrigation, and bunding. While radio had a positive association with all six technologies, video had a positive association with nursery, irrigation and bunding and a negative relationship with spacing, line planting and urea briquette. The implication of this finding is that, rice farmers who received information through a radio network had a higher propensity to adopt nursery, spacing, line planting, urea briquette, irrigation, and bunding more than farmers with no access to a radio. Again, farmers who had watched videos on nursery, irrigation and bunding had a higher tendency of adopting these technologies than those with less or no access to videos. However, those with access to watching videos had a lower tendency of adopting proper spacing, line planting and urea briquette. Radio and TV programmes regularly feature weather and agricultural information in developing countries, and rural telecentres have provided information on education and agricultural issues (Aker, 2011).

Access to mobile phone was also significant and negatively related to harrowing and line planting, meaning that farmers who had access to mobile phones had a decreased probability of adopting harrowing (about 30% less) and line planting (about 23% less). Harrowing is meant to teach farmers about proper conditioning of the soil and also to enhance levelling. Line planting on the other hand, is meant to ensure proper arrangement of the plant on the farm to allow for easy maintenance of farm hygiene and also to ensure the right cropping density per unit area. Line planting also allows for proper aeration on the farm. These two technologies require practical sessions for farmers to visualize how they are done on the field. Accessing them via mobile phone will therefore not offer the farmers the practical experience. Again, considering the poor nature of farmers and the illiteracy rates in the study area and the fact that the use of mobile phones was less in the study area (GSS, 2014), farmers may not be able to afford and use smart phones that have the ability to show pictures and videos with better graphics on the technologies. The low levels of education among farmers in the study area could also limit the use of smart phones which require some level of education to use.

Education was found to have a positive and significant relationship with the adoption of nursery, proper spacing, and urea briquette, but failed to explain the adoption decision of harrowing, line planting, irrigation and bunding. This result means that higher educational status increases farmers' awareness about the benefits of adopting nursery, proper spacing, and the use of urea briquettes. All these three technologies have theoretical underpinnings. Urea briquettes for instance, require some basic understanding of soil physics because of the nature of operation of the urea tablet while underneath water. Some level of education is also required to understand the protocols in the application of urea deep placement technology (Azumah and Adzawla, 2017; and Azumah et al., 2017). Danso-Abbeam and Baiyegunhi (2017), using multivariate probit model to study adoption interdependency among cocoa farmers in Ghana also concluded that education increases farmers' awareness and for that matter, the adoption of improved technologies. A similar study by Ahmed (2015) on the adoption of multiple technologies by farmers of the central rift valley of Ethiopia also found education to influence adoption decisions of farmers. Brick and Visser (2015), underscored the fact that educated people tend to be less risk averse, and so have a higher tendency of adopting improved technologies (Mulwa et al., 2017).

The results presented in Table 5.9 reveal that experience was positive and significantly related to only irrigation and bunding but insignificant in explaining the adoption of the other technologies. This finding implies that farmers with long years of rice production were more inclined to irrigating their farms and constructing bunds as a water conservation practice to boost production. To corroborate these finding during various focus group discussions, the farmers mentioned that experienced farmers are found mostly to have higher dependency rate and were more willing to take the risk in raining more income to support their families. One option for them is to adopt a double cropping system (i.e. irrigation) which can earn them more output and income. Bunding and irrigation are also highly interdependent, and so must be adopted together for effectiveness. To conserve more water in an irrigation system, bunds must be constructed to prevent the escape of water. Ahmed (2015), and Azumah, Tindjina, Obanyi, and Wood (2017), found experience to be insignificant in explaining the adoption of improved production technologies. However, Azumah, Donkoh, and Ansah (2017), found experience to significantly and positively influence farmers' adoption of climate smart coping strategies in northern Ghana.

Consistent with the finding of Ahmed (2015), membership of FBOs was found to significantly and positively influence the adoption of nursery, line planting, urea briquette, and irrigation. However, the variable had a significant and negative relationship with harrowing. Mulwa et al. (2017), also found a negative relationship between membership of FBO and the adoption of improved technologies. Adoption of line planting, urea briquette, nursery establishment and irrigation were found to be labour demanding. Belonging to an FBO therefore, helped farmers to offer labour services to members to practice these technologies. Harrowing on the order hand was delivered as a paid service to farmers for levelling purpose, mostly by a mechanised process. The cost of harrowing could not be taken up by the FBOs on behalf of its members. Most farmers did not therefore, practice harrowing because of the high cost.

Access to research institutions/service was found to significantly and positively influence the adoption of harrowing. Contrary to our a *priori* expectation however, research had a significant but negative relationship with the adoption of nursery, urea briquette, irrigation, and bunding, contradicting the finding of Danso-Abbeam and Baiyegunhi (2017), but corroborating the findings of Anang and Amikuzuno (2015), and Denkyiral et al. (2016). Most of the identified technologies where being researched and promoted by NGO led projects such as the ATT and ADVANCE II projects. State-led research agents in the study area did not provide extension services on the selected technologies to rice farmers, hence, the negative relationship between the adoption of those technologies and the action of the state-led research agents. Evidence from the focus group discussions indicated that there was a general weakness in the state-led research and agricultural extension system, leading to the arrogation of responsibility of researching and disseminating information to farmers by the NGO sector in the study area.

Recent studies by Azumah, Tindjina, Obanyi, and Wood (2017), and Danso-Abbeam and Baiyegunhi (2017), have shown that agricultural trainings received by farmers have enhanced farmers' adoption of improved agricultural practices. This study indicates that farmers' access to agricultural trainings significantly and positively influenced their adoption of nursery, spacing, line planting, urea briquette, irrigation and bunding. The education variable however, had a negative and significant relationship with only harrowing because the adoption of harrowing rather had cost implication.

Studies by Onumadu and Osahon (2014), Gyinadu, Bakang, and Osei (2015), and Mmbando and Baiyegunhi (2016) have shown that inadequate access to farm credit impedes the adoption of improved technologies by farmers. Credit constrained rice farmers were rather found to have higher probability of adopting nursery, spacing and irrigation but a lower probability of adopting harrowing. Nursery, spacing and irrigation required the use of farm labour which was mostly supplied by the farmers' households. However, harrowing is provided by tractor or rotovation service operators at a cost, and so farmers who lacked credit would rather apply the little resources they had on services that required upfront payment than those that could be handled with labour from the household or from group members. Meanwhile, Ahmed (2015) found the credit to be insignificant in explaining adoption decisions of farmers, while Kassie et al. (2015) found that credit was necessary to assist farmers in Malawi and Ethiopia to adopt minimum tillage practices. Mulwa et al. (2017), also found access to credit as a major determinant of farmers' decision to adapt to climate change.

Farm size was significant and had a negative relationship with all the technologies except harrowing. Meaning, farmers with bigger farm sizes were less likely going to adopt nursery, spacing, line planting, urea briquette, irrigation and bunding. This could be so because adopting these technologies would come with extra cost aside cost of seed and ploughing. Adopting some of the technologies could also be laborious. This result is in line with the study of Kassie et al. (2015), who suggested that the scarcity of land can induce agricultural intensification through the adoption of improved technologies, but contradicts the study of Bezu et al. (2014), and Danso-Abbeam and Baiyegunhi (2017), who found farm size to be significant and positively related to the adoption of improved technologies.

Household size had negative and insignificant relationship with most of the improved technologies. It was significant and correlated positively with only bunding. The justification is that larger size households had the necessary labour to construct bunds on their farm lands to improve water retention. Kassie et al. (2013; 2015), and Teklewold et al. (2013), in their previous studies, have also established some correlation between the adoption of improved technologies and household size.

The sex of the farmer was positive and significantly influenced the adoption of nursery, spacing and line planting, but redundant in explaining the adoption of the other technologies. This means that male farmers had a higher probability of adopting nursery, spacing and line planting compared to their counterpart female rice farmers. Rice production in the study area is male-dominated with the females providing mostly labour services for planting, harvesting and cleaning of rice. Also, land and productive resources are mostly owned and controlled by male farmers in the study area, naturally placing them ahead of their female counterparts in the application of resources to adopt technologies necessary to enhance the productivity of rice. Mulwa et al. (2017), and Ragasa et al. (2013) also found the sex variable to be positive and significantly influence the adoption of improved agricultural technologies.

The age of the farmer was also significant and positively related to the adoption of nursery, spacing, line planting, and urea briquette, but did not explain the adoption of harrowing, irrigation and bunding. The effect of this result is that as a farmer grew older, he/she had a higher probability of adopting nursery, spacing, line planting, and urea briquette. Simtowe, Asfaw, and Abate (2016), and Danso-Abbeam and Baiyegunhi (2017), also found a positive and significant relationship between the age of a farmer and the adoption of agricultural technology. However, Denkyirah et al. (2016), found a negative effect of age on adoption of pesticides.

Table 5. 9: Factors influencing the adoption of improved rice production technologies – results of multivariate probit regression

	Nursery		Harrowing		Spacing		Line planting		Urea Briquette		Irrigation		Bunding	
Covariate	**Coef.**	**Std. Err**	**Coef.**	**Std. Err**	**Coef.**	**Std. Err**	**Coef.**	**Std. Err**	**Coef.**	**Std. Err**	**Coef.**	**Std. Err**	**Coef.**	**Std. Err**
Regicn	0.?54	0.190	-2.181^{c}	0.261	-0.931^{c}	0.182	-0.960^{c}	0.179	-0.932^{c}	0.193	-0.044	0.185	-0.917^{c}	0.184
HH.	53^{c}	0.151	0.408^{c}	0.167	-0.663^{c}	0.150	-0.553^{c}	0.149	-1.171^{c}	0.160	-0.668^{c}	0.152	-0.365^{b}	0.154
Dem	54	0.162	0.769^{c}	0.193	0.529^{c}	0.160	0.695^{c}	0.152	0.855^{c}	0.190	0.248	0.172	0.523^{c}	0.160
TV	)2^{a}	0.183	0.220	0.193	0.169	0.180	0.298^{a}	0.178	0.312^{a}	0.190	-0.054	0.198	0.397^{b}	0.189
Radi	32^{b}	0.154	0.023	0.183	0.417^{c}	0.152	0.465^{c}	0.147	0.490^{c}	0.166	0.310^{b}	0.154	0.517^{c}	0.159
Vide	56^{a}	0.166	0.241	0.169	-0.568^{c}	0.156	-0.674^{c}	0.149	-0.373^{b}	0.161	1.034^{c}	0.176	0.540^{c}	0.171
Mobi	75	0.157	-0.302^{a}	0.159	-0.121	0.152	-0.232^{a}	0.154	0.010	0.153	0.020	0.150	-0.109	0.151
Educ	25^{a}	0.015	-0.009	0.015	0.022^{a}	0.014	0.014	0.013	0.031^{b}	0.014	0.022	0.014	0.004	0.014
Expe	)5	0.011	-0.001	0.011	-0.002	0.011	-0.013	0.010	0.013	0.010	0.022^{b}	0.011	0.028^{c}	0.011
FBO	55^{a}	0.156	-0.791^{c}	0.155	0.121	0.155	0.478^{c}	0.153	0.520^{c}	0.160	0.364^{b}	0.151	0.082	0.153
Rese	27^{c}	0.181	0.342^{a}	0.180	-0.063	0.175	-0.139	0.164	-0.351^{b}	0.173	-0.743^{c}	0.171	-0.778^{c}	0.165
Trair	34^{c}	0.200	-0.610^{c}	0.216	1.190^{c}	0.186	1.043^{c}	0.180	0.803^{c}	0.213	0.567^{c}	0.187	0.766^{c}	0.183
Cred	34^{c}	0.204	0.457^{b}	0.222	-0.294^{a}	0.193	-0.275	0.188	0.308	0.205	-0.788^{c}	0.213	-0.035	0.214
Farm	55^{c}	0.024	-0.016	0.019	-0.071^{c}	0.015	-0.058^{c}	0.013	-0.048^{b}	0.019	-0.165^{c}	0.039	-0.063^{c}	0.020
HH s	04	0.128	-0.003	0.011	-0.003	0.012	-0.010	0.011	-0.003	0.013	0.004	0.013	0.031^{b}	0.013
Sex	17^{b}	0.183	-0.045	0.194	0.411^{b}	0.170	0.710^{c}	0.171	-0.034	0.179	0.015	0.176	0.003	0.169
Age	5^{b}	0.008	0.002	0.008	0.026^{c}	0.008	0.028^{c}	0.007	0.017^{b}	0.007	-0.001	0.008	-0.002	0.008
Cons	33^{c}		0.356		-1.824^{c}		-2.204^{c}		-2.261^{c}		-0.336		-1.082^{c}	
No. c	*3*	0.368	*543*	0.377	*543*	0.379	*543*	0.382	*543*	0.411	*543*	0.367	*543*	0.380

Log 301.07; Wald chi^2(119) = 757.66^c.
^{a}, ^{b}, a .0%, 5%, and 1% level of significance respectively.
Sourc field data, 2017

[10] The technology transfer methods seek to achieve the same outcome, however, the process through which the result is achieved is different for the various methods

5.3.2.2 Determinants of rice farmers' decision for joint adoption of improved agricultural technologies (adoption intensity)

All seventeen (17) identified rice production technologies were included for the count data model. The results from Table 5.10 reveal that the mean joint adoption of the improved technologies by rice farmers was about eight. Less than 2% of the farmers did not adopt any of the seventeen improved technologies and thus have a zero count (see Table 5.10). Also, 13.26% of the respondents adopted six technologies, with about 11% adopting seven technologies. No farmer adopted all seventeen technologies together (see Table 5.10).

Table 5. 10: Intensity of practice of improved agricultural technologies

No. of improved technologies	Freq.	%
0	10	1.84
1	1	0.18
2	12	2.21
3	20	3.68
4	31	5.71
5	43	7.92
6	72	13.26
7	59	10.87
8	44	8.10
9	54	9.94
10	47	8.66
11	43	7.92
12	26	4.79
13	10	1.84
14	48	8.84
15	13	2.39
16	10	1.84
17	0	0.00
Total	543	100

Mean adoption = 8.3

Source: Analysis of field data, 2017

Parametric results of negative binomial (NB), Poisson regression and zero Inflated Poisson (ZIP) regression are provided in Table 5.11. Table 5.12 presents the parameter estimates of the logit (inflated) model for zero-inflated Poisson regression. Model specification was first tested by using the deviance and Pearson goodness of fit tests, coefficient of the alpha *(α)* parameter and the performance of Vuong test of Zero Inflated Poisson (ZIP) versus standard Poisson regression. AIC and BIC are also presented to aid in the selection of the right model. See Table 5.11 for the model specification test results.

Based on the result, the ZIP model estimation is preferred to the Poisson and the NB model, and therefore was considered for further analysis and discussion. Both the Pearson and deviance statistics in the Poisson model were statically significant, meaning the Poisson regressing model is inappropriate.

The Likelihood Ratio (LR) test of alpha *(α)*=0 in the negative binomial model, was significant at 10% level, leading to a decisive rejection of the null hypothesis of equi-dispersion, suggesting the absence of over dispersion. Negative binomial regression is always safer to run than Poisson regression because even if the overdispersion parameter, alpha, in Stata is not statistically significant, the results will be exactly the same as its Poisson regression form (Cameron and Trivedi, 2010). This is confirmed by our results in Table 5.11. Further tests for model selection revealed that the ZIP model had marginally lower AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion) estimates compared to the Poisson and NB models.

Likelihood ratio test of Vuong (1989) was then performed to identify a better model between the standard Poisson and the ZIP models (see model diagnostic test in Table 5.11). A large positive test value favours a ZIP model whereas a large negative value favours a

Poison model (Cameron and Trivedi, 2010). The Vuong test statistic was 2.51, and statistically significant at 1% level of significance, thereby favouring the ZIP model.

All seventeen identified rice production technologies were modeled for adoption intensity. Out of the thirteen explanatory variables that were included in the ZIP model, seven were statistically significant in explaining the intensity of adoption of improved rice production technologies. Demonstration, education, training, sex and age [11]of a farmer positively and significantly influenced adoption intensity of improved technologies. Access to research service, and farm size were also significant but with inverse relationship with adoption intensity.

Consistent with our a priori expectation and corroborating Uzonna and Qijie (2013), demonstration was significant and positively influenced rice farmers' adoption of more improved agricultural technologies. This implies that farmers who attended field days where improved technologies were demonstrated adopted more improved rice production technologies than their counterparts who did not participate in any technology demonstration filed days. Anandajayasekeram et al. (2008) noted that demonstration shows farmers the results of a practice that has been in use for some time. It is intended to arouse the farmers' interest in the practice. This can also be used to compare older practices or techniques with new ones. Method demonstrations on the other hand, show farmers how a particular activity or task is carried out. It is effective in teaching since farmers can practice, see, hear, and discuss during the demonstration (Anandajayasekeram et al., 2008).

[11] To show long term effect, the squared terms of experience and age were originally added as explanatory variables, but they were not significant in explaining adoption intensity. See appendix 4.

The positive relationship between experience and adoption intensity implies that long years of producing rice (modeled in this study as experience) results in farmers adopting more improved technologies to improve the output of rice in the long run. As farmers continue to produce, they learn new techniques, and are supposed to change or adapt to these new techniques as they progress on the learning curve. This result conforms to our a priori expectation and corroborated by the finding of Azumah, Donkoh, and Ansah (2017), who found a positive correlation between experience and adoption intensity.

Consistent with Olusegun, Dare, and Begho (2014), education was positive and significant in explaining adoption intensity, implying that farmer who were more educated had a higher probability of adopting more improved rice production technologies. Normally, education is supposed to provide knowledge. Education develops in people, the perspective of looking at life. It helps people (farmers) build opinions and have points of view on things such as the adoption of improved production techniques.

Consistent with our *a priori* expectation and in line with Azumah, Tindjina, Obanyi, and Wood (2017), training was positive and significantly related to the adoption of more improved agricultural technologies. The positive association implies that farmers who received training were more inclined to adopting more of the improved agricultural technologies as compared to their counterparts who did not receive any training the previous season. Donkoh and Awuni (2011) in their study on the adoption of farm management practices in lowland rice production in northern Ghana, argued that training is an added input which results in good performance and adoption by farmers. They further stated that the benefits of training included acquiring new knowledge, skills or attitudes being transferred to farmers. Also, Adesina and Baidoo-Forson (1995), found that farmers' participation in on-farm tests, as well as the number of times farmers attended trainings, influenced significantly and positively, their adoption of new agricultural technologies and good farm practices.

Sex (being a male) of the farmer was positive and significant. This implies that male rice farmers in the study area had a higher probability of adopting more improved agricultural technologies than their counterpart female rice farmers. This finding conformed to our a priori expectation. The finding could be attributed to the socio-economics and the socio-cultural orientations in the Northern part of Ghana where ownership of productive resources, especially agricultural land for rice production, is dominantly owned by men. These lands are mostly handed to male children as inheritance from their parents, with the explanation that female members of the household would be married out to other families in the future. The result of this study corroborates with Abdul-Hanan, Ayamga, and Donkoh (2014), who established that male farmers in Northern Ghana had a higher propensity to adopt more soil and water conservation techniques than females. They argued that adoption of these techniques was laborious and needed resources which typically are owned by men. Sadly, however, focus group discussions (FGDs) conducted with a number of farmer groups in the study area suggested that women, aside the tedious responsibility of housekeeping imposed on them by cultural and religious orders that pertain in the study area, women were still responsible for a larger chunk of the labour demands on the various rice fields across the study area. This include transplanting and weeding in rice fields. Again, women are involved in post farm activities across the entire value chain, including the value addition processes and marketing of rice, most of the time, on behalf of their households or husbands who have total ownership of the resources. The FGDs revealed that women were involve in the land preparation process, planting of rice (transplanting in most cases), harvesting, threshing, winnowing, bagging and carting of the rice to their homes. According to Uzonna and Qijie (2013), women play an indispensable role in farming and improving the quality of life in rural areas, especially in Africa. (FAO, 2011), further asserted that, over 80% of women in developing countries provide 60-80% of all agricultural labour, which appear to be the case in the study area.

Age was also positive and significant, implying that older farmers had a higher probability of adopting more improved rice production technologies. Perhaps, it could be said that older farmers have extended experiences. Having learned and applied various technologies over the years, they could adopt them because of the benefits they might have seen out of adopting those particular technologies.

Contrary to our *a priori* expectation, the results revealed that access to research service had a negative but significant relationship with the adoption intensity, suggesting that exposing farmers to agricultural research services (state-led) could actually reduce the adoption of more improved rice production technologies. The reason provided at the various focus group discussions was that the research services provided by the state-led institutions were not related to the technologies that were being promoted.

Another important result is the negative but significant association between farm size and adoption intensity of improved agricultural technologies. The negative association implies that, as the relative amount of land cultivated declines due to increasing population in the study area (GSS, 2014), farmers adopt more improved farm practices. Thus, improved agricultural technologies that encompass a number of intensification efforts are a direct response to an increase in household sizes relative to the amount of land cultivated in order to produce more food. It is likely also that, households with larger farm sizes could be labour constrained and so are not able to mobilize the required labour to apply improved production methods. However, this point seems not to be in operation in the study area as the evidence suggests that household labour use on farm (proxied in this study as household size) was redundant in explaining the intensity of adoption of improved agricultural practices. This result corroborates with Mensah-Bonsu et al (2017), and Nkegbe and Shankar (2014), who also found a negative and significant relationship between farm size and adoption intensity of land and water management practices among smallholder farmers in Northern Ghana. However, Danso-Abbeam and Baiyegunhi (2017), Danso-Abbeam, Setsoafia, and Ansah (2014), and Sharma et al. (2011), have estimated that the total area farmed is positively related to the intensity of technology adopted.

The logistic part of the ZIP model had six variables significantly explaining the adoption of improved technologies by rice farmers in the study area. Here, adoption had binary outcome (i.e. 1 for adopters and 0 for non-adopters). Education and age had positive and significant association with adoption of improved agricultural technologies. This implies that farmers who received more formal education and were older, adopted one or more of the improved technologies.

On the contrary, location (northern region), household size, demonstration, and mass media were significant but with negative association with adoption intensity. Meaning that farmers who were located in the northern region, those with larger household sizes, those who attended technology demonstrations, and those with access to mass media mechanisms for had lower probability of adopting one or more of the improved agricultural technologies.

Table 5. 11: Parameter estimates of the determinants of adoption intensity: comparing Negative binomial and Poisson regression

Variable	Poisson			Zero Inflated Poisson			Negative Binomial Regression		
	dy/dx	Coef.	Std. Err.	dy/dx	Coef.	Std. Err.	dy/dx	Coef.	Std. Err.
region	0.333	-0.021	0.041	-0.417	-0.051	0.042	-0.160	-0.020	0.043
hhsiz	[illegible]1	0.002	0.003	0.000	0.000	0.003	0.018	0.002	0.003
demo	[illegible]8	0.242***	0.044	1.589	0.202***	0.044	1.858	0.242***	0.046
mass	[illegible]5	0.025*	0.014	0.103	0.012	0.014	0.203	0.025*	0.015
educ	[illegible]5	0.004	0.003	0.066	0.008**	0.003	0.033	0.004	0.003
exper	[illegible]9	0.001	0.002	-0.001	0.000	0.002	0.010	0.001	0.002
Fbo	[illegible]6	-0.019	0.035	-0.220	-0.027	0.035	-0.143	-0.018	0.037
resea	[illegible]9	-0.151***	0.036	-1.048	-0.127***	0.037	-1.232	-0.151***	0.038
traini	[illegible]3	0.305***	0.045	2.313	0.299***	0.045	2.320	0.305***	0.047
credi	[illegible]9	0.005	0.049	0.233	0.028	0.050	0.027	0.003	0.051
Farm	[illegible]8	-0.022***	0.006	-0.170	-0.021***	0.006	-0.172	-0.021***	0.006
Sex	[illegible]5	0.176***	0.045	1.507	0.197***	0.045	1.331	0.174***	0.047
Age	[illegible]4	0.004**	0.002	0.044	0.005***	0.002	0.029	0.004**	0.002
_con		1.46***	0.088		1.470***	0.089		1.460***	0.092
alpha								0.011	0.009
No. o	*543*			*No. of Obs.* 543			*No. of Obs.* *543*		
LR c	Prob>chi^2= 0.000			LR chi^2 (13)= 247.97 Prob>chi^2= 0.000			LR chi^2 (13)=190.82 Prob>chi^2= 0.000		
Pseu				Pseudo R^2 = n/a			Pseudo R^2 = 0.0646		
Log l	2.8672			Log likelihood = -1338.447			Log likelihood = -1381.965		
AIC				AIC = 2732.894			AIC = 2793.93		
BIC				BIC = 2853.213			BIC = 2858.387		
Devi	fit = 685.4775***			zero obs. = 10			LR test of alpha=0: chibar2(01) = 1.80		
Pears	t = 603.1557**			non-zero obs. = 533			Prob >= chibar2 = 0.090		
Vuor	andard Poisson: z = 2.51 Pr>z = 0.0061								

*, **, [illegible] nt 10%, 5%, and 1% level of significance respectively.
Sourc[illegible] field data, 2017

Table 5. 12: Logit (inflated) model for zero-inflated Poisson regression

Variable	dy/dx	Coef.	Std. Err.
Region	-0.417	-1.919*	1.068
Hhsize	0.000	-0.526**	0.216
Demo	1.589	-2.640**	1.035
mass_media	0.103	-0.781*	0.429
educ_yrs	0.066	0.233***	0.078
experience	-0.001	-0.070	0.066
FBO	-0.220	-1.153	1.032
Research	-1.048	1.612	1.159
Training	2.313	-0.106	1.156
Credit	0.233	1.474	1.026
Farm_size	-0.170	0.081	0.089
Sex	1.507	14.393	838.337
Age	0.044	0.095**	0.041
_cons		-16.408	838.338

*, **, and *** represent 10%, 5%, and 1% level of significance respectively.

Source: Analysis of field data, 2017 (Stata output)

5.4 Technical efficiency of rice farmers in northern Ghana

This section examines the technical efficiency (TE) of rice farmers in northern Ghana. The choice of an appropriate variable for the first step (selection equation) is necessary for the implementation of the sample selection framework in SFA. This also allows for the determination of the effect(s) of technology adoption on the production frontier as well as TE.

The effect of the various technologies on the production frontier analysis as well as, on Technical Efficacy (TE) could not produce good results because the variables were found to be correlated (see Table 5.8 for the results of correlation analysis of the identified technologies). However, based on expert interviews with project officers who were implementing and managing various project at the time of the study, irrigation was identified as relevant choice variable among the seven technologies to consider for the purpose of modelling. Other literature such as Bravo-Ureta et al. (2012) and Villano et al. (2015) also considered irrigation for similar studies. The results in the next sections have therefore been partitioned for adopters and non-adopters of irrigation.

Therefore, two regimes of farmers (i.e. those producing under rainfed conditions and those producing under irritation) have been established for the purpose of analyses. That notwithstanding, the results of the pooled data have also been presented. [12]

[12] The results from Table 5.8 indicate that the identified technologies were correlated (interdependent). Initially, the variable “adoption intensity” was added to both the frontier and determinants of technical efficiency (TE) models, but did not yield good results, thereby constraining the researcher to the use of irrigation to draw the link between technology adoption and TE. Irrigation was selected based literature such as Bravo-Ureta et al. (2012) and Villano et al. (2015), and also because the study area has a unimodal rainfall pattern which makes the adoption of irrigation important for rice production.

In the preceding sections, the results of the selection equation (adoption of irrigation) is discussed before that of the substantive equation (technical efficiency) by looking also at the frontiers for the different systems or regimes. The estimates of the probit model was used to obtain a propensity score (the predicted probability of participation in irrigation) for each farmer after which each irrigation farmer was matched to a rainfed counterpart with similar propensity score. The propensity score matching technique produced a subsample of 538 matched observations, comprising 223 irrigation farmers and 315 rainfed farmers. The study used the new sub-sample to estimate the production frontier by ensuring that the matched samples were within the common support region to ensure the robustness of the matching. As mentioned above, the common support region indicates values of the propensity scores where the treated (irrigation farmers) and untreated units (rainfed farmers) can be found. Without a common support, suitable matches are unlikely to be obtained.

5.4.1 Determinants of adoption of irrigation technology

This section discusses the selection equation (adoption of irrigation) modeled as first step in the sample selection in stochastic frontier analysis. Table 5.13 presents the results of the probit sample selection model using the matched sample. Although the McFadden pseudo R-squared is low at 0.155, the chi-squared test statistic (113.5) is significant at 1% level, an indication of joint significance of the parameters for the irrigation adoption variables. Age, sex, location, membership of farmer based organisation, farm input subsidy, training, credit, household size, and farmers' perception about climate change, significantly influenced the adoption of irrigation.

Surprisingly, education was insignificant in explaining the adoption decision of farmers, contradicting the finding of Villano et al. (2015), who found the education variable to be significant and positive in determining the adoption of irrigation. Age and sex were found to be negatively related to the adoption of irrigation. The coefficients from Table 5.13 reveal that younger farmers had a 1.7% higher probability of producing rice under irrigated conditions compared to their older counterparts. The reason is that the older farmers were moving more towards rainfed conditions that offered them more land for expansion purpose. Female farmers in the study area also had a 48.8% higher probability of participating in irrigation than their counterpart male farmers. The male farmers who controlled more resource and land were possibly moving to rainfed conditions in order to have more cultivated lands.

The results from Table 5.13 also show a positive and significant relationship between the location variable and adoption of irrigation, indicating that farmers in the northern region had higher adoption drive (30.8% more) for irrigation than those in the upper east region of Ghana. This was possibly because the irrigation schemes in the northern region were undergoing assessment for expansion.

Also, there was a significant but negative relationship between FBO and adoption of irrigation, implying that farmers who belonged to FBOs had a lower probability (36.5% less) of adopting irrigation. The reason is that the farmers who belonged to groups had contractual obligations that compelled them to increase production by acquiring more land which was not available under irrigation conditions. Azumah, Donkoh, and Ansah (2017), and Azumah, Donkoh, and Ehiakpor (2016) found that belonging to a group was a necessary condition for farmers to be contractually engaged by market actors in the crop value chains in Northern Ghana.

Farmers who had access to subsidised farm inputs participated more in irrigation than their counterparts who had no access. Studies (e.g. Druilhe and Barreiro-Hurle, 2012; Chirwa and Dorward, 2013; Dorward and Chirwa, 2013).) suggest that input subsidies have had a wider impact on the economy through increased food crop production, which lead to a reduction in consumer food prices, to the benefit of poor food consumers; and an increase in rural agricultural wages. However, the benefit of agricultural subsidy programmes has varied with the nature of the subsidies and their context in the market, as well as with the weather (Kato and Greeley, 2016), justifying the need for irrigation.

As expected, farmers who attended trainings had a greater probability (about 91% more) of adopting irrigation compared to their untrained counterparts. Many empirical findings including those of Donkoh and Awuni (2011), argued that training is an added input which embraces good performance and adoption. They further stated that the benefits of training included acquiring new knowledge, skills or attitudes being transferred to farmers. In their study also, Azumah, Tindjina, Obanyi, and Wood (2017), found that farmers' participation in trainings influenced positively, their adoption of new and improved agricultural practices including the urea deep placement technology.

Access to credit is expected to influence technology adoption decision of farmers positively (Anang et al., 2016; and Villano, 2015). However, our result shows otherwise where access limited adoption of irrigation by close to 70%, contradicting our *a priori* expectation. Our findings in the previous sections suggested that irrigation farmers had smaller land holdings compared with their counterpart who produced under rain fed system, and so may not require any credit to invest in inputs considering that credit acquisition comes with cost associated with interest payments.

Azumah, Donkoh, and Ansah (2017) have noted the prevalence and the negative effect of climate change in the study area, thereby causing farmers to adjust by employing a number of coping and adaptation strategies. The perception of farmers about the prevalence of climate change was found to be significant and positively related to the adoption of irrigation, corroborating with Azumah, Donkoh, and Ansah (2017), who also found a positive and significant correlation between adopting irrigation and perception of farmers about climate change. Also, the variable household size is inversely related to the adoption of irrigation at the 1% significance level, suggesting that larger households are more averse to adopting irrigation than smaller households.

Table 5. 13: Parameter estimates of probit selection equation for irrigation using matched sample

Variable	Coef.	Std. Err.
Age	-.01711***	0.006
Sex	-0.48832***	0.180
HH head	0.14699	0.154
Education	0.01264	0.012
Commercial	-0.15443	0.125
Experience	0.01211	0.009
Location (Region)	0.30812*	0.161
FBO	-0.36539***	0.129
Subsidy	0.25765*	0.153
Training	0.91004***	0.153
Credit	-0.70239***	0.198
CC Perception	0.35782***	0.138
HH size	-0.02741***	0.010
McFadden pseudo R^2	*0.155*	
Log-likelihood function	*-308.26*	
Chi^2 test statistic	*113.5****	
Number of Obs.	*538*	

*, **, and *** represent 10%, 5%, and 1% level of significance respectively.

Source: Analysis of field data, 2017

5.4.2 Production frontiers

The result of hypotheses tests conducted to select the functional form, i.e. the choice between Cobb–Douglas vs. translog functional form (H_0: $\beta_{jk} = 0$) is first presented and discussed. However, given the complexity of our model and the focus on the empirical significance of the framework applied, the study concentrated on the choice of an appropriate functional form that is also flexible. The generalised likelihood ratio (LR) test (see Table 5.14) confirmed that the translog production function is suitable for the production structure in our case. The translog specification presented a smaller AIC (771.7) compared with the 842.7 for the Cobb-Douglas specification, also providing sufficient justification for our choice of the translog production function.

Table 5. 14: Generalised likelihood-ratio test of hypothesis

Null hypothesis	LR statistic (λ)	Critical value *	Decision
Production function Cobb-Douglas	100.96	36.17	Reject H_0. Use Translog PF
AIC:	Translog = 771.7	Cobb-Douglas=842.7	Reject H_0. Use Translog PF

*Critical value for the production function is obtained from Kodde & Palm (1986) at 5% two tail reading

The maximum likelihood estimates of the conventional and selectivity-corrected stochastic production frontiers (SPFs) using the matched samples [13]are presented in Table 5.15. All variables in the translog models were normalised by their corresponding geometric means so that the first-order coefficients can be interpreted as partial elasticities of output with respect to inputs at mean values (Villano et al., 2015; Coelli et al., 2003).

[13]The study proceeded with the matched sample because of our objective of eliminating both observed and unobserved biases corrected for by the PSM and sample selection framework.

In Table 5.15, we present the results of the stochastic production frontier model corrected for selectivity bias. In the same table, the results for the conventional frontier without correcting for selectivity bias (with technical inefficiency effects), to allow for comparison is also presented.

Both the estimates of σ_u and σ_v in the conventional and sample selection models are significantly different from zero at the 1% level, indicating good model fits. The coefficients on the selectivity bias variables ($\rho_{w,v}$) are significantly different from zero at the 1% level for all the sample selection frontiers, which confirm that selection bias exists, thereby providing sufficient justification for the use of a sample selection framework in the stochastic frontier model. In other words, estimation using observations from only single system of production (either rain fed or irrigation) will provide biased estimates of the frontier, which will then be carried on to the biased estimates of efficiency scores as well (Bravo-Ureta et al., 2012; Villano et al., 2015).

Results from the stochastic production frontiers controlling for selectivity bias reveal that output of rice farmers increased with farm size, diverging from the finding of Donkoh, Ayambila, and Abdulai (2013), but reduced with quantity of seed used in the pooled frontier. Indeed, continuous adjustments in the quantity of seed used could cause overcrowding which in itself can lead to poor performance of crops due to poor air circulation and competition for nutrients among the crops.

Four out of five estimated linear coefficients in the selectivity-corrected SPF for irrigation are significant in explaining the output of rice farmers, with all of them being insignificant in explaining output in the frontier of rain fed farmers.

As expected, farm size and fertilizer had positive relationship with output of irrigation rice farmers corroborating with Azumah and Adzawla (2017), and Mariano et al. (2010). Similarly, Addison et al. (2016), Kea, Li, and Pich (2016), and Donkor and Owusu (2014) also estimated a positive effect of farm size on rice output.

Output of irrigation rice farmers was however found to be inversely related to the quantity of seed and herbicide used. The elasticities from Table 5.15 imply that as farmers increased their usage of seeds and herbicides by a unit, output of rice was reduced by about 15% and 52% respectively. These finding diverged from Anang et al. (2016), and Nkebge (2012). Continuous increases in the amount of fertilizer and herbicides were also found to increase output marginally. Most of the interaction variables were only significant in explaining the output of rice farmers in the irrigation frontier. The interaction of farm size and fertilizer, farm size and herbicide, and Seed and herbicides were necessary for increased production of rice under irrigation ecology.

In both the conventional and sample selection models, farm size had the highest elasticity value, corroborating with Rahman and Barmon (2015), and Rahman et al. (2009). The elasticity of farm size in the sample selection frontiers was 0.92 and 1.34 respectively for the pooled and irrigation frontiers, implying that a 100% increase in land allocated for rice production will increase output by 92% and 134% respectively for the pooled and irrigation frontiers.

This finding, corroborates with Ragasa et al. (2013), that the increases in the output of rice in the study area has largely been due to expansion in farm sizes and not necessarily due to the use of farm inputs and improved production techniques. This phenomenon should be of serious concern to stakeholders of the agricultural sector in Ghana as the present population growth rate and statistics do not support the theory of a positive relationship between farm output and farm size.

The food security drive by Ghana, supported by the agricultural policies of the country should emphasize intensification and the adoption of productivity improving practices by farmers, as the per capita land area continues to reduce due to geometric population growth in Ghana. In the long run, there would not be any more land available for farmers to continue to expand their farm sizes to improve the output of rice.

Table 5. 15: Parameter estimates of SPF model using matched sample

Variable	Convectional SPF						Sample selection SPF					
	Pooled		Irrigation only		Rain fed only		Pooled - sample		Irrigation		Rain fed	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Const.	3.988***	0.044	3.944***	0.062	4.053***	0.063	3.970***	0.066	3.942***	0.023	4.007***	0.114
Farm size	0.920***	0.074	1.205***	0.011	1.283***	0.095	0.923***	0.084	1.336***	0.034	1.144	0.122
Labour	0.067*	0.04	0.044	0.071	0.256***	0.093	0.069	0.053	0.023	0.018	0.11	0.102
Seed	-0.235***	0.027	-0.157***	0.045	-0.235***	0.051	-0.158***	0.034	-0.153***	0.016	-0.107	0.08
Fertilizer	.014	0.047	0.053	0.108	-0.127**	0.057	-0.018	0.049	0.132***	0.028	-0.071	0.113
Herbicide	124*	0.064	-0.266	0.221	-0.074	0.102	0.062	0.081	-0.520***	0.047	-0.076	0.138
Farm size^2	76***	0.026	0.183***	0.042	-0.071**	0.035	0.013	0.02	0.224***	0.01	-0.085**	0.036
Labour^2	0198	0.017	-0.0187	0.017	0.025	0.03	-0.014	0.02	-0.0098*	0.005	0.0022	0.038
Seed^2	46***	0.006	-0.014	0.01	-0.060***	0.011	-0.044***	0.007	-0.012***	0.002	-0.036**	0.015
Fertilizer^2	.004	0.011	0.006	0.014	-0.025	0.015	-0.012	0.009	0.051***	0.007	-0.0277	0.035
Herbicide^2	.033	0.03	0.104	0.073	-0.022	0.034	-0.054	0.037	0.145***	0.022	-0.04223	0.061
Farm Size	0756	0.058	-0.009	0.066	0.207*	0.125	0.066	0.067	-0.052**	0.021	0.26375*	0.142
Farm size*	.036	0.048	-0.069	0.056	-0.085	0.064	0.0097	0.049	-0.071***	0.017	-0.06171	0.089
Farm size*	34***	0.072	0.175*	0.09	0.009	0.102	0.235***	0.072	0.173***	0.027	-0.17683	0.139
Farm size*	.013	0.088	-0.379**	0.151	0.159	0.11	0.182***	0.066	0.473***	0.042	0.28069**	0.123
Labour*Se	049*	0.027	0.026	0.034	-0.145***	0.051	-0.038	0.034	0.0063	0.008	-0.09272	0.065
Labour*Fe	.037	0.052	-0.034	0.073	-0.012	0.068	0.072	0.059	-0.016	0.021	0.05588	0.105
Labour*H	.065	0.063	-0.075	0.074	-0.02	0.125	-0.087	0.07	-0.036	0.025	-0.1116	0.133
Seed*Ferti	)91**	0.036	-0.055	0.069	0.214***	0.06	0.132***	0.04	-0.093***	0.017	0.20680**	0.103
Seed*Herb	31***	0.046	0.06	0.086	0.178***	0.058	0.056	0.054	0.071***	0.022	0.08807	0.082
Fertilizer*	.042	0.073	-0.288**	0.117	-0.151	0.093	0.03	0.074	-0.458***	0.035	-0.01806	0.139
L. Like	-362.855		-35.986		-235.691		-671.929		-187.078		-408.302	
gamı	0.947		0.969		0.972							
lamb							2.056		9.093		1.324	
σ(	12***	0.525	5.618***	1.593	5.866***	1.336	0.689***	0.047	0.644***	0.012	0.627***	0.098
σ (	07***	0.001	0.503***	0.002	0.907***	0.002	0.335***	0.031	0.071***	0.01	0.474***	0.06
Selectivity							0.727***	0.085	0.99998***	0.001	0.823***	0.092
l	*538*		*223*		*315*		*538*		*223*		*315*	

*, **, and * represent 10%, 5%, and 1% level of significance respectively.

Source: Analysis of field data, 2017

5.4.3 Efficiency estimates of rice farmers in Northern Ghana

Summaries of technical efficiency (TE) scores of the matched samples are presented in Table 5.16. The first sets of TE estimates are from the conventional stochastic production frontier (SPF), i.e. TE-Pool, TE-irrigation, and TE-rain fed. The second set of TE estimates are from the selectivity-corrected SPFs (TE-Sample Selection SPFs) models for the matched samples in order to evaluate the efficiency differentials across alternative specifications. Except irrigation, the results reveal that TE estimates improve marginally upon implementing the sample selection framework. Using the pooled estimates (TE-Pool), the mean TE increased from 60.6% to 62.2% (comparing the conventional and sample selection SPF respectively).

The mean technical efficiency of irrigation farmers, corrected for selectivity bias, is estimated at 68%, implying that 32% [100-68] of the production is lost due to technical inefficiency alone. This implies that the average farmer producing under irrigation condition could increase production by improving their technical efficiency.

The mean technical efficiency of rain fed farmers, corrected for selectivity bias, is estimated at 63.4%, implying that 36.6% [100-63.4] of the production is lost due to technical inefficiency alone. This finding, which corroborates with Nkegbe (2012) implies that the average farmer producing under rain fed condition could increase production by about 36.6% by improving their technical efficiency. Overall, the efficiency scores for irrigation farmers were relatively higher compared to their counterpart rain fed farmers for both the conventional and the corrected selectivity bias SPFs, implying that the farmers who produced under irrigation were more technically efficient than those who produced under rain fed condition. For example, while 13.5% of the irrigation farmers operated at efficiency level of 91% and above, only 2.5% of the rain fed farmers operated at this efficiency level for the conventional frontiers. In the corrected selectivity bias frontiers, about 12% of irrigation farmers operated at efficiency level of 91% and above as against 0% for their counterpart rain fed farmers. Previous studies have estimated the technical efficiency of rice farmers in the study area to be high. This obviously could be due to the estimation processes adopted by those authors which did not account for selectivity bias. For example, Azumah and Adzawla (2017) estimated the technical efficiency of rice farmers in the study area to be about 92%, while Donkoh, Ayambila and Abdulai (2013), estimated the technical efficiency of rice farmers in the Tono irrigation scheme to be 81%.

Table 5. 16: Frequency distribution of technical efficiency of rice farmers

Eff. Score	Conventional SPF						Sample selection SPF					
	Pooled		Irrigation		Rain fed		Pooled		Irrigation		Rain fed	
	Freq.	%	Freq.	%	Freq.	%	Freq.	%	Freq.	%	Freq.	%
10-20	0.0	0.0	0.0	0.0	0.0	0.0	10	1.9	1	0.4	2	0.6
21-30	0.0	0.0	0.0	0.0	0.0	0.0	15	2.8	7	3.1	8	2.5
31-40	118	21.9	0.0	0.0	0.0	0.0	35	6.5	20	9.0	13	4.1
41-50	53	9.9	0.0	0.0	127	40.3	68	12.6	22	9.9	32	10.2
51-60	80	14.9	57	25.6	45	14.3	74	13.8	27	12.1	60	19.0
61-70	105	19.5	30	13.5	36	11.4	128	23.8	26	11.7	70	22.2
71-80	73	13.6	64	28.7	43	13.7	132	24.5	40	17.9	105	33.3
81-90	99	18.4	42	18.8	56	17.8	71	13.2	53	23.8	25	7.9
91-100	10	1.9	30	13.5	8	2.5	5	0.9	27	12.1	0	0.0
Total	538	100.0	223	100.0	315	100.0	538	100.0	223	100.0	315	100.0
Min	*33.7*		*59.4*		*40.6*		*13.3*		*18*		*18.4*	
Max	*95.2*		*96.6*		*85.9*		*93.3*		*97.5*		*89.2*	
TE-Mean	*60.6*		*74.4*		*60.0*		*62.2*		*68.0*		*63.4*	

Source: Field data, 2017

5.4.4 Determinants of technical efficiency among rice farmers in Northern Ghana

The determinants of efficiency (or inefficiency) indicate the potential sources of efficiency that could be relevant for policy formulation. In Table 5.17, we present the translog maximum likelihood estimates of the determinants of technical inefficiency. The translog maximum likelihood frontier estimates are from a two-stage selectivity-corrected pooled sample SPF and inefficiency models. For comparison, we present separate estimates for the group (irrigation and rain fed) as well as that of the pooled corrected selectivity bias data. The individual rice producing technologies could not be added to the model because of their correlated nature (see Table 5.8). The coefficients for the technical inefficiency results are interpreted by their signs, such that a positive (negative) coefficient indicates a positive (negative) effect on inefficiency. We only discuss the determinants focusing on variables that are statistically significant at conventional levels.

In the inefficiency model of the pooled results, sex, location, household size, credit and perception of farmers about climate change were found to be significant at conventional levels and positively related to technical inefficiency (negatively related to technical efficiency). The coefficients of subsidy, experience, commercialisation and household head are also found to be significant at conventional levels but negatively related to technical inefficiency (positively related to technical efficiency).

In the 'irrigation only' group, technical inefficacy was influenced by age, sex, education, farmer's commercialisation drive, location, membership of farmer association (FBO) and household size.

The coefficient of age is negative and significantly different from zero, implying that younger farmers were more inefficient compared to older farmers. The coefficient of sex is negative and significantly different from zero at 1% level, indicating that female farmers were more inefficient compared to their male counterparts. The positive and significant sign of the coefficient of the education variable indicates that farmers who received more formal education were more inefficient, contrary to our *a priori* expectation.

The coefficient of commercialisation was also negative and significant at 1% level, implying that irrigation farmers who produced for subsistent purpose were more inefficient compared with their counterparts who had commercialisation drive, corroborating with our *a priori* expectation that commercial farmers were most likely going to commit more resources to production and will invest in improved practices to increase output and their incomes, to compensate for their investments.

Location was also found to bear a significant and negative relationship with technical inefficiency. This means that rice farmers in the Upper East region were found to be more technically inefficient compared to their colleague farmers in the Northern region of Ghana. FBO is positive and significant at 10% level, indicating that farmers who belonged to farmer associations were less inefficient as compared to those who did not belong to any farmer group. This also means that the efficiency of farmers improved based on their association with farmer based organisations. This could be due to the benefits in trainings that farmers can harness by from NGOs who offer such service to farmer-groups. In the groups also, farmers can benefit from the farmer-to-farmer knowledge transfer mechanisms which have the tendency to improve efficiency. The significant and positive association between household size and technical inefficiency imply that households with larger membership were more technically inefficient, while smaller size households exhibited better levels of technical efficiency.

Conversely, technical inefficiency in the 'rain fed only' group was influenced education, experience, subsidy, location, training, and the perception of the farmers about climate change in the study area. The negative and significant sign of the coefficient of the education variable indicates that farmers who received more formal education were less inefficient, agreeing with our a priori expectation. This was rather the reverse for the 'irrigation only' group. The reasons for this diverging situation was not sufficiently explored by this present study and so need further investigations.

Experience was found to be negative and significantly related to inefficiency, implying that farmers with relatively longer years of experience of rice production under rain fed conditions were more efficient. Location was also found to bear a significant and positive relationship with technical inefficiency. This means that rice farmers in the Northern region who produced under rain fed conditions were found to be more technically inefficient compared to their colleague farmers in the Upper East region of Ghana. An important policy variable, subsidy, was also found to be positive and significantly related to technical inefficiency of rice farmers producing under rain fed conditions.

The negative sign of subsidy implies that farmers who received and used subsidised farm inputs were more technically efficient than those who did not receive subsidy. Also, rice farmers producing under rain fed conditions who received training, and those who perceived climate change to be present and dominant in the study area were found to be less technically efficient, as the covariates of training and climate change perception have positive and significant relationship with technical inefficiency.

The findings of this study corroborate similar studies in the area including Al-hassan (2008), who found education, extension contact, age and family size to be the main determinants of technical efficiency among rice farmers in Northern Ghana. Similarly, Anang et al. (2016) also found age, sex, educational status, access to irrigation and specialisation in rice production to be determinants of technical efficiency among rice farmers in northern Ghana.

Table 5. 17: Maximum likelihood estimates of determinants of technical inefficiency

Variable	Irrigation only		Rain fed only		Pooled	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Const.	*2.542*	*0.792*	-5.15***	0.981	-1.552***	0.479
Age	-0.038**	0.016	0.057	0.016	0.014	0.009
Sex	-1.005***	0.366	1.916	0.459	0.656***	0.237
HH head	-0.218	0.315	-0.734	0.299	-0.54***	0.194
Education	0.055***	0.021	-0.018**	0.026	-0.002	0.015
Commercial	-1.467***	0.283	-0.221	0.24	-0.579***	0.163
Experience	-0.002	0.021	-0.078***	0.021	-0.042***	0.012
Location	-0.722**	0.368	1.886***	0.436	0.631***	0.222
FBO	-0.565*	0.311	-0.432	0.287	0.052	0.177
Subsidy	-0.31	0.375	-0.869***	0.285	-0.713***	0.179
Training	-0.273	0.376	0.731***	0.278	0.112	0.184
Credit	0.553	0.508	0.465	0.332	0.575**	0.246
CC perception	-0.064	0.378	0.83***	0.264	0.344*	0.187
HH size	0.006**	0.022	0.035	0.021	0.046***	0.015
Log likelihood	5.77		-160.88		-318.61	
N	*223*		*315*		*538*	

***, **, and * represent 1%, 5% and 10% level of significance respectively

CHAPTER SIX

SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS

6.0 Introduction

This final chapter provides a summary of the study and conclusions emerging from the research. The chapter also contains policy recommendations as well as directions for future research.

6.1 Summary

Chapter 1 gives a general introduction of the study and presents the problem statement. The study noted that rice imports continue to surge ahead of production in Ghana, with accompanying increase in per capita consumption from 17.5 kg during 1999–2001 to about 32kg for 2015. There is evidence of low productivity among rice farmers in the study compared to other regions and national averages, however, net annual output of rice in Ghana continues to increase not due to improved technology by farmers, but through the expansion of farm sizes. The study found that various interventions have been rolled out to improve the rice sector in the study area. However, no significant effect is realised from these interventions. Among others, the study therefore sought to investigate the technology transfer approaches being used in the study area to disseminate information to rice farmers. After this introduction in chapter one, the research questions, objectives and the justification for the study are stated

Chapter two presents an overview of agriculture and the national economy of Ghana, underscoring the challenges of the sector and its relevance to Ghana's economy post-independence. The chapter also looked at the agricultural policy environment as well as the production and consumption patterns of rice in Ghana. Agriculture was found to be the backbone of Ghana's economy in the entire post-independence history, and continue to contribute substantially to Ghana's GDP but at a diminishing rate because the sector's growth was still led primarily by smallholders for subsistence purpose. The contribution of the agriculture sector to the GDP of Ghana has reduced from drastically since the late 1990s to around 18.5% in 2017. The yields of most food crops except cassava and yam have also been decreasing over the past five-year period (2009 to 2013). For instance, in comparing the yields of 2013 with 2012, yield of rice, maize, millet, sorghum, cowpea and soya bean recorded a decrease of 7.86%, 7.36%, 6.26%, 7.46%, and 8.13% respectively. Ghana's agricultural sector policy has evolved from post-colonial era when agricultural policies were geared towards the production of raw materials of export crops for western economies. We have passed through two different 5-year development plans (1951-56, and 1959-64), all aimed at developing Ghana's agricultural sector. Unfortunately, the policies at that time sought to address urban unemployment rather than focusing on rural development. The Economic Recovery Programme (ERP), and subsequently the Structural Adjustment Programme (SAP) in the 1980s saw the roll out of a programme for the agricultural sector dubbed "Ghana Agricultural Policy - Action Plans and Strategies (1984 - 86)". The plan highlighted self-sufficiency in the production of cereals, maintenance of adequate levels of buffer stocks of grains, particularly maize and rice, to ensure availability of food during the lean season, price stability and provision of maximum food security against unforeseen crop failure and other natural hazards. The Medium-Term Agriculture Sector Investment Plan (METASIP) was also designed to implement the Food and Agriculture Sector Development Policy (FASDEP II) over the medium term 2011-2015, aimed at achieving a target agricultural GDP growth of at least 6% annually, and halving poverty by 2015 in consonance with MDG 1. In terms of production, it was revealed that the land area under the production of rice has increased over the years, however, average yield per hectare is still low at about 2.5 MT/Ha as against the achievable yield of 6.5 MT/Ha.

In chapter 3, literature was reviewed on the concepts of agricultural extension approaches, extension models and methods. Agricultural extension is simply defined as the delivery of information and technologies to farmers. This leads to the technology transfer model of extension, seen by many as the main purpose of agricultural extension. By the definition, it was deduced that agricultural extension involves three key stakeholders who can either be linked cyclically or in a linear manner. It involves the researcher, the extension agent and the farmer who is at the receiving end. The relationship is said to be linear if there is no feedback or interaction between the farmers and the originators of the information that the farmers consume. The approach is the style of action within a system and embodies the philosophy of the system. It is like a doctrine for the system, which informs, stimulates and guides such aspects of the system as its structure, its leadership, its program, its resources and its linkages. Extension approach is a basic planning philosophy that is being adopted by an agricultural extension organisation. In the context of this study, extension approach is synonymously used with extension method, which refers to the techniques used by an extension system as it functions. For example, demonstration, or a visit by an extension agent to a farmer. Similarly, an extension model is said to be a schematic description of a system, or a phenomenon that accounts for its known or inferred properties and may be used for further study of its characteristics.

Also, in chapter three, both theoretical and empirical literature related to agricultural technology diffusion and adoption, as well as efficiency of rice farmers was reviewed and discussed. The approaches to measuring efficiency have been identified to include nonparametric programming approach, the parametric programming approach, the deterministic statistical approach and the stochastic frontier approach. All these approaches do not correct for biases stemming from both observed and unobserved errors. To determine the TE of rice farmers in northern Ghana, the study employs a combination of a recently developed stochastic production frontier model to control for biases arising from both observables and unobservables.

The methodology for the study is presented in chapter four, which provides some elaboration on data used and analytical frameworks. Basically, primary data from rice producing communities around the Upper East and Northern regions of Ghana was collected for this study. Descriptive statistics supported by chi squared distribution test and Kendall's coefficient of concordance were employed to identify and assess the various agricultural technology transfer methods and their perceived effectiveness in influencing adoption. Multivariate probit analysis was employed to analyse the factors that influence the adoption of improved rice production technologies. This was supported by the Zero Inflated Poisson model to estimate the factors that account for adoption intensity of improved agricultural technologies. SFA consistent with new approaches to be able to control for both observed and unobserved biases was also implemented. First, the study defined adequate control group using PSM to account for the effect of biases arising from observable variables. Bias stemming out of observed variables was then tested using a recently developed technique for stochastic frontier analysis (SFA) correcting for sample selection. The effects of adoption of various technologies on TE could not produce good results because of the correlated nature of the technologies, therefore, irrigation was selected for the various models based on literature and expert advice.

Chapter five presents the results and discussion of the findings of the study. NGOs, colleague farmers, research institutions, MoFA extension agents, the mass media (video, TV and mobile phones), and produce aggregators where found to be the main sources of information on improved agricultural technologies to rice farmers. Also, farmer-to-farmer approach, technology demonstration fields, household extension, and radio were found as the main agricultural technology transfer methods (extension methods) in use in the study area. There was a significantly low patronage of the mass media and ICT mechanisms such as video, mobile phone, posters, drama, and newspapers for communicating information to rice farmers in the study area. Farmers also perceived demonstrations, farmer-to-farmer, and household extension methods to be the most effective agricultural extension methods in the study area. Newspaper, poster, and TV were ranked the least in terms of perceived effectiveness.

It was revealed by the multivariate correlation coefficients, complementarities (positive relationship) among all the improved production techniques, and that the adoption of a given improved agricultural technology was conditional on the adoption of the others as indicated by the pairwise correlations. The interrelations among these improved production technologies suggest that farm-level policies that affect one improved agricultural technology for rice production can have spillover effects on the other technologies. The estimation results indicated that the variables affecting farmers' decisions to adopt a technology differ between technologies. Among the socioeconomic variables educational level of the farmer, household size, experience of the rice farmer, farm size, sex and age of the farmer play significant roles, partly with differing signs across technologies. Among the institutional factors, FBO membership, research, training and access to credit were significant with differing signs across the improved technologies. The location of the rice farmers also had significant and differing influence on the adoption of the improved technologies. Also, demonstration, TV, radio, video, mobile phones, and household extension methods were the technical/technology transfer methods that had significant and differing influence on the adoption of improved practices. From the estimates of the Zero Inflated Poison (ZIP) model, demonstration, education, training, age and sex of a farmer were found to positively influence the adoption intensity of improved agricultural technologies. Access to research service and farm size had negative relationship with the intensity of adopting improved agricultural technologies. Joint adoption of mass media approaches of technology transfer (i.e. TV, Radio, video, and mobile phone) were insignificant in explaining adoption intensity.

The effect of the various technologies on the production frontier analysis as well as, on Technical Efficacy (TE) could not produce good results because the variables were found to be correlated (see Table 5.8 for the results of correlation analysis of the identified technologies). However, based on expert interviews with project officers who were implementing and managing various project at the time of the study, irrigation was identified as relevant choice variable among the seven technologies to consider for the purpose of modelling.

The results of SPF model corrected for sample selection bias indicated that increase in farm size and fertilizer, as well as reduction in the usage of seed and herbicides were necessary to improve the output of rice farmers under irrigation conditions. No linear production input explained the output of rain fed farmers except for the interactions of the inputs. Except irrigation, the results reveal that TE estimates improve marginally upon implementing the sample selection framework. Using the pooled estimates (TE-Pool), the mean TE increased from 60.6% to 62.2% for the conventional and sample selection SPF respectively. The mean technical efficiency of irrigation farmers, corrected for sample selection bias, was estimated to be higher (68%) compared with their rainfed counterparts (63.4%). This meant that 32% [100-68] of the production is lost due to technical inefficiency alone for adopters of irrigation, and 36.6% [100-63.4] production lost for rainfed farmers. The results showed that without the appropriate corrections for sample selection, inefficiency was overestimated, while the performance gap between irrigation farmers and their rain fed counterparts was underestimated. The inefficiency model estimates for the "irrigation only" group indicate that technical inefficacy is influenced by age, sex, education, commercialisation drive, location, membership of farmer association, and household size. The inefficiency model estimates for the 'rain fed only' group indicates that technical inefficacy is influenced by some socio-economic, location and policy variables such as education, experience, subsidy, location, training, and the perception of the farmers about climate change in the study area.

6.2 Conclusions

Based on the key findings, the study concludes that non-governmental organisations, colleague farmers, and research institutions are the commonest source of information on improved production practices to rice farmers. Farmer-to-farmer method, use demonstration fields for training, household extension, and radio are the main extension methods in use in the study area. There is low use of mass media and ICT such as video, mobile phone, posters, drama, and newspapers for disseminating information to rice farmers.

There is complementarity among improved rice production technologies (nursery establishment, harrowing, line planting, spacing, urea briquette, irrigation, and bunding), meaning that the adoption of a given improved agricultural technology was conditional on the adoption of the others. This also implies that farm-level policies that affect one improved agricultural technology for rice production can have spillover effects on the other technologies. The study also concludes that variables affecting farmers' decisions to adopt a technology differ among technologies. Educational level of the farmer, household size, experience of the rice farmer, farm size, sex, age of the farmer, FBO membership, location, research, training and access to credit play significant roles, partly with differing signs across technologies.

Also, agricultural extension methods such demonstration, TV, mobile phones, radio, video, and household extension methods have significant influence on the adoption of improved rice production techniques.

Technical Efficiency (TE) estimates is higher for adopters of irrigation, and improved marginally upon implementing the sample selection framework in SFA, as the mean TE increased from 60.6% to 62.2% for the conventional and sample selection SPF respectively. The results revealed that without the appropriate corrections for sample selection, inefficiency would be overestimated, while the performance gap between irrigation farmers and their rainfed counterparts is underestimated.

6.3 Recommendations

The government of Ghana should collaborate with NGOs to empower nucleus farmers to establish technology demonstration farms where they can train other farmers on improved technologies. The nucleus farmers could be given technical trainings to equip them to be able to deliver community level extension services. The nucleus farmers could be assisted to use ICT and mass media mechanisms such as video, mobile phones, and radio since these methods can be used to reach out to many farmers at a lower cost.

Irrigation has been found to improve the technical efficiency levels of rice farmers in northern Ghana. Therefore, the government of Ghana should continually work with development partners and the NGO sector to develop the existing irrigation schemes in terms of irrigable land, and also construct bunds around the rice production valleys in the study area so that rice farmers could have more access to farm lands to increase production.

Older farmers who received more education were less technically inefficient. It is therefore important to revamp the “night school” programme to train younger farmers under irrigation schemes since they cannot sit in formal educational institutions. Agricultural content could be taught alongside numeracy and literacy to enhance the knowledge of the farmers.

Farmers are also advised to join or form groups to be able to learn new techniques of production from their colleague farmers, and also stand the chance of contracting loans and technologies which could increase their efficiency and output of rice.

The study recommends also that the estimation approaches (multivariate probit, and PSM with sample selection framework within SFA) be replicated for a national level study on the rice sector since our present study was limited to only two out of ten of the administrative regions of Ghana. Cross commodity studies could also be conducted using similar approaches as in this study.

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APPENDICES

Appendix 1: Reliability test for research instrument – Cronbach coefficient alpha

Item	Sign	item-test correlation	item-rest correlation	average interitem correlation	alpha
region	-	0.555	0.486	0.134	0.794
individual	-	0.246	0.156	0.145	0.809
demo	+	0.460	0.382	0.137	0.799
radio	+	0.239	0.149	0.145	0.809
TV	-	0.352	0.267	0.141	0.804
video	-	0.240	0.150	0.145	0.809
mobile phone	-	0.241	0.151	0.145	0.809
Education	-	0.271	0.182	0.144	0.808
experience	+	0.227	0.136	0.145	0.810
FBO	-	0.297	0.209	0.143	0.806
Research	-	0.309	0.222	0.142	0.806
training	+	0.456	0.378	0.137	0.799
credit	-	0.184	0.093	0.147	0.812
farm size	-	0.225	0.134	0.145	0.810
Commercial	-	0.656	0.598	0.130	0.789
Age	+	0.377	0.293	0.140	0.803
Sex	+	0.240	0.150	0.145	0.809
Household size	+	0.185	0.094	0.147	0.811
Nursery	+	0.479	0.403	0.136	0.798
harrowing	+	0.359	0.274	0.141	0.804
line planting	+	0.737	0.690	0.127	0.784
Spacing	+	0.763	0.720	0.126	0.783
urea briquette	+	0.692	0.639	0.129	0.787
Irrigation	+	0.470	0.393	0.137	0.798
Bunding	+	0.645	0.585	0.130	0.789
adoption intensity	+	0.870	0.845	0.122	0.777
Test scale				0.139	0.807

Appendix 2: Questionnaire for the collection of primary data

UNIVERSITY FOR DEVELOPMENT STUDIES

FACULTY OF AGRIBUSINESS AND COMMUNICATION SCIENCES

Department of Agriculture and Resource Economics

PhD (Agricultural Economics)

Name of respondents: ……………………………… Community: ………………………

SECTION A: SOCIO-ECONOMIC, INSTITUTIONAL AND LOCATION FACTORS THAT INFLUENCE ADOPTION

Socio-economic factors

1. Age of respondent: …………………………………………………….years
2. Sex of respondent: a) Male b) Female
3. Current marital status: a) Single b) married
4. Are you the household head? a) Yes b) No
5. Educational status: a) No formal edu. b) Primary c) JHS/Middle Sch. d) SSS/SHS e) Tertiary
6. Number of years in formal education: ………………………………… years
7. Type of farmer: a) for profit b) for subsistence
8. Household size: Male………Female………… # who earn income: …………
9. On a scale of 0-5, what is your level of access to television and radio?………
10. On a scale of 0-5, what is your level of access to mobile phone? ……………
11. Are you willing to pay for information about a new technology via mobile phone?

    a) Yes b) No

12. Ownership of livestock: a) Yes b) No

13. Experience in cultivating rice? …………….. years

14. Did you engage in off-farm activity in the last season? a) Yes b) No

15. If yes in Q14, what is the activity? …………………………………………….

16. What is the total annual income from this activity? …………………… GHC

17. Farm size for rice cultivation last season: ……………………………… acres

18. Total rice output last season (in 100kg bags): …………………………. bags

19. Unit price of rice last season: …………………………………………... GHC

20. Total revenue from rice last season: ……………………………………. GHC

21. Ownership of mechanised equipment for tilling the soil: a) Yes b) No

22. Total weekly HH food consumption expenditure: ………………….…... GHC

23. Total weekly HH non-food consumption expenditure: ……….………… GHC

Institutional and location factors

24. Region: a) Upper east b) Northern

25. District…………………..

26. Type of rice farmer: a) Irrigation b) rain fed c) both

27. Are you into contract farming? a) Yes b) No

28. If yes, has the contract helped in the adoption of any new technology?

a) Yes b) No

29. Are the contractual agreements favourable? a) Yes b) No

30. Farmer group membership a) Yes b) No

31. Length of being a group member: …………………………….. years

32. Farm land tenure system? a) Own b) Rented

33. Access to credit last season: a) Yes b) No

34. Amount of credit received last season: ………………………………. GHC

35. Access to research services: a) Yes b) No

36. Number of times of extension visits in the last season: ………… times

37. Have you had any training on rice production? a) Yes b) No

38. Distance of farm to market: …………………………………….. km

39. Distance from home to farm: …………………………………… km

40. Do you have adequate storage and processing equipment: a) Yes b) No

41. Did you have access to input last season? a) Yes b) No

42. Distance of farm to input dealer: ………………………………. km

43. Access to portable roads: a) Yes b) No

44. Beneficiary of fertilizer subsidy policy: a) Yes b) No

45. Quantity of subsidised fertilizer (in 50kg bags): ………………… bags

46. How do you perceive the rainfall pattern of this locality?

(a) Reducing b) increasing

47. How do you perceive the temperature regime of this locality?

(a) Reducing b) increasing

48. Is crop yield reducing as a result of climate change? a) Yes b) No

SECTION B: AGRICULTURE TECHNOLOGY TRANSFER METHODS AND THEIR PERCEIVED EFFECTIVENESS

49. Where do you often get information about improved agricultural technologies from? ***Choose as many as possible and rank from 1st to 6th.***

SN	Source	Yes/No	Rank
49a	MoFA extension agents		
49b	NGOs (i.e. IFDC)		
49c	Researchers (i.e. SARI)		
49d	Colleague farmers		
49e	Media (radio, TV, mobile phone etc.)		
49f	Others (i.e. produce aggregators)		
49g			

50. Indicate the level of use of the following technology transfer methods by extension agents on your location. Also rank them from **1st to 10th** according to the most used method **(1 being the most used approach):**

SN	Method		Level of use		Rank
			Often	Rarely used	
50a	Individual/HH				
50b	School approach	Lectures/discussions			
50c		Demonstration plots			
50d	Mass media	Radio			
50e		TV			
50f		Video			
50g		Mobile phone			
50h		Drama			
50i		Posters			
50j		News paper			
50k	Farmer to farmer				

51. What is the level of effectiveness of the following agriculture technology transfer methods in terms of influencing your adoption? *(Choose from a scale of 5-1). 5 being very effective and 1 being least effective.*

SN	Method	Level of effectiveness				
		5	**4**	**3**	**2**	**1**
51a	Individual/HH					
51b	Lectures/discussions					
51c	Demonstration plots					
51d	Radio					
51e	TV					
51f	Video					
51g	News paper					
51h	Drama and durbars					
51i	Posters					
51j 51k	Farmer to farmer					

52. Challenges associated with any of the above technology transfer methods:

…………………………………………………………………………………...

………………………………………………………………………………

………………………………………………………………………………

………………………………………………………………………………

SECTION C: EFFECT OF IMPROVED TECHNOLOGY ADOPTION ON OUTPUT AND INCOMES

53. Which of the following technologies did you practiced last season and how long have you been practicing these improved methods?

SN	Improved method	Adoption Yes/No	# of years of practice	Which organisation introduced the technology?	Mention the extension method used to introduce the technology
53a	nursery establishment				
53b	ploughing/rotovation				
53c	Harrowing				
53d	use of organics				
53e	leveling				
53f	puddling				
53g	transplanting				

53h	line planting				
53i	proper spacing (20x20cm)				
53j	dibbling/drilling				
53k	NPK and urea application				
53l	Use of urea briquettes				
53m	improved seed-early maturing				
53n	improved seed-drought tolerant				
53o	changing planting period				
53p	Bonding				
53q 53r	Irrigation				

54. How would you rate the price/cost of adopting the improved technologies? ***Please tick.***

SN	Improved method	high	moderate	low	No price
54a	nursery establishment				
54b	ploughing/rotovation				
54c	harrowing				
54d	use of organics				
54e	leveling				
54f	puddling				
54g	transplanting				

54h	line planting				
54i	proper spacing (20x20cm)				
54j	dibbling/drilling				
54k	NPK and urea application				
54l	use of urea briquettes				
54m	improved seed-early maturing				
54n	improved seed-drought tolerant				
54o	changing planting period				
54p	bunding				
54q 54r	irrigation				

55. Kindly indicate your level of agreement on the following practices as they help improve crop output and incomes *(5 being strongly agree and 1 being strongly disagree)*

SN	**Improved method**	**Level of agreement**				
		5	**4**	**3**	**2**	**1**
55a	nursery establishment					
55b	Ploughing/rotovation					
55c	Harrowing					
55d	Use of organics					
55e	Leveling					
55f	Puddling					
55g	Transplanting					
55h	Line planting					
55i	Proper spacing (20x20cm)					
55j	Dibbling/drilling					
55k	NPK and urea application					
55l	Use of urea briquettes					

55m	Improved seed-early maturing					
55n	Improved seed-drought tolerant					
55o	Changing planting period					
55p	Bunding					
55q	Irrigation					
55r						

56. What are the challenges to the adoption of these improved technologies? ……..

……………………………………………………………………………………..

………………………………………………………………………………………

SECTION D: INPUT USE BY RICE FAMERS

57. Kindly fill the table below on the inputs used in cultivating rice in the last season (cost in GHC)

SN	**Input**	**Only rice farm**	
		Total quantity used	*Unit cost (GHC)*
57a	Farm size (acres)		
57b	Family labour		
57c	Hired labour		
57d	NPK ***(# of 50kg bags)***		
57e	Urea/SA (Prilled) ***(# of 50kg bags)***		
57f	Urea (briquettes) ***(# of 50kg bags)***		
57g	Organic fertilizer ***(# of 50kg bags)***		
57h	Local Seed (in kg)		
57i	Improved seed (in kg)		
57j	herbicides (# of litres)		
57k	Insecticides (# of litres)		
57l	Ploughing /Rotovation		
57m			
57n			

58. Please rank the following challenges of rice production in your locality.

SN	Challenge	Rank (1^{st} to the last)
58a	High input cost	
58b	Access to credit	
58c	Poor management practices by farmers	
58d	Access to improved planting materials	
58e	Soil degradation	
58f	Pest and diseases	
58g	Access to markets	
58h	Poor commodity price	
58i	Research	
58j	Poor rainfalls	
58k	Availability of labour	
58l	Lack machinery	
58m		

59. What are the potentials of rice production in the region?

………………………………………………………………………………………

60. What needs to be done to enhance rice production in the region? ……………

………………………………………………………………………………………

Thank you

Appendix 3: GPS Coordinates of selected communities

COMMUNITY	REGION	DISTRICT	GPS COORDINATES	
			LAT	LONG
Yigwania	Upper East	Kasena Nankana East	10.88350000	-1.11656000
Konsingo	Upper East	Kasena Nankana East	10.89010000	-1.07397000
Boania	Upper East	Kasena Nankana East	10.86520000	-1.12450000
Gaani	Upper East	Kasena Nankana East	10.82480000	-1.07240000
Chuchuliga	Upper East	Builsa North	10.81650000	-1.18240000
Gowrie	Upper East	Bongo	10.85780000	-0.84190000
Vea	Upper East	Bongo	10.87350000	-0.86440000
Yikene	Upper East	Bolgatanga Municipal	10.81160000	-0.90353000
Bolga	Upper East	Bolgatanga Municipal	10.78660000	-0.85010000
Sumbrungu	Upper East	Bolgatanga Municipal	10.82260000	-0.92390000
Yorogo	Upper East	Bolgatanga Municipal	10.84390000	-0.83100000
Zaare	Upper East	Bolgatanga Municipal	10.81730000	-0.86330000
Tunayili	Northern	Tolon	9.58528000	-1.09490000
Gbinjari	Northern	Tolon	9.34493000	-0.96142000
Adumbiliyili	Northern	Tolon	9.55021000	-1.20002000
Wuba	Northern	Kumbumgu	9.44625000	-1.01367000
Botanga	Northern	Kumbumgu	9.57381000	-0.99604000
Kushibo	Northern	Kumbumgu	9.54494000	-1.03563000
Gbugli	Northern	Kumbumgu	9.56102000	-0.98455000
Yipelgu	Northern	Kumbumgu	9.59546000	-1.00872000
Bogu	Northern	Kumbumgu	9.52860000	-0.89430000
Dalung	Northern	Kumbumgu	9.62410000	-1.00700000

Kpalisogu	Northern	Kumbumgu	9.56870000	-1.03270000
Kumbungu	Northern	Kumbumgu	9.56090000	-0.94940000
Sakuba	Northern	Kumbumgu	9.59440000	-0.99740000
Tibung	Northern	Kumbumgu	9.57330000	-1.06150000
Voggu	Northern	Kumbumgu	9.53490000	-1.03720000
Zangbalung-Yipielgu	Northern	Kumbumgu	9.59400000	-1.00680000
Kupali	Northern	Karaga	10.12120000	-0.51609000
Tamaligu	Northern	Karaga	9.89137000	-0.39950000
Duna	Northern	Karaga	10.04540000	-0.43143000
Nyengbolo	Northern	Karaga	9.95727000	-0.37020000
Bagli	Northern	Karaga	10.20200000	-0.36340000
Karaga	Northern	Karaga	9.92270000	-0.43070000
Kpasablo	Northern	Karaga	9.89500000	-0.47960000
Monkula	Northern	Karaga	9.87140000	-0.46750000
Namburugu	Northern	Karaga	10.13000000	-0.37940000
Nanduli	Northern	Karaga	10.06200000	-0.40370000
Nangunkpang	Northern	Karaga	9.97330000	-0.44050000
Nyingali	Northern	Karaga	9.93700000	-0.31550000
Shellilanyili	Northern	Karaga	9.92050000	-0.34190000
Zogu	Northern	Karaga	9.91990000	-0.32670000
Sampibiga	Northern	Gushiegu	10.00050000	-0.26658000
Kpatili	Northern	Gushiegu	9.93009000	-0.27949000
Gaa Yapala	Northern	Karaga	9.80880100	-0.44512300
Kparum	Northern	Kumbumgu	9.55835000	-0.99064800
Namdu	Northern	Kumbumgu	9.53865800	-1.09406100

Libga	Northern	Savelugu Nanton	9.59125900	-0.84741100
Galinkpegu	Northern	Tolon	9.37499300	-0.95617700
Gbulahigu	Northern	Tolon	9.35266100	-0.95816900
Golinga	Northern	Tolon	9.35580800	-0.94538300
Bolga Nyariga	Northern	Tolon	10.84977400	-0.89853400
Biu	Upper East	Kasena Nankana East	10.76789500	-1.11243200
Korania	Upper East	Kasena Nankana East	10.86250900	-1.11175200
Paga	Upper East	Kasena Nankana West	10.95820400	-1.11004700
Wuru	Upper East	Kasena Nankana East	10.88526800	-1.12011100

Appendix 4: List of journal articles from the thesis – published and under review

1. Azumah, S. B., Donkoh, S. A., & Awuni, J. A. (2018). The perceived effectiveness of agricultural technology transfer methods: Evidence from rice farmers in northern ghana. *Cogent Food & Agriculture*, 4: 1-11. https://doi.org/10.1080/23311932.2018.1503798
2. Awuni, J.A., Azumah, S.B., and Donkoh, S.A. (2018). Drivers of Adoption Intensity of Improved Agricultural Technologies Among Rice Farmers: Evidence from Northern Ghana. *Review of Agricultural and Applied Economics, 21 (2): 48-57.* doi:10.15414/raae.2018.21.02.48-57.
3. Adoption of Improved Agricultural Technologies among Rice Farmers in Ghana: A Multivariate Probit Approach. Ghana Journal of Development Studies. Under review.
4. Correcting for Sample Selection in Stochastic Frontier Analysis: Insights from Rice Farmers in Northern Ghana. Agriculture and Food Economics. Under review.

Appendix 5: Some raw output from regression analyses

```
.  poisson adopt_int2 region hhsize  demo mass_media educ_yrs experience fbo resext training credi
> t farmsize sex  age age2 experience2

Iteration 0:   log likelihood = -1382.0607
Iteration 1:   log likelihood = -1382.0594
Iteration 2:   log likelihood = -1382.0594

Poisson regression                                Number of obs     =        543
                                                  LR chi2(15)       =     261.75
                                                  Prob > chi2       =     0.0000
Log likelihood = -1382.0594                       Pseudo R2         =     0.0865
```

adopt_int2	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
region	-.0242151	.0419082	-0.58	0.563	-.1063537	.0579235
hhsize	.002549	.0026332	0.97	0.333	-.002612	.00771
demo	.2432076	.0439355	5.54	0.000	.1570955	.3293196
mass_media	.0235144	.0143181	1.64	0.101	-.0045486	.0515775
educ_yrs	.0042597	.0032269	1.32	0.187	-.0020649	.0105842
experience	.0094282	.0068741	1.37	0.170	-.0040448	.0229013
fbo	-.0202539	.0355551	-0.57	0.569	-.0899407	.0494328
resext	-.1516073	.0364401	-4.16	0.000	-.2230286	-.080186
training	.3065713	.0453024	6.77	0.000	.2177802	.3953624
credit	.0044881	.0491752	0.09	0.927	-.0918935	.1008697
farmsize	-.0220098	.0058895	-3.74	0.000	-.033553	-.0104666
sex	.1756882	.0451937	3.89	0.000	.0871101	.2642663
age	.0004038	.0082593	0.05	0.961	-.0157842	.0165917
age2	.0000392	.0000936	0.42	0.675	-.0001442	.0002226
experience2	-.0002698	.0002134	-1.26	0.206	-.000688	.0001485
_cons	1.480172	.1787489	8.28	0.000	1.129831	1.830514

```
.  poisson adopt_int2 region hhsize  demo mass_media educ_yrs experience fbo resext training credi
> t farmsize sex  age

Iteration 0:   log likelihood = -1382.8684
Iteration 1:   log likelihood = -1382.8672
Iteration 2:   log likelihood = -1382.8672

Poisson regression                                Number of obs     =        543
                                                  LR chi2(13)       =     260.14
                                                  Prob > chi2       =     0.0000
Log likelihood = -1382.8672                       Pseudo R2         =     0.0860
```

adopt_int2	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
region	-.0214966	.0414949	-0.52	0.604	-.1028251	.0598319
hhsize	.0023408	.002596	0.90	0.367	-.0027472	.0074288
demo	.242151	.0438959	5.52	0.000	.1561165	.3281854
mass_media	.0254715	.0141937	1.79	0.073	-.0023476	.0532906
educ_yrs	.0041006	.0031531	1.30	0.193	-.0020793	.0102805
experience	.0012239	.0022992	0.53	0.594	-.0032824	.0057303
fbo	-.0191102	.035277	-0.54	0.588	-.0882518	.0500315
resext	-.1511368	.0363751	-4.15	0.000	-.2224307	-.0798429
training	.3046432	.0452512	6.73	0.000	.2159525	.3933338
credit	.0052529	.0491763	0.11	0.915	-.0911309	.1016368
farmsize	-.0219813	.0059155	-3.72	0.000	-.0335756	-.0103871
sex	.1759191	.0452126	3.89	0.000	.0873039	.2645342
age	.003558	.0017076	2.08	0.037	.0002112	.0069048
_cons	1.463385	.0878665	16.65	0.000	1.29117	1.635601

```
. zip adopt_int2 region hhsize  demo mass_media educ_yrs experience fbo resext training credit far
> msize sex  age, inflate (region hhsize  demo mass_media educ_yrs experience fbo resext training
> credit farmsize sex  age) forcevuong

Fitting constant-only model:

Iteration 0:   log likelihood = -1806.0889
Iteration 1:   log likelihood = -1475.9755
Iteration 2:   log likelihood = -1466.6453
Iteration 3:   log likelihood = -1462.6796
Iteration 4:   log likelihood = -1462.4385
Iteration 5:   log likelihood = -1462.4339
Iteration 6:   log likelihood = -1462.4339

Fitting full model:

Iteration 0:   log likelihood = -1462.4339
Iteration 1:   log likelihood = -1341.9027
Iteration 2:   log likelihood = -1338.7925
Iteration 3:   log likelihood =  -1338.541
Iteration 4:   log likelihood = -1338.4689
Iteration 5:   log likelihood = -1338.4521
Iteration 6:   log likelihood =  -1338.448
Iteration 7:   log likelihood = -1338.4472
Iteration 8:   log likelihood = -1338.4471
Iteration 9:   log likelihood =  -1338.447
Iteration 10:  log likelihood =  -1338.447

Zero-inflated Poisson regression                Number of obs     =        543
                                                Nonzero obs       =        533
                                                Zero obs          =         10

Inflation model = logit                         LR chi2(13)       =     247.97
Log likelihood  = -1338.447                     Prob > chi2       =     0.0000

------------------------------------------------------------------------------
  adopt_int2 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
adopt_int2   |
      region |   -.051395   .0417643    -1.23   0.218    -.1332515    .0304616
      hhsize |  -.0000903   .0026259    -0.03   0.973    -.0052369    .0050563
        demo |   .2015793   .0441552     4.57   0.000     .1150367    .2881219
  mass_media |   .0124461    .014389     0.86   0.387    -.0157557     .040648
    educ_yrs |    .008014   .0032217     2.49   0.013     .0016997    .0143284
  experience |  -.0001271   .0023011    -0.06   0.956    -.0046372    .0043829
         fbo |  -.0268263   .0353605    -0.76   0.448    -.0961315     .042479
      resext |  -.1265572   .0365943    -3.46   0.001    -.1982808   -.0548336
    training |   .2988168    .045058     6.63   0.000     .2105047     .387129
      credit |   .0283773   .0497401     0.57   0.568    -.0691115    .1258662
    farmsize |  -.0206538   .0057214    -3.61   0.000    -.0318675   -.0094401
         sex |    .196627   .0452497     4.35   0.000     .1079392    .2853149
         age |   .0053821   .0017392     3.09   0.002     .0019734    .0087908
       _cons |   1.470462   .0886735    16.58   0.000     1.296665    1.644259
-------------+----------------------------------------------------------------
inflate      |
      region |  -1.919149   1.068084    -1.80   0.072    -4.012555    .1742566
      hhsize |  -.5259931   .2162624    -2.43   0.015    -.9498596   -.1021266
        demo |  -2.639531   1.035001    -2.55   0.011    -4.668096    -.610966
  mass_media |  -.7812206   .4291483    -1.82   0.069    -1.622336    .0598946
    educ_yrs |   .2328073   .0778345     2.99   0.003     .0802544    .3853602
  experience |  -.0701201   .0656694    -1.07   0.286    -.1988299    .0585896
         fbo |  -1.152865   1.031991    -1.12   0.264     -3.17553    .8698004
      resext |     1.6123    1.15902     1.39   0.164    -.6593374    3.883938
    training |  -.1055921   1.155594    -0.09   0.927    -2.370515    2.159331
      credit |   1.474129   1.026001     1.44   0.151    -.5367953    3.485054
    farmsize |   .0814556   .0886516     0.92   0.358    -.0922983    .2552095
         sex |   14.39272   838.3367     0.02   0.986    -1628.717    1657.502
         age |   .0947178   .0411155     2.30   0.021     .0141329    .1753026
       _cons |  -16.40758    838.338    -0.02   0.984     -1659.52    1626.705
------------------------------------------------------------------------------
Vuong test of zip vs. standard Poisson:            z =     2.51  Pr>z = 0.0061
```

```
. nbreg adopt_int2 region hhsize  demo mass_media educ_yrs experience fbo resext training credit f
> armsize sex  age, dispersion (mean)

Fitting Poisson model:

Iteration 0:   log likelihood = -1382.8684
Iteration 1:   log likelihood = -1382.8672
Iteration 2:   log likelihood = -1382.8672

Fitting constant-only model:

Iteration 0:   log likelihood = -1724.9725
Iteration 1:   log likelihood = -1477.4273
Iteration 2:   log likelihood = -1477.3755
Iteration 3:   log likelihood = -1477.3754

Fitting full model:

Iteration 0:   log likelihood = -1400.6613
Iteration 1:   log likelihood = -1384.8176
Iteration 2:   log likelihood = -1382.2454
Iteration 3:   log likelihood = -1381.9778
Iteration 4:   log likelihood =  -1381.965
Iteration 5:   log likelihood =  -1381.965

Negative binomial regression                    Number of obs     =        543
                                                LR chi2(13)       =     190.82
Dispersion     = mean                           Prob > chi2       =     0.0000
Log likelihood =  -1381.965                     Pseudo R2         =     0.0646
```

adopt_int2	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
region	-.0198218	.0434089	-0.46	0.648	-.1049017	.0652581
hhsize	.002227	.0027419	0.81	0.417	-.0031471	.007601
demo	.2424483	.0455906	5.32	0.000	.1530924	.3318042
mass_media	.0251482	.0148216	1.70	0.090	-.0039017	.0541981
educ_yrs	.0041243	.0033158	1.24	0.214	-.0023745	.0106232
experience	.0012953	.0024168	0.54	0.592	-.0034417	.0060322
fbo	-.0176848	.0369851	-0.48	0.633	-.0901743	.0548047
resext	-.15122	.0380115	-3.98	0.000	-.2257213	-.0767188
training	.3051983	.0470361	6.49	0.000	.2130092	.3973874
credit	.0033214	.0514424	0.06	0.949	-.0975038	.1041465
farmsize	-.0213344	.0059977	-3.56	0.000	-.0330897	-.0095791
sex	.1743869	.0469881	3.71	0.000	.082292	.2664818
age	.0036023	.0017933	2.01	0.045	.0000874	.0071171
_cons	1.460488	.0917506	15.92	0.000	1.28066	1.640316
/lnalpha	-4.512387	.7905854			-6.061905	-2.962868
alpha	.0109722	.0086745			.00233	.0516705

```
LR test of alpha=0: chibar2(01) = 1.80                 Prob >= chibar2 = 0.090
```