Assessing the exposure and effect of adoption of improved rice varieties on technical efficiency and net rice income of rice farming households in Ghana

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Declaration

I confirm that this is my own work and the use of all material from other sources has been properly and fully acknowledged. I have also not submitted this thesis for a degree at any other university.

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Abstract

This study analysed exposure to improved rice varieties, and the effect of adoption on output and net rice income, whilst separating production technology gap from technical inefficiency in rice cultivation of 576 Ghanaian households using 2012/2013 production data. This was complemented with qualitative interviews to assess rice varietal diffusion, access and adoption, farmers' perceptions of varietal traits and constraints to rice cultivation. Exposure to improved rice varieties was estimated to account for non-exposure bias followed by determinants of adoption using treatment effect. A stochastic metafrontier was estimated to separate productivity differences due to technology gaps from technical inefficiency after correcting selection bias.

Adoption under incomplete exposure under-estimated the adoption rate as 55.9%, producing a non-exposure bias of 11.3%. The exposure rate and adoption rate of improved rice varieties were 82.5% and 67.2%. Community participation in rice projects, colleague farmers, agricultural extension agents and input dealers were sources of knowledge about improved rice varieties. Adoption was positively influenced by rice projects, participation in model and block farming, agricultural extension, higher rice yield motive, and cultivating irrigated rice. Traditional varieties were cultivated because of localized market demand and perceived resistance to bird infestation due to longer maturity period. Training rice processors on correct parboiling of jasmine 85 can increase its consumption in the local market. Meanwhile, seed, farm size, fertilizer, labour and herbicides application increased rice output of adopters whereas farm size and fertilizer had positive effect on the output of non-adopters. The mean difference in metafrontier technical efficiency of adopters (42.7%) and non-adopters (44.5%) were statistically not significant, although adopters had a higher metatechnology ratio of 0.91 compared with 0.79 for non-adopters. Thus, non-adopters were behind in applying the best available technology represented by the stochastic metafrontier. Adoption increased net rice income per hectare by GH¢374.6, whereas the potential gain if the non-adopters had adopted would have been GH¢867.5. Agricultural extension, controlling plot water levels and weeding twice using herbicides increased the technical efficiency of adopters. Applying ammonia fertilizer and weeding increased the technical efficiency of non-adopters.

The original contribution of this study is using nationally representative plot level data to establish that exposure to improved rice varieties and subsequent adoption increased the net rice income of smallholder Ghanaian farmers through increased yield, whilst weed and bird infestation, labour constraints, intermittent flash flooding and drought hampered rice cultivation.

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Dedication

This thesis is dedicated to the Abdulai family.

TABLE OF CONTENTS

List of Tables

List of Figures

List of Abbreviations

AE	Allocative Efficiency
AEA	Agricultural Extension Agents
AfDB	African Development Bank
AFD	French Agency for Development
AGRA	Alliance for Green Revolution in Africa
AMSECs	Agricultural Mechanization Service Enterprise Centres
ATE	Average Treatment Effect
ATT	Average Treatment effect on the Treated
ATU	Average Treatment effect on the Untreated
BH	Base Heterogeneity
CAADP	Comprehensive African Agriculture Development Programme
CARD	Coalition for African Rice Development
CGIAR	Consultative Group on International Agricultural Research
CRI	Crops Research Institute
CSIR	Council for Scientific and Industrial Research
DFID	Department For International Development
ECOWAS	Economic Community of West African States
EE	Economic Efficiency
ESR	Endogenous Switching Regression

FAOSTAT	Food and Agriculture Organization Statistics
FASDEP	Food and Agriculture Sector Development Policy
FBO	Farmer-Based Organisation
FIML	Full Information Maximum Likelihood estimation
GDP	Gross Domestic Product
GSS	Ghana Statistical Service
ICOUR	Irrigation Company of Upper Region
IRRI	International Rice Research Institute
IV	Instrumental Variable regression
JEA	Joint Exposure and Adoption
JICA	Japan International Cooperation Agency
METASSIP	Medium Term Agriculture Sub-Sector Investment Plan
MoFA	Ministry of Food and Agriculture
MiDA	Millennium Development Authority
MTR	Metatechnology Ratio
NAFCO	National Food Buffer Stock Company
NEB	Non-Exposure Bias
NERICA	New Rice for Africa
NGO	Non-Governmental Organization
NPK	Nitrogen, Phosphorus, Potassium

NRDS	National Rice Development Strategy
OLS	Ordinary Least Squares
PSB	Population Selection Bias
PSM	Propensity Score Matching
RELCs	Research Extension Liaison Committees
SARI	Savannah Agricultural Research Institute
SFA	Stochastic Frontier Analysis
SPF	Stochastic Production Frontier
SHS	Senior High School
SSA	Sub-Saharan Africa
TGR	Technology Gap Ratio
TE	Technical Efficiency
TI	Technical Inefficiency
USAID	United States Agency for International Development
USD	United States Dollar
VAT	Value Added Tax

CHAPTER ONE

INTRODUCTION

1.1 Background

A study by Carpenter (1978) revealed that domestication of *oryza glaberrima* (African rice) occurred in the central Niger Delta basin about 3,500 years ago. *Oryza sativa* (Asian rice) was first introduced over 500 years ago to West Africa by Portuguese explorers who brought it from India (Carpenter, 1978). Globally, the Philippines, China and Nigeria are the largest importers of rice whereas India, Thailand and Vietnam are the major exporters (DFID, 2015). About 20 million farmers in sub-Saharan Africa grow rice and nearly 100 million people depend on it for their livelihoods (Nwanze *et al*., 2006; Diakité *et al*., 2012). Major producers in Africa are Nigeria and Egypt and for West Africa they include Nigeria, Guinea, Ivory Coast, Sierra Leone, Mali, Ghana and Senegal which together produces 91% of the regional output (Dalton and Guei, 2003).

Despite rice being a major source of food and cash for smallholder farmers, recurring droughts and floods[1], and over-reliance on rainfall with limited use of irrigation potential[2] continue to affect rice production. Similarly, other cultivation related factors such as low use of yield enhancing inputs such as improved seed, fertilizer and other crop management practices, soil fertility depletion, pests and diseases as well as poor value chain systems

[1] AfricaRice released flood resistant varieties, WITA 4 Sub1 and NERICA L-19 Sub1 for farmers.
[2] Only 4% of irrigable land in Africa is under cultivation (AfricaRice Centre, 2007; Macauley, 2015).

constitute a continuous challenge to agricultural production in Africa (Abdoulaye *et al.*, 2011). For instance, the average fertilizer use on the continent is between 13-14 kg/ha compared with 141 kg/ha in South Asia, 154 kg/ha in the European Union, 175 kg/ha in South America (Macauley, 2015; Bonilla Cedrez *et al*., 2020). The low fertilizer application rate in sub-Saharan Africa is partly due to high fertilizer prices and low prices for crop produce (Otsuka and Kalirajan, 2006). Rice yields in Asia grew dramatically during the Green Revolution because of the continuous development and adoption of fertilizer-responsive high-yielding varieties (Otsuka and Kalirajan, 2006).

Use of unimproved seed, particularly cereals[3], in Africa has been blamed on poor access (World Development Report, 2008) to high yielding varieties due to the non-existence of well-functioning and highly trained seed production system. Therefore, most farmers rely on own seed from harvest and friends resulting in seed recycling with compromised genetic purity (Dao *et al*., 2015; Macauley, 2015). This means attempts made at addressing these constraints will enhance crop production.

Africa's poor population directly or indirectly depends on agriculture for food, employment and income (FAOSTAT, 2006). Thus, fostering agricultural growth is central to development strategies aimed at reducing poverty and hunger in Africa (Thirtle *et al.,* 2003). Nonetheless, productivity in agriculture in Africa has been low, where per capita food production has fallen and cereal yields are largely below their potential yields amid rapid population growth (CAADP, 2009). Low on-farm productivity results in low farm incomes, low purchasing power and lower incentives for investment in productivity growth (Bresciani and Valdes, 2007; World Bank, 2007). Low agricultural productivity also contributes to food insecurity. This is because poor households spend a significant

[3] Only 24% of cereal land area was planted with improved seed in 2000 in Africa (WDR, 2008).

proportion of their household resources on food, either by directly purchasing it or by producing it (CAADP, 2009). Against this backdrop, the African Union's agricultural policy is focusing on increasing agricultural productivity and reducing production costs in order to achieve its poverty reduction and food output targets.

1.2 Problem Statement

Ghana depends on imports due to a deficit in domestic rice production (Amanor-Boadu, 2012; Bruce *et al*., 2014). In order to narrow the gap between domestic demand and supply of high-quality rice, the national rice development strategy targets a 10% annual output increment (NRDS, 2009). The deficit in national output over the years has been attributed to low yield (4.0mt/ha) which is less than the achievable yield of 6-8mt/ha (Ragasa *et al.*, 2013; MoFA, 2019). Over the years, various improved rice varieties have been released for cultivation in Ghana with desirable traits such as high yield, early maturity, disease and drought resistance, aromatic and parboiling qualities. In spite of the release of these improved rice varieties, they have not been widely disseminated and commercialised (Tripp and Mensah-Bonsu, 2013) to convince farmers that, they will reap profitable returns by cultivating these improved varieties. Studies such as Manu-Aduening *et al*. (2005) have attributed the low uptake of improved farming technologies in Ghana to a mismatch of technology characteristics with farmers preferences and specific requirements. Moreover, adoption of improved crop varieties that offer higher yield potentials may be low if they do not possess other traits that farmers and consumers prefer (Pingali *et al*., 2001; Mkumbira *et al*., 2003; Asrat *et al*., 2009). Some traits farmers consider important include disease and pest resistance, high yielding, early maturity and adaptability to harsh environments; consumption characteristics such as taste and colour (Nweke, 2004; Wale *et al*., 2005).

Indeed, Smale *et al*. (2001) explained that farmers take into consideration production constraints, own consumption preferences and market requirements of farm surplus. Agricultural technology adoption decisions are also influenced by risk and uncertainties relating to how the technology affect production output, cost and farm profitability (Abara and Singh, 1993; Rogers, 1995; Koundouri *et al*., 2002; Weldegiorges, 2014).

Therefore, it is important to provide a comprehensive understanding of why some farmers in Ghana adopt and why others not adopt improved rice varieties by assessing farmers' perceptions of rice varietal traits in addition to identifying the farm and farmer characteristics, socioeconomic and institutional factors that influence adoption as well as constraints to rice cultivation. Ragasa *et al*. (2013) conducted a descriptive analysis of adoption of improved rice varieties and rice cultivation practices in Ghana. A study by Buah *et al*. (2011) on enhancing access to improved rice seed by farmers in northern Ghana identified higher yield, early maturity, ease of threshing and milling as well as good taste as reasons for adoption. Another study by Coffie *et al*. (2016) on choice of rice production practices and farmers willingness to pay in northern Ghana revealed preference for high yielding and early maturing rice varieties with less labour requirements.

However, the extent of dissemination and level of farmer awareness and adoption of these improved rice varieties and the resulting effect of adoption on farm output and net rice income using a nationally representative plot level data has not been extensively researched in Ghana. This study fills this research gap by assessing exposure to improved rice varieties, and the effect of adoption on output and net rice income, whilst separating production technology gap from technical inefficiency in rice cultivation. This is complemented with in-depth interviews and focus group discussions with farmers, agricultural extension agents and improved seed suppliers to assess the importance of rice cultivation to farmers, rice varietal diffusion, access and adoption, farmers' perceptions of varietal traits, constraints to rice cultivation and how to ease these constraints.

1.3 Research Objectives

The broad objective is to assess the adoption of improved rice varieties, and how adoption reflects in physical output and net rice income, whilst identifying constraints to rice cultivation by smallholder Ghanaian farmers.

The specific objectives are to:

1. Identify the factors that influence exposure and adoption of improved rice varieties by smallholder rice farmers in Ghana.
2. Analyse the effect of adoption of improved rice varieties on physical output and technical efficiency of smallholder rice farmers in Ghana.
3. Examine the effect of adoption of improved rice varieties on the net rice incomes of smallholder rice farmers in Ghana.
4. Identify specific constraints to smallholder rice cultivation and farmers' perceptions of specific rice varietal traits in Ghana.

1.4 Research Questions

The broad research question is: What determines Ghanaian smallholder farmers' exposure and adoption of improved rice varieties, how does adoption reflect in physical output and net rice income, and what are the constraints to smallholder rice cultivation in Ghana?

The specific questions are:

1. What factors influence exposure and adoption of improved rice varieties by smallholder rice farmers in Ghana?
2. What is the effect of adoption of improved rice varieties on physical output and technical efficiency of smallholder rice farmers in Ghana?
3. What is the effect of adoption of improved rice varieties on the net rice incomes of smallholder rice farmers in Ghana?
4. What are the specific constraints to smallholder rice cultivation and farmers' perceptions of specific rice varietal traits in Ghana?

1.5 Justification of the study

Rice is second to maize as the most important staple cereal crop in Ghana (MoFA, 2018). However, due to increasing per capita consumption and lower crop yield, domestic production only meets 30 to 40% of national demand resulting in significant imports (Osei-Asare, 2010; Amanor-Boadu, 2012; Bruce *et al*., 2014). Improved rice varieties released in Ghana possess superior qualities (high yielding, early maturity, disease resistance, aromatic, etc.) over the traditional ones and their adoption can improve household food security and income given that rice is grown both for sale and own consumption. Smallholder rice farmers produce 80% of domestic output (DFID, 2015; MoFA, 2016), and improved rice varietal exposure and subsequent adoption supported by complementary inputs could result in increased yield and net rice income to support household consumption of the vast majority of the rural population.

Against this background, this study examines farmers' exposure to improved rice varieties and how exposure reflects in the adoption of improved rice varieties. This will help to identify the specific factors that influence farmer exposure and the overall diffusion of the improved rice varieties within the rice farming population. Estimation of the exposure rate will also give an indication of the proportion of rice farmers yet to be exposed in order to increase the adoption rate. Moreover, results of determinants of adoption of improved rice varieties and adoption rate will help to improve adoption rates through effective planning of dissemination efforts by the agricultural extension service of the Ministry of Food and Agriculture in Ghana.

Moreover, applying the stochastic frontier with correction for selection bias to assess the effect of adoption of improved rice varieties on output will reveal the specific determinants of rice output and technical inefficiency of adopters and non-adopters respectively. It will also identify the socio-economic and cultivation practices that influence technical inefficiency in rice production and how to improve the efficiency of inefficient farmers to raise individual farm performance. Similarly, estimating a metafrontier separates productivity differences due to rice production technology gaps from technical inefficiency in order to improve farmers' managerial performance to raise farm productivity.

Furthermore, a switching regression is applied in assessing whether adoption of improved rice varieties translates into increased net rice income. A positive net rice income implies adoption offers profitable returns to farmers, providing an empirical basis to further promote the adoption of improved rice varieties as a strategy to increase household income to support expenditure.

Lastly, in-depth interviews and focus group discussions are applied to assess farmers' perceptions and preferences of rice varietal traits, diffusion and adoption, and constraints to rice cultivation. Personal interviews with agricultural extension agents and improved seed suppliers will the identify constraints to dissemination and access to improved rice varieties and how to improve adoption rates as service providers to rice farmers. The results of the qualitative interviews together with the quantitative analysis of the determinants of exposure and adoption will provide a better understanding why some farmers adopt improved rice varieties and others do not.

1.6 Organization of the thesis

This thesis has thirteen chapters. Chapter one includes a background to the study, problem statement, research objectives and questions as well as the justification of the study. Chapter two provides an overview of rice production including improved rice seed production and rice cultivation in Ghana, rice programmes and policies in Ghana as well as constraints to adoption.

The third chapter presents the literature review on diffusion and adoption of agricultural technologies. Chapter four explains the theoretical underpinnings of the application of average treatment effect in evaluating exposure and adoption of improved rice varieties. Chapter five presents the literature review on application of the stochastic production frontier with correction for selectivity bias in analysing the effect of adoption of improved rice varieties on rice output and farmers' technical efficiency. Chapter six reviews literature on the application of switching regression in assessing the effect of adoption of improved rice varieties on household net rice income per ha. The literature review in Chapters four to six include a review of empirical studies in relation to research objectives one to four.

Chapter seven contains a description of the study area, sampling and data collection. It also contains the empirical models of exposure and adoption of improved rice varieties, effect of adoption on rice output and farmer efficiency and how that translate into household net rice income per ha. It ends with a method of analysis of the focus group discussions and in-depth interviews.

Chapter eight begins the data analysis process by presenting a summary description of all the variables, as well as a discussion of the demographic characteristics and summary statistics of the respondent households. Chapters nine, ten and eleven presents the results and discussion of the determinants of exposure, and adoption of improved rice varieties; the effect of adoption of improved rice varieties on farmers' output and technical efficiency; and how adoption of improved rice varieties translates into household net rice income. These chapters address the first, second and third objectives of this study. The results and discussion in Chapter twelve address the fourth objective of this study that assesses farmers' perceptions and preferences of rice varietal traits, diffusion and adoption, and specific constraints to rice cultivation in the study area. Lastly, Chapter thirteen presents a summary of the study findings from the results and discussion chapters, the conclusions and recommendations emerging as well as recommendations for future research.

CHAPTER TWO

OVERVIEW OF RICE PRODUCTION

2.1 Introduction

This chapter focuses on rice production in Africa and Ghana as well as production challenges. Additionally, it examines domestic rice production and cultivation practices, processing and marketing, rice seed industry, rice policies in Ghana, and constraints to adoption.

2.2 Rice production in Africa

Rice is an important food security crop in Africa with rising consumption due to population growth and urbanization[4] (Seck *et al*., 2012; Seck *et al*., 2013; Macauley, 2015). Despite this huge consumption potential (projected to reach 30 million tonnes by 2035), rice production[5] on the continent has not been able to meet supply due to poor yield and investment and most countries rely heavily on imports annually from the international market (Diakité *et al*., 2012; Seck *et al*., 2012; Macauley, 2015). Indeed, Africa accounts for a third of global rice imports (Seck *et al*., 2012). Similarly, West Africa imports 12% of world rice trade because only two-thirds of consumption demand is met by regional production (Dalton and Guei, 2003).

Against this backdrop, continental initiatives such as the Coalition for African Rice Development (CARD) together with AfricaRice[6] have assisted countries to develop

[4] Africa's urban population is expected to grow by 48% by 2030 (Macauley, 2015).
[5] Only 60% of rice consumption is met by domestic production in Africa (Seck *et al*., 2012).
[6] Africa Rice Research Centre, part of the CGIAR. It is located in Ivory Coast.

national rice development strategies which *inter alia* seeks to support the breeding and mass production of high yielding rice seed by certified private seed out-growers to expand access to smallholder farmers (Macauley, 2015). Past interventions in West Africa (Ghana, Mali, Nigeria and Senegal) included the Emergency Rice Initiative Project in 2009 implemented by AfricaRice. The project received funding from United States Agency for International Development (USAID) with the objective[7] of expanding access to improved certified rice seed and fertilizer to increase rice production (Buah *et al*., 2011). Other complementary efforts to boost rice production are improved access to agricultural mechanization to provide services such as planting, weeding, harvesting, and threshing to reduce drudgery and attract young people into rice production.

2.3 Rice production in Ghana

Agriculture in Ghana accounts for more than 20% of national GDP (MoFA, 2016) and three-quarters of export earnings. It employs over 40% of the labour force (GSS, 2014; MoFA, 2018). The agricultural sector grew by 8.4% in 2017 following the introduction of the Planting for Food and Jobs programme following a period of slowed growth averaging 4% from 2010-2015 (MoFA, 2016 and 2018). Rice is ranked the second most important staple crop after maize in Ghana (MoFA, 2011 and 2018). Imports into the country represent 58% of cereal imports (CARD, 2010) and 5% of overall agricultural imports (Angelucci, Asante-Poku and Anaadumba, 2013). The crop occupies over 11% of total land area under cereals cultivation (MoFA, 2011; Martey *et al.,* 2013). Rice is mostly cultivated by smallholder farmers with farm sizes of 2.5 ha or less (MoFA, 2016) who produce about 80% of domestic rice output (DFID, 2015). Nonetheless, domestic production[8] only meets 30 to 40% of

[7] The project was an adhoc measure to deal with the 2008 global food crisis in these countries.
[8] This has led to a declining self-sufficiency ratio of rice in Ghana over the years.

demand (Osei-Asare, 2010; Amanor-Boadu, 2012; Bruce *et al*., 2014) due to increasing per capita consumption[9] which has more than doubled over the years (MiDA, 2010; MoFA, 2011; Coffie *et al*., 2016; MoFA, 2016). According to MoFA (2016), the country in 2015 imported 620,811mt of rice at a cost of USD 285.32 million. This import volume was almost the same quantity of domestic output of 641,000mt in 2015 as shown in Figure 2.1.

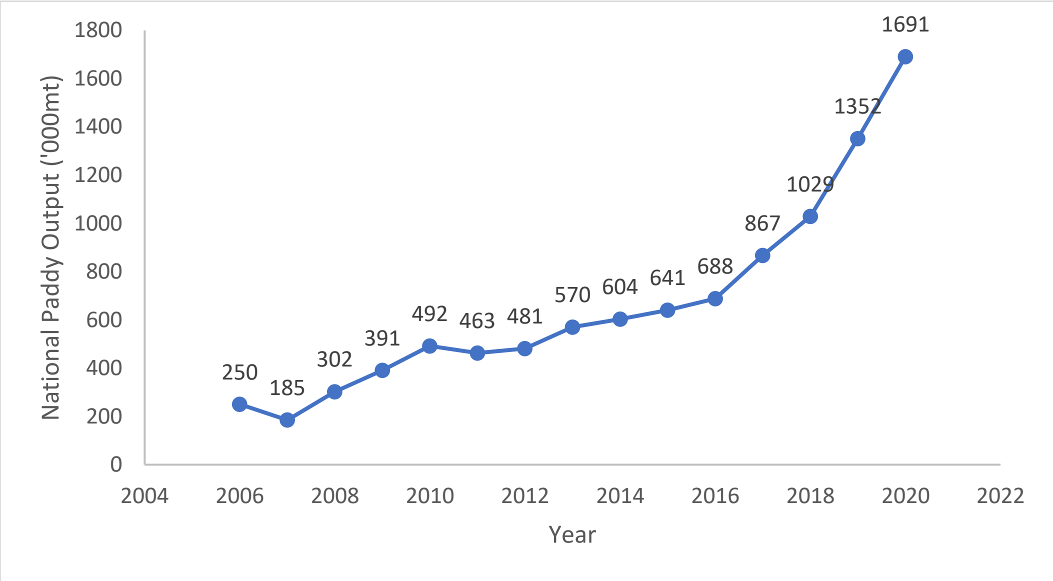

Figure 2.1: National output of rice in Ghana from 2006-2020. (Source: MoFA, 2016 and 2019). Note, 2020 figure is projected output.

Meanwhile, lowland rain-fed cultivation constitutes 78%, upland rain-fed 6% and irrigated land cultivation represents 16% of the national output (NRDS, 2009; DFID, 2015). Additionally, lowland rain-fed cultivation with better water management and cultural practices is the most profitable although irrigated production gives the highest yield (NRDS, 2009). The bulk of imported[10] long grain aromatic rice consumed by 76% of the urban

[9] Rice per capita consumption increased from 13.3kg in 1990 to 32kg in 2015.
[10] Major importers are Finatrade (35%), OLAM (25%), and Stallion (10%) and others (Imexco, Royal Bow Ltd, City Investment Group, and Ezal Ltd).

population[11] in Ghana comes from Thailand (36%), Vietnam (30%) and USA (21.6%) (CARD, 2010; Angelucci *et al*., 2013; DFID, 2015). Ghana lies within a hot humid tropical lowland climate producing an average daylight of 12 hours, and warm nights that encourage respiration, thereby depleting daylight photosynthetic accumulation which makes it difficult to attain maximum yield (Tinsley, 2009). Nonetheless, Ghana has a comparative advantage in rice production relative to other countries in West Africa (Assuming-Brempong, 1998). The major rice producing areas in Ghana are the Volta, Northern, Upper East, Ashanti and Eastern Regions (Kranjac-Berisavljevic', Blench, and Chapman, 2003; USAID, 2009; MoFA, 2016) with 84% of cultivation being rain-fed (CARD, 2010). The Volta Region has overtaken the Northern Region partly resulting from weather fluctuations (Ragasa *et al.*, 2013) as the largest producer as shown in Figure 2.2.

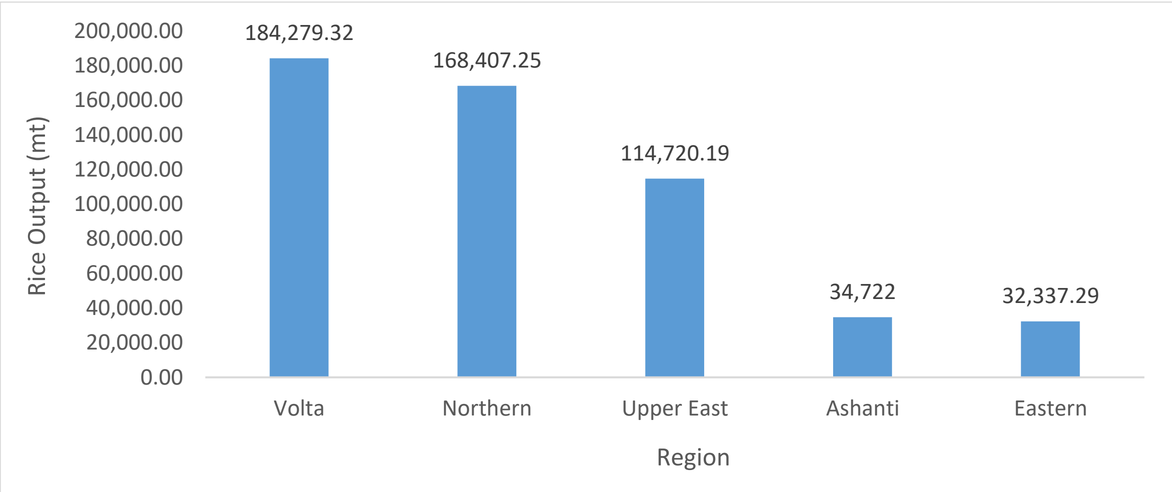

Figure 2.2: Average regional output of rice from 2013-2015. (Source: MoFA, 2016).

Nonetheless, much of the rice is produced in northern Ghana (Ragasa *et al.*, 2013) with the Northern and Upper East Regions contributing about 53% of national output (MoFA, 2016).

[11] Meanwhile, the urban centres consume only about 20% of locally produced rice due to its inability to substitute and compete with foreign rice (Angelucci *et al*., 2013).

Agricultural growth in Ghana is mainly driven by area expansion (MoFA, 2016) unlike the Green Revolution in Asia which was productivity driven (Abdulai, 2015) through the adoption of fertilizer-responsive modern rice varieties (Otsuka and Kalirajan, 2006). Potential for such productivity-led growth exists in rice, exemplified by significant gaps between current and achievable yields (in Figure 2.3). Although, there have been a steady rise in yield over the years, the national average yield of 4mt/ha in 2018 was still below the achievable yield of 6.0mt/ha under rain-fed cultivation. The average yield is also very low in comparison with 7.8mt/ha and 9.8mt/ha in United States and Egypt respectively (USAID, 2009).

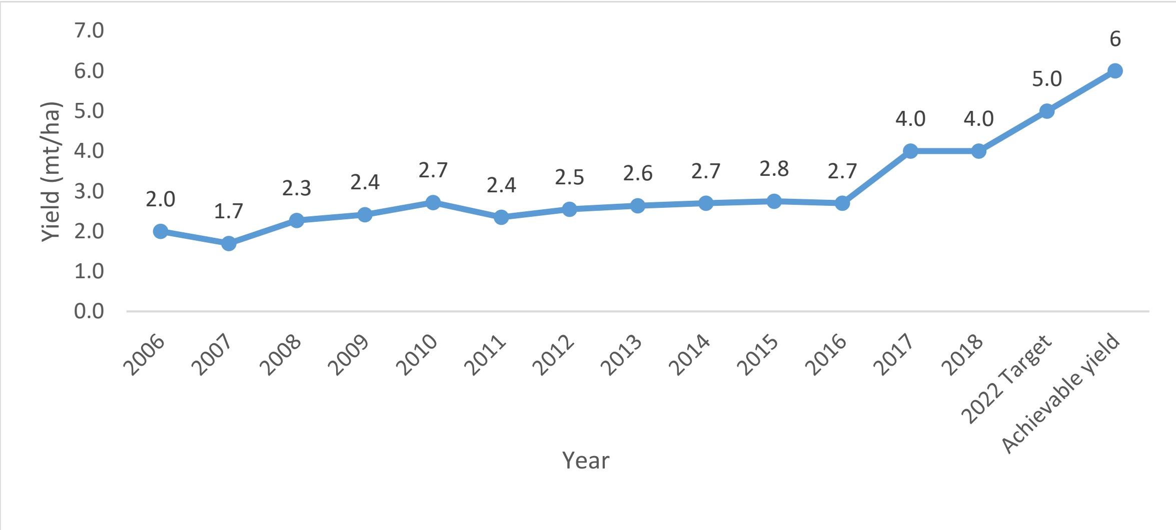

Figure 2.3: Average yield of rain-fed rice from 2006 to 2018. (Source: MoFA, 2016 & 2019).

Irrigated rice cultivation gives the highest average yield of 4.5mt/ha in Ghana (CARD, 2010), although much of the irrigation potential remains untapped with few irrigation schemes located across the country (Osei-Asare, 2010). The main schemes are the Tono and Vea irrigation schemes in the Upper East Region, the Kpong, and Afife irrigation schemes in Greater Accra Region, Bontanga and Golinga irrigation schemes in Northern Region which are mostly used for rice and vegetable production especially in the dry season (CARD, 2010). Rice cultivation is largely labour intensive, with an average labour use of 125 mandays/ha reported in Ghana compared with 80 mandays/ha and 14 mandays/ha in Senegal and Thailand respectively (DFID, 2015). Except ploughing by tractor, most of the cultivation practices, harvesting and post-harvest activities such as threshing and winnowing are done manually using both hired and family labour.

2.4 Pre-harvest services available to support rice cultivation in Ghana

2.4.1 Agricultural mechanization services

A baseline survey by the Ministry of Food and Agriculture revealed about 40% of Ghanaian farmers employed some form of agricultural mechanization services in their farming activities (MoFA, 2005). Agricultural mechanization is labour-saving and as labour becomes scarcer and expensive, the demand for mechanization services increases (Pingali *et al*., 1987). In line with the national rice development strategy (MoFA, 2009), the government of Ghana is supporting the supply of tractors and accessories, water pumps, transplanters, seed drills, rice reapers, threshers and dryers as well as providing training on their operation to modernize rice cultivation. A recent study by Diao *et al*. (2019) revealed a 32.5% rise in the use of mechanization services by rural households in Ghana between 2006 to 2012. For instance, in northern Ghana farmers engage the services of farm tractors for ploughing, threshing and carrying farm produce from farms to homes and to market centres (Abdulai, 2015). In rice cultivation, tractors are used in land preparation and combine harvesters for harvesting. A farmer who relies only on hand hoes is able to prepare about 0.5ha for cultivation per season (Fonteh, 2010). Access to agricultural mechanization reduces the drudgery and tedium associated with farming which in turn can lead to increased productivity (Benin *et al.,* 2011). Tractor owners in Ghana aside ploughing their own farms, provide ploughing services of up to 160 hectares per year to other farmers (Houssou, Diao, and Kolavalli, 2014).

The Agricultural Mechanization Services Enterprise Centres (AMSECs) is a government intervention implemented by the Ministry of Food and Agriculture that provided tractors and supporting equipment to farmers on hired purchase in response to their high capital cost (Benin, *et al.,* 2011). However, a study by Houssou *et al*. (2014) on the economics of tractor ownership revealed that many of the AMSECs had unprofitable business models and struggled to repay their loans to the government. One way of improving the profitability of the AMSECs is diversifying beyond ploughing and stimulating demand for other services. A study by Benin *et al*. (2012) revealed that close to 90% of revenue for the AMSECs was from ploughing services alone. Under the national agriculture investment plan, the government intends to revive 168 agricultural mechanization services centres (AMSECs) and expand the number of centres to 290 by 2022 (MoFA, 2019). The government encourages private sector participation to attain the goal of at least one AMSEC in each district across the country to provide mechanization services to farmers to achieve the target of bringing a million hectares of additional farm land under mechanization by 2021 (MoFA, 2018). Moreover, 300 (to be increased to 500 by 2022) agricultural machinery operators and mechanics were trained in 2018 on proper use of farm machinery and repairs in line with the national agricultural engineering policy (MoFA, 2019). Nonetheless, the unavailability of spare parts and maintenance services have been identified as major challenges to the AMSECs (Houssou *et al*.,2014) which hampered their effective operations. As a result, the government is facilitating backup and availability of spare parts for the AMSECs in line with the Ghana Agricultural Engineering Policy (MoFA, 2018).

2.4.2 Rice seed industry in Ghana

A study by Ragasa *et al.* (2013) indicated about 20 rice varieties have been introduced in Ghana over the past four decades mostly by the International Rice Research Institute (IRRI) and AfricaRice, with the collaboration of the national agricultural research institutes. For instance, the lowland GR varieties shown in Table 2.1 were obtained from IRRI in the 1980-90s with average maturity of 4 months which is compatible with the length of the growing season in Northern Ghana.

Table 2.1: Rice varieties released in Ghana

Variety	Ecology	Release Year	Potential yield (mt/ha)	Maturity days	Distinctive characteristics
FARO 15	Lowland	1970s	3-5	140-145	Good for parboiling. Short and sticky grain with low consumer patronage.
GR 17, GR 18, GR 19, GR 20, GR 21, GRUG7	Lowland	1982-86	4-6.5	120-130	Good for parboiling. Short and sticky grain with low consumer patronage.

GR 22 (Sikamo)	Lowland, upland	1997	4.5-8	120-130	Uses nitrogen efficiently; blast & drought tolerant; difficult to thresh, good taste.
Digang (Abirikukuo)	Lowland	2002	4-5	115-120	Early maturing, drought-tolerant.
NERICA 1, NERICA 2	Upland	2009	3-4	95-100	Early maturing, drought-tolerant.
Jasmine 85 (Gbewaa)	Lowland, irrigated	2009	4.5-8	110-120	Aromatic long grain, good taste, preferred by consumers.
Otoomu, Emo teaa	Upland	2009	4-5	110-115	Resistant to blast disease, long and slender grain, non-aromatic.
Marshall	Lowland	2010	6-8	115-120	Resistant to blast disease, aromatic long grain, superior milling with low broken grains.
Wakatsuki, Bodia	Lowland	2010	6-8	125-130	Resistant to blast disease, grains break easily, non-aromatic & sticky after cooking.
Sakai	Lowland	2010	6-8	135-140	Resistant to blast disease, grains break easily, non-aromatic & sticky after cooking.

*AGRA-CRI-LOL-2-27 (CRI-Dartey)	Lowland	2017	6.5-9	120-125	Excellent cooking quality, aromatic.
*CRI-1-11-15-5 (CRI-Emopa)	Lowland	2017	6-8	125-130	Excellent cooking quality, slightly aromatic.
*AGRA-CRI-LOL-1-7 (CRI-Mpuntuo)	Lowland	2017	5.8-8	115-120	Good cooking quality, aromatic, good processing quality.
*CRI-1-11-15-21 (CRI-Aunty Jane)	Lowland	2017	6.6-9.5	125-130	Excellent cooking quality, slightly aromatic.
*Nerica-L-41 (CRI-Kantinka)	Upland	2017	6.3-8.5	120-125	Excellent cooking quality.
*FAROX 508-3-10-F43-1-1 9 (CRI-Oboafo)	Lowland	2017	6-8.5	130-135	Good cooking quality, good processing quality.

Source: Ragasa *et al.* (2013). Varieties with * were released in 2017 by the Crops Research Institute with financial support from AGRA.

Upland early maturing and drought-tolerant varieties, NERICA 1 and 2 were released in 2009 by the Africa Rice Centre in Ivory Coast to mitigate against adverse weather patterns. Long grain aromatic varieties like Jasmine 85 and Marshall were officially released in 2009 and 2010 respectively. These aromatic varieties have good taste and usually preferred by consumers (Ragasa *et al.,* 2013). Similarly, the recently released varieties by the Crops Research Institute such as AGRA-CRI-LOL-2-27, CRI-1-11-15-5, AGRA-CRI-LOL-1-7, and CRI-1-11-15-21 are high-yielding, aromatic, resistant to rice yellow mottle virus disease and iron toxicity. Iron toxicity occurs when iron concentration in the roots reaches 300-500ppm or 30 ppm in potassium and phosphorus deficient soils, saline and acidic soils resulting in discoloration of leaves for lowland rice ecologies (Moormann and van Breemen, 1978, IRRI, 1982; Singh *et al*., 2004).

According to Tripp and Mensah-Bonsu (2013), the amount of improved rice seed produced in 2009 was only sufficient to cultivate 5% of the total rice area in Ghana. Moreover, certified rice seed production over the past decade has concentrated on three[12] varieties, namely Jasmine 85, GR 18, and GR 21 (Ragasa *et al.,* 2013). In spite of the release of improved varieties through donor support with government of Ghana counterpart funding, they have not been widely disseminated and commercialised (DFID, 2015) to convince farmers that they will reap profitable returns by cultivating these new varieties (Tripp and Mensah-Bonsu, 2013). This is largely because of the non-existence of thriving private

[12] Represented 91% of certified seed production with Jasmine 85 alone nearly 50% from 2001-2011.

certified seed producers to link up with the national agricultural research institutes in charge of crop breeding leading to low adoption rates (Ibrahim and Florkowski, 2015).

A well-developed commercial seed supply system should be able to obtain foundation seeds from agricultural research institutes to produce large quantities of certified seeds of higher uniformity and genetic purity than farmer-saved seeds[13] selected from harvest (Tripp and Mensah-Bonsu, 2013). The national rice development strategy and the national agriculture investment plan (2018-2021) acknowledge the importance of planting improved seed varieties and seeks to expand access to high quality seeds by supporting seed producing companies and trained private sector growers with access to breeder and foundation seed to increase the production of certified seeds (MoFA, 2009 and 2018). It is recommended that farmers renew their rice seeds at least once every three years (Ragasa *et al.,* 2013). In this regard, about 19,000mt of certified seed was available in 2018 to cultivate 375,000 ha of rice (MoFA, 2018).

2.4.3 Fertilizer subsidy programme and other agrochemical inputs services

The introduction of a nation-wide fertilizer subsidy by the government of Ghana in July 2008 sought to partly absorb the cost of fertilizer to enable farmers buy chemical fertilizers to boost their crop output (Banful, 2008). It initially targeted small-scale farmers who were offered vouchers to purchase the subsidised fertilizer and later expanded in 2010 to include all farmers. The subsidy covers fertilizer types such as NPK15:15:15, NPK 23:10:05, urea, and sulphate of ammonia and runs annually between May and October to coincide with the major growing season (Benin *et al*., 2011; MoFA, 2016). The four major fertilizer companies (Yara-Wienco, Chemico, Dizengoff and Golden Stock) participating in the

[13] Rice is self-pollinating.

subsidy import the fertilizers and sell to farmers through their registered sales agents (Banful, 2008). The subsidy is paid to the fertilizer distribution companies after presentation and reconciliation of receipts, a process described by the distributors as very bureaucratic (Benin *et al*., 2011). Moreover, studies such as Diao *et al*. (2019) have criticised the fertilizer subsidy as not targeting very specific crops, unsustainable due to rising costs and risk of a sharp decline in fertilizer use once the subsidies are removed.

Nonetheless, there has a rise in fertilizer application since the introduction of the subsidy programme. For example, fertilizer use increased from 8kg/ha before the subsidy to 15kg/ha in 2018 (MoFA, 2007 and 2019). The national agriculture investment plan aims to further increase the application rate to 25kg/ha by 2022 (MoFA, 2019). In 2019, 438,900mt of inorganic fertilizers and 30,000mt of organic fertilizers were subsidised under the planting for food and jobs programme (MoFA, 2019). Regarding rice, the national strategy is to take advantage of the subsidy to engage fertilizer companies to blend appropriate straight fertilizers adapted to the ecology, soil type and rice variety (MoFA, 2009).

The recommended fertilizer applications rates for rice are 200–300kg/ha of *NPK 15-15-15*, followed by 150kg/ha of sulphate of ammonia or 75kg/ha of urea (Ragasa *et al.,* 2013; Abdulai *et al*., 2018). Farmers mostly apply fertilizer to replenish soil nutrient depletion resulting from increased crop production (Diao *et al*., 2019). Indeed, fertilizer use can be constrained by farmers' risk aversion and cash constraints. Unless the returns to fertilizer use reflects in higher yield, risk averse farmers may not spend much on fertilizer (Gyimah-Brempong, Johnson and Takeshima, 2016). This is particularly important given that many improved rice varieties respond better to fertilizer when the application rates and timing are strictly followed (Abdulai *et al*., 2018). Moreover, even with increased fertilizer application, rice yield may be affected by diseases, drought or flooding in some years.

Closely related to fertilizer application is the use of herbicides in land preparation and weed control. Herbicides application has become a labour-saving strategy for many Ghanaian farmers as a result of declining availability of communal labour and increasingly expensive hired labour for weeding operations (Xinshen *et al*., 2019). Nonetheless, the wrongful application of agro-chemicals can pose adverse effects on the environment and public health. The government through its investing in food and jobs strategy (2018-2021) is implementing regulatory and quality control systems on agro-chemicals alongside training and educating farmers on the handling of agro-chemicals (MoFA, 2018). In Ghana, the sale of fertilizers and agro-chemicals is through agricultural input dealers or suppliers.

2.4.4 Agricultural extension services

Although, recent approaches to extension are in favour of participatory and pluralistic methods tailored to farmer needs and conditions, the delivery of agricultural extension services was initially a top-down transfer of technologies to farmers (Davis, Babu and Ragasa, 2020). Moreover, the term "agricultural extension" is gradually being replaced by the term "agricultural advisory services" that embraces stakeholder participation, facilitation, adult education, local capacity development and regards farmers as clientele (Swanson and Rajalahti, 2010; Davis and Heemskerk, 2012; Faure, Desjeux, and Gasselin, 2012; World Bank, 2012). Birner *et al*. (2009) explained that agricultural extension and advisory services encompasses the facilitation and delivery of information, skills and technologies to support people in agricultural production to solve problems and improve their livelihoods and well-being. Agricultural advisory services are crucial to improving crop output. Farmers who have adequate agricultural extension service acquaint themselves with modern agricultural technology regarding input mobilization, input use and disease control (Alhassan, 2012).

In a pluralistic extension system, service providers may have very different objectives and use a mix of extension delivery channels (Davis *et al.*, 2020). For instance, the district agricultural development units under the district assemblies of the local government service are in-charge of delivering agricultural extension services to the general farming population at the local level in Ghana. At the district level, the agricultural extension agents are assigned to operational areas (MoFA, 2018). Moreover, the national rice development strategy through the Agriculture Ministry is employing a mix of approaches including training and visit extension delivery, farmer field schools and on-farm demonstrations, training manuals, videos, and posters in their dissemination of improved technologies for cultivation rice in Ghana (MoFA, 2009). At the same time, Agriculture Ministry is partnering farmer-based organizations with knowledge in the rice production subsector to augment state extension services whilst encouraging farmer-to-farmer extension under the national rice development strategy. The recommended rice cultivation practices being disseminated by the agricultural extension service are tractor ploughing followed by harrowing, planting improved rice varieties by direct sowing or transplanting at optimum density, applying fertilizer at the recommended rate and time, and lowland rice field water management amongst others (MoFA, 2009; Ragasa *et al.*, 2013; Abdulai *et al*., 2018).

The poor diffusion and adoption of improved agronomic practices has been attributed to a poorly resourced agricultural extension service with a higher extension agent-farmer ratio (Alhassan, 2008). As a result, the government under its investing for food and jobs programme (2018-2021) intends to reinvigorate the agricultural extension services by recruiting more agents (2,700) to further reduce the agricultural extension agent to farmer ratio which was 1:1850 in 2018. The government intends to reduce it to 1:1500 by employing an additional 2,700 in 2022 (MoFA, 2018). To further improve service delivery, the government distributed 216 brand new pickups and 3,000 motor bicycles to the Departments of Agriculture of the District Assemblies in 2018. Relative to rice, the national rice development strategy (MoFA, 2009) sought to increase the number of rice agricultural extension specialists from 2,300 to 5,630 and rice research specialists from 48 to 60 within the 2008-2018 period. However, the gains from retooling and recruiting more extension agents can only be realised if there are improved technologies available for agents to extend to farmers (Diao *et al.,* 2019). Moreover, extension services indirectly affect agricultural productivity through the increased adoption of modern inputs (Davis *et al*., 2020). The channelling of new knowledge to extension agents requires a strong coordination between research institutes and extension services. Although, there are functioning research-extension linkage committees (RELCs) in Ghana, the national rice development strategy acknowledges that technology generation and dissemination have not been effective due to staffing and logistical challenges (MoFA, 2009).

2.5 Domestic post-harvest rice processing and marketing

Studies have showed Ghana has comparative advantage compared with other African countries (Asuming-Brempong, 1998) and with good post-harvest processing it can also attain competitive advantage (Diakité *et al*., 2012). Post-harvest value chain addition and marketing begins after harvesting of rice on paddy fields. Rice threshing in Ghana by farmers is mostly done on bare floors and soil particles and stones get mixed up with the paddy which produces low-grade rice (Kranjac-Berisavljevic' *et al*., 2003). The bulk of domestic rice is parboiled, milled and sold by women in local markets and rarely in supermarket shops because many urban consumers find it unattractive. Notwithstanding, domestic rice is regarded as nutritious with a higher mineral content (Acheampong, Marfo, and Haleegoah, 2005; Diako *et al*., 2011). The parboiling process involves soaking paddy in water for a day and followed by steaming in a pot. Parboiling increases rice shelf life because it deactivates enzymes during the process, makes rice grains harder and resistant to insect pests during storage (Houssou and Amonsou, 2004). Moreover, parboiled rice grains remain firm, do not stick and loses less starch during cooking (Manful et *al*., 2007).

The high demand for imported rice amongst the urban population has been attributed to consumer preferences such as aroma and taste of the rice when cooked (Tomlins *et al*., 2005; Diako *et al*., 2010). Against this background, the national rice development strategy (MoFA, 2009) has set out to increase domestic rice consumption through quality improvement and value addition. Specifically, it seeks to build capacity of processors and facilitating access to equipment such as pre-cleaners, destoners, hullers, polishers, paddy separators, aspirators, drying patios for parboiling rice, and graders to process paddy to meet marketable standards.

Recently, the National Food Buffer Stock Company (NAFCO) in line with Government policy provides a reliable market by buying rice from local farmers at a guaranteed minimum price. NAFCO supplies the milled rice to selected basic schools under the Ghana School Feeding Programme, assisted senior high schools, Prisons Service, and the National Disaster Management Organization as food aid to disaster victims. The United Nations' World Food Programme also buys domestic rice under its 'Purchase for Progress' initiative for their emergency relief operations. In 2013, Avnash Company Limited constructed the largest privately owned rice processing factory in Ghana with a capacity to mill 150,000mt per annum in Tamale. It also planned to set up two additional rice mills with 500mt/day capacity in Daboya and Bolgatanga (DFID, 2015). Avnash currently relies on rice out-growers and paddy aggregators to feed its factories, although, there concerns the milling plants may not be able to operate at full capacity in future due to supply shortfalls. Contract farming is another way of incentivising farmers, coordinating output and providing ready market for domestic rice especially with the establishment of the rice milling factories. Nonetheless, very weak contract enforcement can undermine contract growing as is the case with maize where many farmers bypassed the contracted company and secretly sold their produce to others (DFID, 2015).

Given the annual increment in demand of 11.8% (MiDA, 2010), and the economic viability of production[14] (Winter-Nelson and Aggrey-Fynn, 2008; Akramov and Malek, 2011), domestic rice can compete favourably with imported rice if the milling quality, appearance and taste are acceptable by consumers (DFID, 2015). For instance, excluding the cost of on-farm hired labour and production margins, irrigated rice farmers may be able to produce at 24% the cost of imported premium Thai rice (USD 377 per ton), while rain-fed lowland farmers could produce at 21% the cost of imported Thailand[15] premium rice at USD 331 per ton (Diakité *et al*., 2012). To further stimulate domestic rice consumption, rice imports attract higher tariffs. Current duties and levies are as follows: 20% free-on-board price import duty, 12.5% VAT, 2.5% National Health Insurance Levy, 0.5% Export Development and Investment Fund Levy, 1% inspection fee, 0.5% ECOWAS Levy, and 0.4% Ghana Customs Network giving a total tariff of 37.4% (MoFA, 2009; DFID, 2015).

Nonetheless, many urban and affluent consumers prefer imported long grain aromatic rice because they do not regard domestic rice as a substitute (Gyimah-Brempong *et al*., 2016). Therefore, until there is a higher substitutability between imported and domestically

[14] Supported by tariffs on imported rice.
[15] About 36% of rice imported into Ghana comes from Thailand.

processed rice, and consumer tastes for local rice rivals their taste for imported rice, tariff imposition will not effectively reduce imports, but can encourage smuggling because there will always be demand for imported rice (Gyimah-Brempong *et al*., 2016). Meanwhile, import tariffs could be combined with improved processing, good branding and marketing of domestically produced rice (Demont *et al*., 2013).

In conclusion, given the large number of Ghanaians who consume rice, technologies that succeed in increasing the productivity of resources devoted to its production, whilst improving post-harvest processing, branding and marketing can bring about real income gains for the vast majority of rice farmers.

2.6 Rice related programmes and policies in Ghana

There have been about 20 rice related programmes implemented in Ghana between 2003 and 2015 (Ragasa *et al*., 2013). Most of these programmes were funded by donors such as the African Development Bank (AfDB), French Agency for Development (AFD), Food and Agriculture Organization (FAO), United States Agency for International Development (USAID), Alliance for Green Revolution in Africa (AGRA), Japan International Cooperation Agency (JICA) amongst others. For instance, the Rice Sector Support Project (2008-2014) sponsored by AFD supported lowland rice production of up to 6,000 ha in the Northern, Upper East, Upper West and northern parts of the Volta Region of Ghana. Other projects financed by the AfDB included the NERICA Rice Dissemination Project (2005-2010) which sought to increase rice seed production, marketing as well as agricultural extension. The AfDB also supported the Lowland Rice Development Project with similar objectives of improving the livelihood of poor farmers in the targeted regions through the development of a sustainable economic activity based on the natural potential of the regions.

Projects funded by JICA (2004-2015) focused on agricultural extension, irrigation improvement, soil fertility management, credit and post-harvest marketing. Other funded programmes specifically in the northern part of the country that cover rice include the Northern Rural Growth Programme and Ghana Commercial Agriculture Project that aim to develop out-grower farmers, invest in infrastructure and improve access to finance.

Nonetheless, many of the interventions in the rice sub-sector have often focused on producing high yielding varieties with little attention to post-harvest processing and marketing (Angelucci *et al*., 2013). Traditional threshing is unable to separate impurities and dirt particles from the paddy and parboiling results in harder brownish rice with longer cooking time making it unattractive to many consumers (Kranjac-Berisavljevic' *et al*., 2003). High input costs have also severely limited production potential as they make the overall production process uncompetitive. Ghana's rice development strategy seeks to facilitate the establishment of mills equipped with pre-cleaners, destoners, hullers, polishers, paddy separators, aspirators, and graders to process rice into premium marketing standards (NRDS, 2009).

Government of Ghana policy initiatives over the years to improve agriculture and ensure self-sufficiency in food production include the Food and Agriculture Sector Development Policy (FASDEP I), which sought to modernize agriculture and promote rural development. Specifically, FASDEP I sought to increase domestic rice output to 370,000mt and decrease rice imports by 30% by 2004. This target had not been achieved at the time FASDEP II came into being in 2007 (CARD, 2010). FASDEP II, aside targeting the modernization of rice cultivation methods to increase national output by 50%, also placed emphasis on post-harvest value addition. As part of FASDEP II, the Medium-Term Agriculture Sector Investment Plan [METASSIP] (2009-2015) was developed to engage and support more private sector investment in the agricultural sector. METASSIP has been succeeded by the National Agriculture Investment Plan [NAIP] (2018-2021) which seeks to modernize the agricultural sector through government supported initiatives such as ‘planting for food and jobs; rearing for food and jobs; planting for export and rural development’. The NAIP aims to implement these interventions through the provision of subsidies on agricultural inputs such as certified seeds and fertilizers, expanding access to agricultural extension services, mechanisation services, irrigation services, improving post-harvest processing and facilitating ready markets for farm produce. For instance, the number of farmers who accessed subsidized fertilizers and certified seed increased from 202,000 to 577,000 between 2017 and 2019 (MoFA, 2019). The Agriculture Ministry has lauded the initial success of the NAIP as evidenced in yield increases for major crops such as maize (from 1.8mt/ha to 3.0mt/ha) and rice (from 2.7mt/ha to 4.0mt/ha) between 2017 and 2019.

The National Rice Development Strategy developed in 2009 is the main driver of rice policy in Ghana (NRDS, 2009). The policy aims to double domestic rice output by working with upland, lowland and irrigated land growers[16] as well as to promote its consumption. The strategy seeks to achieve the above by tackling priority areas such as: access to improved rice seed varieties; expanding access to fertilizer through marketing and distribution; irrigation and water control investment; enhance access to agricultural mechanization equipment and spare parts for maintenance; research and technology dissemination; post-harvest handling and marketing; and strengthening farmer-based organizations and microcredit management.

[16] The policy targets yields of 2.5mt/ha for upland, 3.5mt/ha for lowland and 6.0mt/ha for irrigated and overall average yield of 4.0mt/ha.

2.7 Rice cultivation technologies in Ghana

Ghana's National Rice Development Strategy (NRDS, 2009) has an ambitious target of increasing annual output by 10%. The average rice yield before 2017 on farmers' fields was 2.8mt/ha against on-farm trials achievable yield of 6–8mt/ha (MoFA, 2016; Ragasa *et al.*, 2013). Although, the yield has significantly risen from 2.8mt/ha to 4.mt/ha within the 2017-2019 period with the implementation of the government's planting for food and jobs programme, it is still below the achievable yield of 6-8mt/ha (MoFA, 2019). To further address this yield gap, the Council for Scientific and Industrial Research (CSIR) and the Agriculture Ministry have recommended the following agronomic technological package to boost rice production and yield. The package includes:

(1) Land preparation and weed control: Ploughing and harrowing should be done using tractor (Abdulai, Zakariah and Donkoh, 2018). Herbicide are increasingly being used to complement manual weeding to suppress weed growth. Pre-emergence herbicide application is recommended 2–3 days after sowing, whereas post-emergence herbicide is applied 21–25 days after sowing (Ragasa *et al.,* 2013).

(2) Planting of improved rice seed varieties: Over the last four decades, various rice varieties have been released for cultivation in Ghana with desirable traits such as high yield, early maturity, disease resistance, aromatic and parboiling qualities (Ragasa *et al.,* 2013). Some of these varieties are NERICA (for upland ecology), GR 18, Digang, Jasmine 85, and Togo Marshall are lowland varieties. Varieties that are deemed to be modern or improved are promoted through projects (Ragasa *et al.,* 2013). For instance, under the Emergency Rice Initiative Project implemented in 2009, the Savannah Agricultural Research Institute (SARI) provided technical training and breeder foundation seeds of GR 18, Digang, and Jasmine 85 varieties to certified private seed growers to produce 278.3mt of certified seeds for rice farmers in northern Ghana (Buah *et al.*, 2011). Similarly, the Sustainable

Development of Rain-fed Lowland Rice Project (2009 to 2014) by JICA promoted the cultivation of Jasmine 85 seed variety (Abdulai *et al*., 2018). Jasmine 85 is a high yielding variety (4.5-8mt/ha), early maturity (110-120 days), long grain aromatic with good taste when cooked and mostly preferred by consumers (Ragasa *et al.*, 2013). Thus, Jasmine 85 stands a good chance of competing favourably with imports from Thailand (DFID, 2015).

(3) Seed priming: This is the soaking of rice seeds in clean water for 12–24 hours and drying it in the open for 24–48 hours before sowing (Abdulai *et al*., 2018). According to the Crops Research Institute (CRI) of the CSIR, field trials showed primed seed could boost yield by 25 to 40% relative to non-primed seed (Ragasa *et al.*, 2013). Furthermore, Bam *et al.* (2006) argued that soaking rice seeds with water containing a small quantity of potassium and phosphorus improves germination and seedling emergence. Chemical treatment of rice seed during storage and before planting is also helpful against insects and diseases infestation (CRI, 2005).

(4) Optimal plant density: The recommended planting density is 45–50kg/ha of rice, at a spacing of 20cm x 20cm (Buah *et al*., 2011) with two plants in a hole for transplanting which takes place 21–28 days after sowing (Ragasa *et al.*, 2013). A plant density of 100-126kg/ha for broadcasting, although direct sowing, dibbling or drilling at 45-50kg/ha is strictly advised for efficient use of seed and optimum plant density (Buah *et al*., 2011; Ragasa *et al.*, 2013; Abdulai *et al*., 2018).

(5) Appropriate fertilizer use (rate and timing of application): The CRI and SARI recommend first fertilizer application one week after planting for transplanting and two to three weeks after planting for direct sowing. The second fertilizer application should take place seven to eight weeks after planting. The recommended fertilizer rates are 200–300kg/ha of compound fertilizer (NPK 15-15-15) for the first application and 150kg/ha of

sulphate of ammonia or 75kg/ha of urea (Ragasa *et al.,* 2013; Abdulai *et al*., 2018). Subsurface placement is promoted over the broadcasting method in the application of compound fertilizer, urea super granules as well as micronutrients (Actyva NPK, 23-10-5+2MgO+3S+0.3Zn) which efficiently uses nitrogen and soluble phosphorus to increase yield (Buah *et al*., 2011).

(6) Adoption of sawah system: This includes bund construction, farrowing, puddling, and levelling in lowland rice fields for better water control and nutrient management (Buri *et al*., 2012; Ragasa *et al.,* 2013; Abdulai *et al*., 2018). Other studies such as Bam *et al*. (2010) have reported yield gains for adoption of the sawah system in Ghana.

2.8 Review of empirical studies on constraints to agricultural technology adoption

Farmers usually tend to adopt innovations that reduce the average cost of production and result in higher farm returns and profitability (Kosarek *et al*., 2001; Kijima *et al*., 2011; Kasirye, 2013; De Brauw and Eozenou, 2014). Thus, the adoption of agricultural technologies influences the allocation of factors of production (Nin-Pratt and McBride, 2014). Farmer adoption decisions are also influenced by risk preferences (Koundouri *et al*., 2006; Carletto *et al*., 2007; Foster and Rosenzweig, 2010; Jaeck and Lifran, 2013; Kariyasa and Dewi, 2013) and the amount of fixed cost (Abara and Singh, 1993) required by the technology particularly for small scale farmers.

Other factors such as inadequate infrastructure and production incentives, low literacy rates, liquidity challenges, soil infertility, uncertainty and information imperfection have also been broadly identified as constraints to technology adoption in many developing countries (Just and Zilberman, 1988; Ali and Byerlee, 1991; Jayne *et al*., 2003; Bezu and Holden, 2008;

Marenya and Barrett, 2009; Becerril and Abdulai, 2010). Similarly, Karsiye (2013) and Langat *et al*. (2013) explained that longer travel distances to inputs markets has negative influence on the profitability and the time it takes to adopt. It is also argued the availability and access to arable land can facilitate experimentation with new agricultural technologies (Pingali *et al.*, 1987; Carletto *et al*., 2007), and also determine the pace of adoption as large land owners are more likely to be early adopters (de Janvry *et al*., 2011).

Although, agricultural technological complexities can be mitigated by farmer education (Rogers, 1983), the failure of a technology to meet expectations such as yield and other characteristics may lead to doubt regarding its reliability and eventual rejection by farmers (Singh *et al.*, 2011). Indeed, a study by Kijima *et al*. (2011) revealed over 50% of farmers who adopted Nerica rice variety in Uganda abandoned the variety within two years. The source of information about a technology is known to influence agricultural technology adoption (Feder and Slade, 1985; Rees *et al*., 2000; Koundouri *et al*., 2006; Oster and Thorton, 2009; Conley and Udry, 2010; Kasirye, 2013). For instance, research by Conley and Udry (2010) on pineapple production in Ghana revealed farmers learned from their colleagues and social networks. Another study in Uganda by Karsiye (2013) showed farmers' peers had positive influence on adoption of improved seed and fertilizer.

The key constraints to rice production in Ghana are erratic rainfall and floods, low soil fertility, pests[17] and weeds[18] infestation, diseases[19] and lack of credit facilities (Kranjac-Berisavljevic' *et al*., 2003; Faltermeier and Abdulai, 2009). A study by Ragasa *et al*. (2013) revealed the majority of farmers continuously cultivated rice on the same lowland fields for

[17] Birds attack rice at the grain filling and ripening stages. Farmers drive them away through shouting and bird scaring.
[18] Common weeds are *Andropogon gayanus, Vetiveria spp., Pennisetum spp*., *Cyperus rotundus, Cynodon dactylon, Imperata cylindrica, Chromolaena odorata* and *Panicum spp*.
[19] Diseases include rice smut, blast, rust etc.

over a decade which brings to the fore, the need to invest in integrated soil management practices. Although, Ghana has vast unexploited lowland rain-fed rice fields, it is hampered by a land tenure system which limits acreage expansion and investments (NRDS, 2009). A study by Nin-Pratt and McBride (2014) revealed high labour costs stifled the adoption of labour-intensive cultivation practices in Ghana. In the main rainy season, rice competes against other crops for farm labour. Timely planting, weeding, harvesting and drying are key to producing good quality rice and greater mechanisation would help to address this constraint (Tripp and Mensah-Bonsu, 2013). Low literacy rates, especially in the northern part of Ghana, also adversely affect agricultural technology adoption and utilization.

CHAPTER THREE

THEORETICAL FRAMEWORK ON AGRICULTURAL TECHNOLOGY DIFFUSION AND ADOPTION

3.1 Introduction

This chapter presents a theoretical framework on the diffusion and adoption of agricultural technologies by farmers. Specifically, the chapter contains an overview of agricultural technology adoption, the agricultural innovation decision process, attributes of agricultural innovations as well as the categories of adopters of agricultural technology, other theories that explain human and chapter conclusion.

3.2 General overview of agricultural technology adoption

Many studies have been carried out on the adoption of new technologies by agricultural producers. For instance, some studies (Griliches, 1957; Mansfield, 1961; Just and Zilberman, 1983) have argued that technology adoption is determined by economic factors. Indeed, Just and Zilberman (1983) used household expected utility to model technology adoption under uncertainty subject to input constraints. Similarly, researchers such as Feder *et al*. (1985), Adesina and Zinnah (1993) and Rogers (2003) opine that access to information about a technology determines adoption decisions. This is because technology adoption is expected to increase with time as information, knowledge, and experience with the new technology grows (Jones, 2005). Another paradigm that explains adoption decisions is the technology characteristics and its user(s) context which recognises the agro-ecological, socioeconomic and institutional contexts of technology adoption and allows stakeholder participation in technology development (Biggs, 1990; Negatu and Parikh, 1999; Scoones and Thomson, 1994) such as the participatory varietal selection approach.

3.3 Theoretical framework of diffusion and adoption of agricultural technology

Feder *et al*. (1985) defined adoption as the decision to accept and to fully practice a new technology by a farmer and diffusion as the spread of a technology amongst its end users. Adoption is also described as a process that an individual goes through from first hearing about a technology or an innovation to the decision to continuously use it or reject it (Dasgupta, 1989; Rogers, 1995; Ray, 2001). Thus, adoption involves knowing about a technology and making a decision to accept or reject it in the long run based on assessment of its potentials (Donkoh and Awuni, 2009). Initial studies on adoption and diffusion behaviours of humans were carried out by rural sociologists such as Ryan and Gross (1943), Griliches (1957), Mansfield (1961) and Rogers (1962).

Rogers (2003) defined diffusion as the spread of an idea or practice that is perceived as new over time amongst a social system using specific channels. It involves movement over time via communication from the source of the technology to the end user (Ray, 2001; Stoneman, 2002). Rogers (2003) differentiated adoption from diffusion by describing adoption as an individual decision within a social system and diffusion as a collective occurrence within a community. Thus, the unit of analysis for adoption is the individual/farm household that makes a decision (Katungi, 2007). New technologies most often spread gradually within a social system and therefore, the time element gives rise to classification of adopter categories and to describe diffusion using an S-shaped curve (Shoemaker and Rogers, 1971; Rogers, 2003). Diffusion increases slowly at first when there are few adopters, rising to a maximum by which time half of the individuals in the population would have adopted and finally increasing at a gradual rate to cover the remaining individuals yet to adopt (Rogers, 2003) as shown in Figure 3.1.

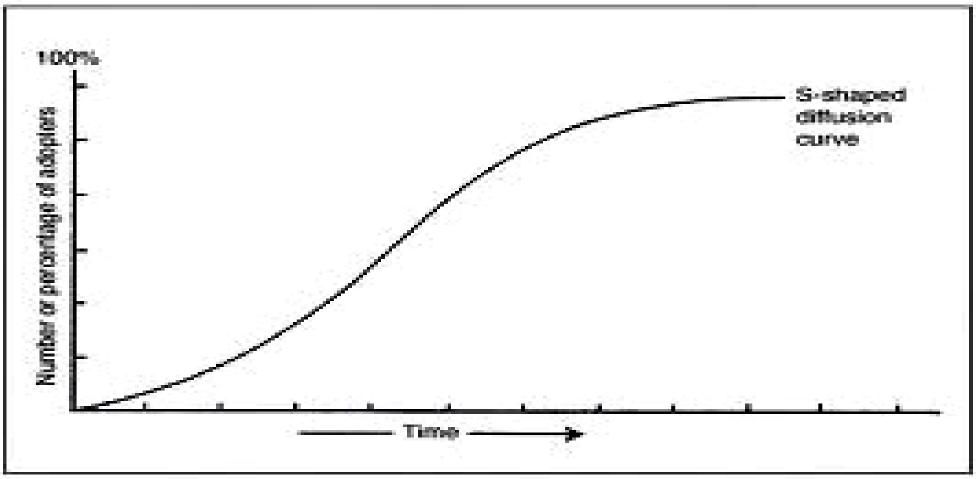

Figure 3.1: S-shaped curve depicting the diffusion of an innovation.
(Source: Rogers, 2003).

The rate of technology adoption thus initially increases, and finally decreases, with the first few adopters of an innovation influencing the other members of a community to adopt the innovation (Dasgupta, 1989). Farmers evaluate the potential benefits of an innovation by relating its suitability with existing practices and farmer characteristics. Ryan and Gross (1943) underscored the gradual process of adoption, where after the first five years, only 10% of farmers in Iowa in the USA had adopted hybrid maize seed.

Similarly, Campbell (1966) explained that the adoption of an innovation is not instant, but develops over a period of time and is influenced by a series of actions including awareness, interest, trial, evaluation and adoption. Rogers (2003) re-categorized the innovation adoption decision process into (i) knowledge, (ii) persuasion, (iii) decision, (iv) implementation, and (v) confirmation.

This is because an individual first gains knowledge of an innovation; forms an attitude towards the innovation, decides to adopt or reject it, and subsequently implements the adoption decision.

3.3.1 Agricultural innovation decision processes

1. *The Knowledge Stage*: According to Rogers (2003), the knowledge stage starts the innovation decision process where an individual learns about the existence of an innovation and begins to seek information to understand how it works. This knowledge stage relates to the exposure or awareness about the existence of improved rice varieties by a household in this study.

2. *The Persuasion Stage*: At this stage, the individual seeks information that helps him to evaluate and reduce uncertainty about the innovation and eventually forms a favourable or unfavourable attitude towards the innovation (Nutley *et al*., 2002; Rogers, 2003). Regarding the adoption of improved rice varieties, the persuasion stage involves getting information from agricultural extension agents, improved seed sellers and or colleague farmers about an improved variety.

3. *The Decision Stage*: This is the stage where the farmer engages in activities to determine the usefulness and compatibility of the innovation to their situation and makes a choice to adopt or reject it (Nutley *et al*., 2002; Rogers, 2003). Trial reduces uncertainty about the consequences of an innovation. Rogers (2003) distinguishes two types of rejection; active rejection and passive rejection. For an active rejection, a household considers a trial of an improved rice variety and chooses to reject afterwards, whereas passive rejection is outright rejection without trial.

4. *The Implementation Stage*: This is where an innovation is put into practice. Rogers (2003) explains that an individual continues to seek active information on how to use the innovation, the operational challenges likely to be encountered and how to solve those challenges.

5. *The Confirmation Stage*: At this stage, an adoption decision would have been made and the individual seeks to reinforce the innovation decision arrived at, but may consider reversing his/her decision if conflicting ideas begin to occur (Rogers, 2003). There may be discontinuance (replacement or disenchantment) at this stage. Replacement discontinuance occurs, for example, when an improved rice variety is rejected to adopt another improved variety with better characteristics whereas disenchantment discontinuance is rejection resulting from dissatisfaction with the performance of an improved rice variety (Rogers, 2003).

3.3.2 Attributes of agricultural innovations

Rogers (2003) identified five attributes that affect a person's choice to adopt an innovation as relative advantage, compatibility, complexity, trialbility, and observability. These attributes affect the rate of adoption (the relative speed with which an improved technology is adopted) by members of a social system.

1. *Relative Advantage*: This is the extent to which an individual is perceived as being better (regarding understanding, accessibility or cost) relative to accessing an improved technology (Rogers, 2003). Relative advantage may be affected by economic factors and social status (Whitney, 2009) as well as the nature and relevance of the innovation to the potential adopters (Rogers, 2003).

2. *Compatibility*: Compatibility describes how an innovation is perceived as consistent with the existing values, past experiences, and needs of potential adopters (Rogers, 2003). When a farmer finds the cultivation of improved rice varieties compatible with farm objectives, the level of uncertainty regarding that improved variety reduces, thus increasing the adoption rate (Pannel, 1999). Rogers (2003) relates technology compatibility with the socio-cultural values and beliefs within the population, previously introduced ideas, and how the new technology meets the needs of end users.

3. *Complexity*: Rogers (2003) defines complexity as the degree to which an innovation is perceived as difficult to understand and use. Complexity is negatively related to the rate of adoption of an improved rice variety.

4. *Trialbility*: This is defined as the extent to which an innovation can be experimented with on a limited basis (Rogers, 2003). There is a positive correlation between trialbility and the rate of adoption, because trial exposes how an innovation works in a particular environment and reduces the uncertainty regarding adoption (Pannel, 1999). Early adopters of improved rice varieties take trialbility more important than late adopters because they may not have past information about these improved varieties. On the other hand, late adopters depend on their peers who already have adopted for information regarding the improved variety and trial may not be very crucial for them (Ryan, 1948; Rogers, 2003).

5. *Observability*: This describes how the results of an innovation are visible to the potential beneficiaries or users of that technology (Rogers, 2003). Parisot (1997) identified peer observation as a key motivational factor in the adoption and diffusion of technology. Some technologies are easily observed and transferred whereas others are difficult to observe and transfer. In the case of an improved rice variety, observability can reflect in higher yield, disease, pest or drought tolerance, taste etc. in comparison with a traditional variety.

Rogers (2003) concluded that innovations that are perceived to be relatively advantageous, compatible, easy to try and observe and less complex are rapidly adopted.

3.3.3 Categories of adopters of agricultural technologies

The concept of adopter categories is important because most newly released agricultural technologies, such as improved rice varieties, go through a natural, predictable, and sometimes lengthy process before becoming widely adopted within a society (Rogers, 1995). Adopter categories in a population are classified based on their responsiveness to innovation, namely innovators, early adopters, early majority, late majority and laggards (Rogers, 2003). According to Rogers (2003), there is usually a normal distribution of the various adopter categories that forms the shape of a bell curve as presented in Figure 3.2.

Innovators most often take the risk of accepting new technologies at the very early stages of their introduction and make up about 2.5% of any population (Rogers, 2003). They move beyond their communities to seek information and are always ready to experience new ideas. Innovators usually have the financial resources to absorb possible losses from an unprofitable innovation in addition to the ability to understand and apply complex technical knowledge as well as cope with the uncertainty regarding the innovation at the time of adoption.

Early adopters are mostly local opinion leaders who reduce uncertainty about a new agricultural technology by adopting it. Given their status as community leaders, they provide information and subjective evaluation of the innovation to other community members through interpersonal networks. Rogers (2003) argued that because early adopters are not too far ahead of the average individual in innovativeness, they serve as a role model for many other members within the society. Early adopters usually make up approximately 13.5% of the population.

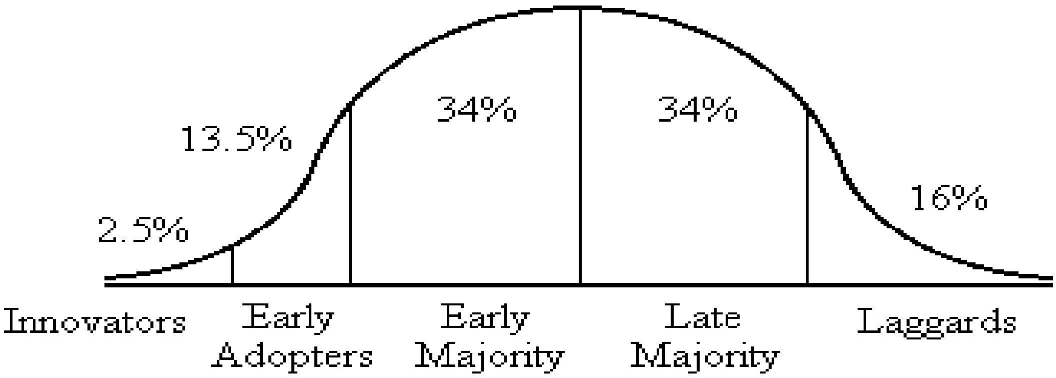

Figure 3.2: Adopter categories of farmers. (Source: Rogers, 2003).

Rogers (2003) explained that the early majority are an important linkage between the very early and late adopters. They have a unique position in the diffusion process because their innovation decision period is relatively longer than that of the innovators and the early adopters. The members in this category are the largest constituting 34% of a given population.

The next group are the late majority (34% of the population) who initially delay adoption because of the reservations they may have about the improved rice variety making a positive contribution to farm objectives, but adopt in the long run owing to peer influence (Rogers, 2003). Last but not least are the laggards (16% of the population) who usually are extremely cautious to adopt and compare the improved rice variety with their experience, values, economic situation and farm needs (Rogers, 2003). The laggards are the last category of adopters in the population.

3.4 Other theories that explain human behaviour outcomes

In this section, the theories of reasoned action and planned behaviour as well as the technology acceptance model in explaining human behaviours towards accepting.

3.4.1 Theories of reasoned action and planned behaviour

The theory of planned behaviour (Ajzen, 1985 and 1991; Ajzen and Madden, 1986) is built on the theory of reasoned action (Ajzen and Fishbein, 1980), both of which are based on the notion that attitudes had a significant influence on human behaviour (Thurstone and Chave, 1929; Stagner, 1942; Nisson and Earl, 2015). Fishbein and Ajzen (1975) argued that behaviour could be determined based on behavioural intentions which in turn is influenced by attitudes toward the behaviour and subjective norms. The theory of reasoned action is based on the assumption that actual behaviour is shaped by an individual's beliefs, attitudes, and intentions. Sheppard, Hartwick, and Warshaw (1988) explained that behavioural intentions embody the willingness to subsequently perform the actual behaviour. Individual beliefs and attitudes are in turn influenced by people and factors (salient social referents) that are considered important to that individual. Regarding technology adoption, subjective norms relate to the perceived social pressure arising out of choosing to adopt or not to adopt improved rice varieties whereas attitude toward the adoption behaviour encompasses existing beliefs that predict the likelihood of cultivating improved rice varieties.

Nonetheless, a shortcoming of the theory of reasoned action is an individual's inability to translate behavioural (adoption) intentions into actual behaviour. As a result, the theory of reasoned action was modified into the theory of planned behaviour (Ajzen, 1991) by incorporating perceived behavioural control which specifies an individual's capacity to perform the target behaviour (to adopt improved rice varieties). Perceived behavioural control assesses the ease of performing the behaviour taking into consideration individual abilities and access to required resources (Madden, Ellen, and Ajzen, 1992). For instance, the performance of some behaviours requires resources such as money and time, and ability in the form of knowledge, skills, confidence and willpower (Armstrong *et al*., 1999). Farmers will adopt improved rice varieties if they have the capacity and believe adoption will help them attain farm objectives. A technology with a lower perceived usefulness will not achieve acceptance and usage despite dissemination efforts by its implementers (Robey, 1979; Alavi and Henderson, 1981; Davis, 1989).

Thus, in the theory of planned behaviour, subjective norms, attitudes toward the behaviour and perceived behavioural control are used in predicting behavioural (adoption) intentions and how that translates into behavioural outcomes. Unlike the theory of reasoned action, the theory of planned behaviour is able to predict behavioural intentions for non-volitional behaviours or where individuals have limited control (Rossi and Armstrong, 1999). The theory of planned behaviour is useful in evaluating how behavioural intentions reflect behaviour outcomes and can be applied in promoting and targeting behavioural changes (Fishbein and Manfredo, 1992; Hillhouse, Adler, Drinnon, and Turrisi, 1997).

Notwithstanding, Fredricks and Dossett (1983) have criticised both the theories of reasoned action and planned behaviour for not including past behaviour in predicting future behaviour. The authors suggested the addition of past behaviour to attitudes, subjective norms and planned behavioural control in predicting future behaviour because past habitual behaviour can influence subsequent behaviour. Another shortcoming of these two theories is their reliance on self-reported measures of behaviour which is prone to over-reporting of desirable behaviour and under-reporting of undesirable behaviour (Edwards, 1953; Schroder, Carey and Vanable, 2003). Moreover, Davis (1986) states that perceived usefulness and ease of use on behaviour are subjective forms of evaluation and do not reflect objective reality. Although, Fishbein and Ajzen (1975) theory of reasoned action explains that beliefs influence behaviour indirectly through attitudes, Triandis (1977) and Davis (1989) argue that beliefs and attitudes are both determinants of behavioural intentions. Moreover, Davis, Bagozzi, and Warshaw (1989) observed that subjective norms produced no significant influence on behavioural intentions beyond perceived usefulness and ease of use.

3.4.2 Technology acceptance model

In the technology acceptance model, technology usage behaviour is influenced by usage intention, which in turn is determined by perceived usefulness and perceived ease of use (Davis, Bagozzi, and Warshaw, 1989). Venkatesh and Davis (2000) modified the technology acceptance model where perceived usefulness is affected by social influence processes (subjective norm, voluntariness, and image) and cognitive instrumental processes (job relevance, output quality, result demonstrability, and perceived ease of use). Subjective norms through salient referents can positively influence image and identification where technology usage behaviour can enhance one's social status (Kelman, 1958; Moore and Benbasat, 1991; Venkatesh and Davis, 2000). Voluntariness depicts how technology usage is perceived to be non-mandatory (Agarwal and Prasad, 1997). Subjective norms can have a significant influence on technology usage intentions in mandatory settings and not in voluntary situations (Hartwick and Barki, 1994). Nonetheless, the effect of subjective norm on perceived usefulness reduces with increasing direct experience with the technology and provides a basis for cognitive evaluation in terms of relevance, quality of results to inform continued use (Fazio and Zanna, 1981; Doll and Ajzen, 1992; Venkatesh and Davis, 2000).

3.5 Review of empirical studies on farmers perceptions of rice varietal traits

Farmers' perceptions of the appropriateness or otherwise of technology characteristics affect adoption decisions (Adesina and Zinnah, 1993; Baidu-Forson *et al*., 1997; Sall *et al*., 2000; Dalton, 2004; Dandedjrohoun *et al*., 2012; Acheampong, 2015). For instance, in Burkina Faso, high yield trait was the motivation for farmers choosing to cultivate improved sorghum over local varieties (Adesina and Forson, 1995). Manu-Aduening *et al*. (2005) identified a mismatch of technology characteristics with farmers preferences as reason for the low adoption of improved farming practices in Ghana. Asfaw *et al*. (2012) indicated farmers assessed varietal traits such as yield, drought, disease tolerance, and market price of output in their choice of adoption of improved pigeon pea and chick pea in Tanzania and Ethiopia respectively.

Specifically, on rice, production and consumption related characteristics such as maturity period and plant height, grain colour, grain elongation, swelling, and tenderness had significant influence on rice varietal preference decisions by farmers in Sierra Leone, Cote d'Ivoire, and Senegal (Dalton, 2004). A study by Joshi and Bauer (2006) on choice of adoption of modern rice varieties in Nepal rain-fed ecosystems indicated farmers looked out for early maturity, less water demand, ease of threshing, taste etc. in making such adoption decisions. This is because a technology's inability to meet farmers' expectations such as yield creates doubt and can lead to its rejection by farmers (Singh *et al*., 2011). In Ghana, a study by Buah *et al*. (2011) on enhancing access to improved rice seed by farmers identified higher yield, early maturity, disease and pest-resistance, ease of threshing and milling as well as good taste as reasons for adoption. Similarly, farmers in Bihar, India preferred rice varieties with shorter maturity days, lower seeding rate with the ability to obtain good planting seed from harvested paddy (Ward *et al.*, 2013). Another study by Coffie *et al*. (2016) on choice of rice production practices and farmers willingness to pay in Ghana concluded that farmers preferred high yielding and early maturing rice varieties with less labour requirements.

Thus, farmers' perceptions and preferences of rice varietal characteristics played key roles in influencing adoption decisions (Ghimire *et al*., 2015). For this reason, this study applied qualitative interviews to assess the influence of smallholder farmers' perceptions and preferences of specific rice varietal traits on their adoption decisions in Ghana. This qualitative approach complements the quantitative approach that applies the method of treatment effect to identify the farm and farmer characteristics, socioeconomic and institutional factors that influence adoption of improved rice varieties by smallholder farmers in Ghana.

3.6 Conclusion

Although, the theories of reasoned action, planned behaviour and the technology acceptance model are applied in in literature, they are not without limitations particularly in explaining farmer exposure to and adoption of improved rice varieties. For instance, individual adoption intentions may fail in translating into actual adoption of improved rice varieties outcomes under the theory of reasoned action. Even though the theory of planned behaviour is an improvement over the theory of theory of reasoned action by incorporating perceived behavioural control and usefulness, it is based on subjective evaluation that is prone to farmer reporting bias and do not reflect objective reality of adoption behaviour. In the technology acceptance model, usage intention is influenced by the technology's perceived usefulness and perceived ease of use. However, the effect of perceived usefulness and perceived ease of use in explaining technology adoption outcomes diminish with increasing direct experience with the technology and does not explain continued technology use.

Rogers (2003) provides a comprehensive description of the technology diffusion and adoption process in an agricultural setting. Specifically, Rogers' agricultural innovation decision processes, attributes of agricultural innovations, and categories of adopters of agricultural technologies explained in section 3.3 closely fit the exposure and adoption of improved rice varieties process of this study.

CHAPTER FOUR

THEORETICAL FRAMEWORK AND LITERATURE REVIEW ON THE AVERAGE TREATMENT EFFECT

4.1 Introduction

This chapter presents the theoretical underpinnings of the method of average treatment effect in evaluating awareness about improved rice varieties as well as the adoption of improved rice varieties. The last section of the chapter includes a review of empirical studies on agricultural technology adoption and evaluation and chapter conclusion.

4.2 The average treatment effect model in technology adoption and evaluation

4.2.1 Treatment effect in joint exposure and adoption of technology

The sheer preponderance of literature in agricultural technology adoption and evaluation following studies such as Rubin (1974), Rosenbaum and Rubin (1983), Moffit (1991) and Heckman *et al*. *(*1998) cannot be over-emphasized. Recent studies building on the work of earlier researchers such as Angrist *et al*. (1996); Heckman *et al.* (1999); Blundell and Costa Dias (2000); Wooldridge (2002); Imbens (2004); Smith and Todd (2005); Wooldridge (2005); Caliendo and Kopeinig (2008) have applied propensity score matching and instrumental variables estimations. However, in assessing the effect of technology adoption within a population, it is important to first analyse awareness (exposure) about the technology by its intended users in the area, and estimating adoption rate using only those who are exposed. Moreover, analysing farmer technology adoption and its determinants using probit, logit, tobit or poisson without first analysing technology exposure produce biased and inconsistent estimates (Diagne and Demont, 2007). Furthermore, the estimation of adoption rates (either by land area allocation of a crop or proportion of all farmers adopting) and its determinants do not correctly estimate population adoption rates. This is because such estimations would only provide a joint estimate of exposure and adoption effects which is different from the average treatment effect of adoption alone which is what is usually sought (Diagne, 2006; Diagne and Demont, 2007).

It is important to note that where awareness, ω about a technology is non-uniform, proceeding to estimate the probability of adoption ($P(y_1 = 1)$) without first estimating the probability of exposure gives the undesirable results of joint probability of exposure and adoption, $P(\omega y_1 = 1) = P(\omega = 1, y_1 = 1)$ in spite of random sampling (Diagne, 2006; Diagne and Demont, 2007). The population mean joint exposure and adoption parameters (JEA) are estimated using the full random sample without controlling for exposure bias and is expressed as:

$$JEA = E\omega y_1 = P(\omega = 1) \times ATT + (1 - P(\omega = 0)) \times ATU \qquad (4.1)$$

Similarly, the average treatment effect of joint exposure and adoption for the full sample is expressed as:

$$J\hat{E}A = \frac{1}{n}\sum_{i=1}^{n} \omega y_i \qquad (4.2)$$

However, the JEA estimate is biased and inconsistent because it treats farmers without exposure as non-adopters, although they could have adopted upon exposure, leading to non-exposure and selection bias and incorrect estimates of the adoption rate in such estimations even for a random sample (Diagne, 2006). This is very crucial given that adoption is defined as the decision to accept and apply a new technology by a farmer and diffusion as the spread of knowledge about that technology amongst a population (Feder *et al.*, 1985; Dasgupta, 1989; Rogers, 1995 and 2003; Ray, 2001). This implies exposure to (awareness about) a technology is central to adopting it, even though exposure does not necessarily mean adoption (Diagne and Demont, 2007). Selection bias may be addressed by estimating a two-stage probit sample selection model. This will involve the estimation of the determinants of exposure to improved rice varieties for the full sample, followed by the estimation of joint exposure and adoption also using the full sample in the second stage, which does not eliminate non-exposure bias.

The weakness of the JEA in providing unbiased, consistent and correct estimates leads to the estimation of technology adoption with correction for technology exposure.

4.2.2 Treatment effect in technology adoption with correction for technology exposure

Following Diagne and Demont (2007), exposure to improved rice varieties is defined as a farmer being aware of the existence of improved rice varieties. In this study, exposure determines treatment. Considering a population of N households, Ne is the number of households who are exposed. At the household level, the interest is adoption status (a binary outcome), exposure rates (Ne/N) at the population level, adoption rates (Na/N) under incomplete exposure, and adoption rates amongst the exposed (Na/Ne) assuming universal exposure to improved rice varieties (Kabunga *et al*., 2012). Using a simple case of adoption with a dichotomous variable, y_1 represents the adoption outcome of a randomly selected farmer exposed to an improved rice variety and y_0 is the adoption outcome without exposure from the population. The effect of treatment for farmer i is the difference, $y_{i1} - y_{i0}$, and the population adoption impact of exposure to the improved varieties is the mean value of $(y_{i1} - y_{i0})$, or the average treatment effect, ATE (Diagne and Demont, 2007). However, for the same individual farmer, it is not possible to observe both adoption and the counterfactual, and because exposure precedes adoption, it means adoption $y_0 = 0$ at the exposure stage. Therefore, for a farmer who adopts, $ATE = Ey_1$ because that farmer cannot be an adopter and non-adopter of improved rice varieties simultaneously.

Wooldridge (2002) and Diagne and Demont (2007) have argued that the method of average treatment effect provides a better estimation of the population adoption rate because it measures the improved rice variety adoption outcome of a farmer randomly drawn from the population when everyone is exposed to the improved rice varieties. Diagne and Demont (2007) suggested the $ATE(x)$ methodology which identifies and provides consistent estimates of the population adoption rate and determinants of adoption based on Wooldridge (2002) and Imbens (2004) conditional independence assumption. The conditional independence assumption is also called the 'ignorability' or 'uncounfoundness' assumption (Rosenbaum and Rubin, 1983; Wooldridge, 2002; Imbens, 2004; Cameron and Trivedi, 2005) and states that exposure and adoption outcomes can be independent when the observed covariates of x are controlled. Similarly, the exposure treatment status ω is independent of the potential outcomes of adoption $y_1$and y_0 conditional on the observed set of covariates for exposure, z: $P(\, y_1 = 1/\omega, z) = P(\, y_1 = 1/z) i = \, 0, 1$, where z comprises the vector of covariates that determine exposure to the improved rice varieties. In the same vein, exposure is independent from x conditional on z: $P(\omega = 1 \mid x, z) = P(\omega = 1 \mid z)$ and potential adoption is also independent from z conditional on x: $P(y_1 = 1 \mid x, z) = P(y_1 = 1 \mid x)$.

Under the conditional independence assumption, variables in the conditioning vector of covariates x and z can be endogenous for the identification of the causal effect of exposure on adoption as long as the values of these pre-treatment variables (age, gender, educational status of farmer meet this criteria) remain unchanged even when the exposure status of the farmer changes (Heckman and Vytlacil, 2005; Lee, 2005).

The first stage estimates the determinants of exposure to improved rice varieties as well as the propensity score of exposure to improved rice varieties and is given as:

$$P(\omega = 1 \mid z) \equiv P(z) \qquad (4.3)$$

The second stage is the parametric estimation of $ATE(x)$ under the conditional independence assumption (Diagne, 2006; Diagne and Demont, 2007), from which the ATE and ATT are written as:

$$ATE\ (x) = E(\, y/x\ , \omega = 1) = g(x, \beta) \qquad (4.4)$$

Assuming a probit model, $g(x, \beta) = \Phi(x\beta)$

where, g is a nonlinear function of the vector of covariates x and the unknown parameter vector β that can be estimated by maximum likelihood using the observations (y_i, x_i) from the subsample of exposed farmers only with y as the dependent variable (adoption outcome) and x, the vector of explanatory variables. With an estimated parameter $\hat{\beta}$, the predicted values $g(x_i;\ \hat{\beta})$ are computed for all the observations i and ATE, ATT and ATU are estimated by taking the average of the predicted $g(x_i;\ \hat{\beta})$ $i = 1, \ldots n_e$ across the exposed sample for $ATE(x)$ and the respective subsamples for the average treatment effect on the treated (ATT) and for the untreated (ATU).

The estimates of the ATE, ATT, ATU and JEA are then used to calculate the non-exposure bias and the population selection bias. The non-exposure bias (NEB), or adoption gap, is calculated as follows:

$$NEB = J\hat{E}A - A\hat{T}E \qquad (4.5)$$

The population selection bias (PSB) accounts for the bias that arises as a result of using the exposed subsample to estimate the expected adoption rate which most often overestimates the true population adoption rate due to self-selection and targeting bias and is given by:

$$PSB = A\hat{T}T - A\hat{T}E \tag{4.6}$$

The JEA estimates the average of joint exposure and adoption outcome without controlling for exposure bias whereas ATE measures the average treatment effect of adoption within the subsample exposed to improved rice varieties. The population adoption gap measures the potential demand for improved rice varieties by the population that is hampered by non-exposure.

Diagne and Demont (2007) explained that estimating the probability of joint exposure and adoption using the classical probit model produces inconsistent estimates of the determinants of adoption. Similarly, it is worthy to point out the issue of selectivity bias in the classical joint exposure and adoption. Selectivity bias is addressed by the estimation of a two stage Heckman probit sample selection model. The first stage involves the estimation of the determinants of exposure to improved rice varieties using all the random sampled observations, followed by the estimation of the classical joint exposure and adoption also using the full random sample in the second stage.

Relative to the $ATE\ (x)$ corrected adoption model, the issue of selectivity bias is relaxed (Diagne and Demont, 2007). This is because unlike the classical joint exposure and adoption estimation which uses the full random sample, the $ATE\ (x)$ corrected adoption model estimates the average treatment effect of adoption using the random subsample of only farmers with exposure to improved rice varieties, which in this study determines treatment.

Therefore, the untreated (non-exposed) farmers who are also non-adopters of improved rice varieties are not included in the estimation of the $ATE\ (x)$ corrected probit model.

The estimation of exposure and its determinants provide information on the diffusion and level of awareness about the improved rice varieties within the population (Kabunga *et al*., 2012) and differs from adoption which happens after being exposed to these improved rice varieties (Diagne and Demont 2007; Simtowe *et al*., 2016). The classical probit model is used to estimate the determinants of exposure whereas the second stage, which controls for awareness, estimates unbiased adoption parameters following Diagne and Demont (2007).

4.3 Review of empirical studies on agricultural technology adoption and evaluation

Many studies have analysed the rates and determinants of adoption of new agricultural technologies. Although such studies have tried to explain the adoption decisions of farmers, they often suffer non-exposure, selection and targeting bias producing biased and inconsistent estimates. For instance, Asfaw and Admassie (2004) estimated the effect of education on household decision to adopt chemical fertilizers in Ethiopia using the binary logit model. Jones (2005) applied the probit model to analyse the adoption and dis-adoption of soybeans by farmers along the Togo-Benin border. Jones (2005) defined adoption as the choice of cultivation of soybeans and dis-adoption as the farmers' decision not to grow soybeans during the 2003/2004 planting season. The author argued that the rates and determinants of adoption and dis-adoption provide information on why farmers choose to adopt and or abandon technologies so as to improve the acceptability, longevity and efficacy of improved technologies. Although Jones (2005) tried to model adoption and dis-adoption decisions, her approach failed to deal with non-exposure bias, selection bias or even endogeneity, thereby producing biased and inconsistent estimates. Similarly, Alene and Manyong (2007) analysed the effect of adoption of improved cowpea varieties on the cowpea productivity of farmers in Nigeria. To correct for possible endogeneity and selection bias, a two-stage switching regression model was used to estimate separate equations for the adopters and non-adopters of cowpea. Nonetheless, the flaw from Alene and Manyong (2007) was their inability to separate exposure to improved cowpea varieties from the subsequent decision by the farmers to adopt them. Farmers would only adopt improved cowpea varieties when they are aware of their existence.

Asfaw, Shiferaw, Simtowe and Lipper (2012) used the probit model to analyse the determinants of adoption of improved pigeon pea and chick pea in Tanzania and Ethiopia. Asfaw *et al*. (2012) reported adoption rates of 33% for pigeon pea in Tanzania and 32% for chick pea in Ethiopia. Nonetheless, the authors did not separate farmers who knew about the improved varieties and could adopt them from those who were not exposed to the varieties and thus, could not adopt. The low adoption rates reported could be attributed to low diffusion or awareness of the varieties amongst the population which was not accounted for in the analysis. Therefore, estimates of the rates and determinants of adoption had non-exposure bias.

Building on the adoption and treatment effect literature, Diagne and Demont (2007) in their study 'taking a new look at empirical models of adoption: average treatment effect estimation of adoption rates and their determinants' criticised studies that fail to account for incomplete diffusion in technology adoption. They described such studies as having both non-exposure and selection bias. This is because a farmer cannot adopt a new crop variety if that farmer does not even know the variety exists, and thus only those who are aware of the new variety can proceed to make an adoption decision. Diagne and Demont (2007) argue that estimating adoption rate and its determinants using the classical probit, logit, or tobit produces biased and inconsistent estimates unless exposure to the technology is accounted for. Using a sample of 1,500 rice farmers in Ivory Coast to study the adoption of Nerica rice varieties, Diagne and Demont (2007) employed the $ATE\,(x)$ adoption framework to calculate the population adoption rate (ATE), non-exposure bias and the population selection bias. The number of Nerica rice varieties known by the farmer, village contact with development agencies, cultivation of upland rice, ethnic group and secondary occupation of the farmer had positive and significant effect for the joint exposure and adoption estimation using the classical probit model. The determinants of adoption relative to the preferred $ATE(x)$ probit model were the number of Nerica varieties known in the community, community participation in varietal selection, ethnic group and agro-ecological zone.

The joint exposure and adoption (JEA) rate[20] estimate of 4% obtained from the full sample fails to account for non-exposure bias because of incomplete diffusion of the Nerica rice varieties. The average treatment effect on the treated adopters (ATT) obtained from using the subsample of exposed farmers in the estimation under complete varietal diffusion was 37%. The average treatment effect on the untreated (ATU) was 17% whereas the unbiased and consistent estimate of the average adoption rate (ATE) under full exposure assumption for Nerica rice was 19%. The non-exposure bias, $JEA - ATE, (4 - 19)$ was -15%, whilst the population selection bias, $ATT - ATE, (37 - 19)$ which revealed the bias from estimating the population adoption rate using the subsample of the exposed farmers alone was 18%. Diagne and Demont (2007) concluded the adoption gap of -15% which indicated

[20] This was estimated using the classical probit model.

the potential demand for the rice variety resulted from poor dissemination of the Nerica rice variety and therefore recommended improved diffusion of the rice variety to increase its adoption amongst the population of rice farmers in Ivory Coast.

A similar study by Diagne (2006) applied the poisson ATE on the diffusion and adoption of Nerica varieties in Ivory Coast. The author estimated separately the determinants of exposure using a logit model whereas the rate and determinants of adoption were estimated using an ATE corrected poisson-instrumental variable approach. Rice farmers in communities that participated in varietal selection, and with knowledge of both improved and traditional upland rice varieties as well as contact with rice development and extension agencies had higher probability of exposure to Nerica rice varieties. The average exposure rate of Nerica within the full sample was 10%. The determinants of Nerica rice adoption for the ATE corrected poisson-IV model were the number of Nerica varieties known by the farmer, the number of Nerica varieties cultivated by the farmer, growing rice partly for sale, participation in varietal selection, upland rice cultivation, and household size had positive and significant effect on adoption whereas age and attainment of secondary education had negative influence on adoption of Nerica rice. The average Nerica adoption rate for the full population under incomplete diffusion (JEA) was 4%. However, under conditions of complete diffusion, the full population adoption rate (ATE) would have been 27%, and for the non-exposed subsample, the Nerica adoption rate would have been 25%. Thus, the non-exposure bias (adoption gap, 4%-27% = -23%) of -23% is the demand for the technology by the population hampered by incomplete diffusion of the Nerica rice varieties. The average treatment effect on the treated (ATT) within the exposed subsample was 46%. Similarly, the population selection bias (46-27= 19%) of 19% is the bias due to over-estimation of the true population adoption rate using the exposed subsample only. Diagne

(2006) recommended further dissemination of the Nerica rice varieties to increase potential adoption.

Simtowe *et al*. (2016) studied the adoption of pigeon pea varieties under partial population awareness involving 400 households in Malawi. The authors defined awareness as having knowledge about the existence of improved pigeon pea varieties and going further to seek information about its attributes. From their results, age of the household head and distance to input markets reduced the probability of exposure to improved pigeon pea. On the other hand, membership of social groups, number of years a farmer lived in the community and value of household assets positively influenced exposure. Female headed households, older farmers and farmers with access to credit had higher probability of adoption. The mean joint exposure and adoption rate under incomplete exposure for the population was 14% which could have increased to 41% (ATE) if the whole population was exposed to the pigeon pea variety, thus producing a non-exposure bias of 27%. Within the sample of non-exposed households, pigeon pea adoption rate would have risen to 42% with the benefit of exposure. The estimated adoption rate (ATT) within the exposed subsample was 39%. The value of the population selection bias was not statistically significant which means that the probability of adoption for a farmer with exposure would not be significantly different from the adoption probability for any farmer randomly sampled within the population under conditions of complete awareness of the pigeon pea variety. Moreover, the negative value of the population selection bias (-2%) means that the adoption rate for the exposed sample was likely to reduce. The authors concluded that the potential adoption gap of 27% due to incomplete exposure could be reduced by increased awareness via agricultural extension workers about pigeon pea in the population supported by enabling easy access to the seeds.

4.4 Conclusion

The joint exposure and adoption model is estimated under the assumption of partial exposure because, it contains both the exposed and non-exposed households. This produces biased and inconsistent estimates of the population adoption rate and determinants of adoption due to non-exposure and selection bias exists because not everyone in the population is exposed to the new technology due to incomplete diffusion of the improved rice varieties. On the other hand, the $ATE(x)$ corrected model recognises non-exposure bias by estimating the adoption of improved rice varieties using the sub-sample of households with exposure to improved varieties. Therefore, the $ATE(x)$ corrected model gives the correct, unbiased and consistent estimates of the determinants of adoption and adoption rate of improved rice varieties, and thus applied in this study.

CHAPTER FIVE

LITERATURE REVIEW ON STOCHASTIC FRONTIER ANALYSIS

5.1 Introduction

This chapter presents the conceptual framework of production and efficiency as well as the theoretical framework of the stochastic production frontier. It also provides the theoretical background of the application of the stochastic production frontier with correction for sample selection in analysing the effect of adoption of improved rice varieties on farmers' technical efficiency, which is the second objective of this study. Lastly, it includes a review of empirical studies on the stochastic production function with correction for sample selection and chapter conclusion.

5.2 Conceptual framework of production and efficiency

This section explains the concepts of both production and efficiency and how the two concepts help us to understand the relationship between inputs, output and efficiency under a given production technology.

5.2.1 The concept of production

Production is defined as the transformation of resources (inputs) into finished products (outputs). Relative to rice cultivation, the conventional production inputs are land, seed, fertilizer, labour and herbicides with the physical quantity of rice obtained from the farm as the output. A production function expresses the relationship between inputs and output levels under a given technology. According to Johnes (2006), there are mainly two basic ways of estimating a production function. The statistical (parametric) approach such as the stochastic frontier specifies a functional form as well as a distributional assumption and separates the effect of random (measurement) error outside the control of the farmer from the inefficiency component. The non-statistical and non-parametric approach such as the data envelopment analysis does not make assumptions regarding the functional form of the production function nor the distribution of inefficiencies, albeit it does impose some technical restrictions such as monotonicity and convexity (Fare, Grosskopf and Lovell, 1994). The non-parametric models also assume any deviation from the frontier function is due to inefficiency. When measuring technical efficiency, a production function is used.

5.2.2 Properties of a production function

Given a production function of the form, $y_i = f(x_i\beta + \varepsilon_i)$, where y_i is the physical output of rice, and x_i represents the quantities of production inputs such as farm size, seed, fertilizer, labour, fertilizer etc., and $f(x_i)$ is the production function. For a typical production function (Chambers, 1988), the following regularity conditions hold:

1. Non-negativity in $f(x_i)$: The value of $f(x_i)$ is finite, positive, non-negative and a real number.
2. Weak essentiality: This assumes the production of positive output (y_i) is impossible without the use of at least one input (x_i). This implies zero input gives zero output, $f(0) = 0$. However, the weak essentiality assumption is replaced with stronger essentiality when every input is essential for production.
3. Non-decreasing in x_i: This is also known as the monotonicity condition, where an additional unit of input will not decrease output. If the production function is

continuously differentiable, monotonicity means all marginal products are non-negative. If $x^0 \geq x^1$, then $f(x^0) \geq f(x^1)$. However, the monotonicity condition may be relaxed where heavy input use leads to input congestion.

4. Concavity in x: A linear combination of input vectors x^0 and x^1 will produce an output that is no less than the linear combination of $f(x^0)$ and $f(x^1)$.
5. If the production function is continuously differentiable, concavity means all marginal products are non-increasing, which implies diminishing marginal productivity.

5.2.3 The concept of efficiency

Efficiency is achieving good result with little waste of effort. Efficiency measurement is very important because it is a factor for productivity growth. According to Farrell (1957), technical efficiency (TE) is a component of economic efficiency (EE) where the latter is defined as the product of TE and allocative efficiency (AE). In turn, AE refers to the ability to produce a given level of output using cost-minimising input ratios. Allocative efficiency deals with the extent to which farmers make efficient decisions by using input up to the level at which their marginal value product is equal to the marginal factor cost or price of input (Abdulai and Huffman, 2000). Technical efficiency is the ability of a firm to obtain maximum output from a given set of inputs. Similarly, technical inefficiency occurs when a given set of inputs produces less output than what is possible given the available production technology. Where, there is technical inefficiency, there is room to increase output without increasing input amounts at the present level of production technology. For example, a 75% TE level for a rice farm means that, it is operating at 75% of its potential output. That is, the rice farm could produce an additional 25% of output without changing the levels of inputs used if it were to improve its efficiency and operate on the production frontier.

A graphical illustration of technical, allocative and economic efficiency is presented in Figure 5.1. A rice farm operating at R is technically efficient because it is operating on the isoquant $IS - IS'$. However, if a rice farm is operating at H it is not efficient because it is far away from R. In this regard, the technical inefficiency of H is measured by the distance RH, which is the amount by which the rice farm's inputs can be proportionally reduced without reducing rice output. Thus, in a ratio form the technical efficiency of this firm is measured by $TE_i = OR/OH$ which is equal to $1 - RH/0H$.

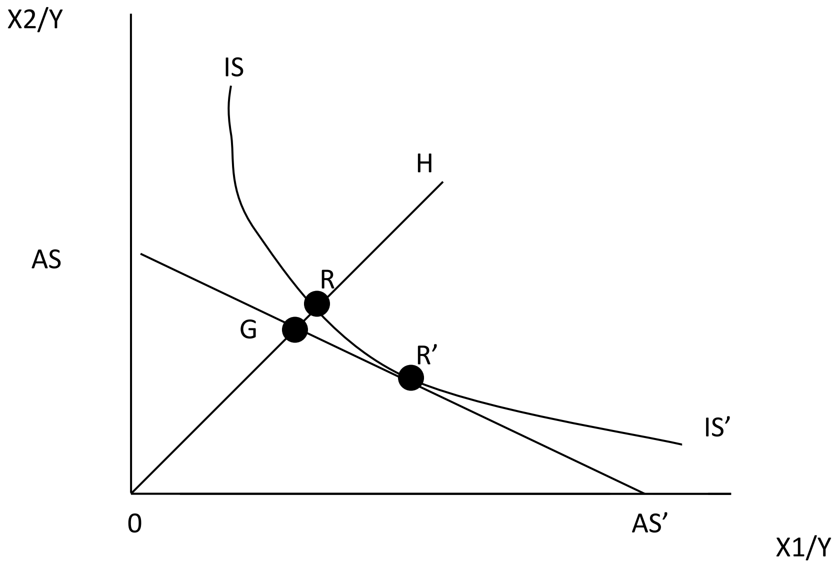

Figure 5.1: Technical, Allocative and Economic Efficiency (Adapted from Coelli, 1996).

The level of technical efficiency is measured by the distance a particular farm is from the production frontier and it takes a value between zero and one. Thus, a technical efficiency of one implies the farm is fully efficient, otherwise it is inefficient. From Figure 5.1, the input price ratio is represented by the slope of the straight line $AS - AS'$. With this, the allocative efficiency of the firm can be determined. At point H, the allocative efficiency is defined as the ratio $AE_i = OG/OR$ since the distance GR represents the reduction in production costs if production were to occur at the allocatively and technically efficient point R' instead of the technically efficient, but allocatively inefficient point R. The product of technical efficiency (TE) and allocative efficiency (AE) is economic efficiency (EE) and is given as:

$$EE = TE_i \times AE_i = (OR/OH) \times (OG/OR) = (OG/OH) \quad (5.1)$$

The estimation of technical efficiency gives an indication of the potential gains in output if inefficiencies in production were to be eliminated.

Economic theory indicates that productivity change can be decomposed into two sources: change in technology (such as adoption of improved rice varieties) and change in efficiency (Coelli, Rao and Battese, 1998). Technological change shifts the production possibility frontier outward, and improving efficiency means the rice farm is operating very close to the available production possibility set. A measure of technical efficiency indicates the extent to which a farm could produce additional output without changing the levels of inputs used if it were to operate on the production frontier, which is determined by the best-practice rice farms. The production frontier indicates the minimum inputs required to produce any given level of output for a farm operating with full efficiency. The productive efficiency of a production unit refers to the ratio of actually achieved aggregate output to optimal aggregate output it can achieve with the same level of aggregate input.

5.3 Theoretical framework of the stochastic frontier function

The stochastic frontier model was developed by Aigner, Lovell and Schmidt (1977) and Meeuseen van den Broeck (1977) building on previous work done by Farrell (1957) as well as Aigner and Chu (1968). Ever since, there has been wide acceptance of the stochastic frontier approach in the realm of production economics with numerous publications. It is consistent with theory, versatile and relatively easier to estimate (Kokkinou, 2010). The error term of the stochastic frontier model has two components, one which measures technical inefficiency and another which accounts for the effects of random shocks outside the control of farmers.

The stochastic frontier model is suitable for analysing farm level data where measurement errors are substantial, and the weather is likely to have a significant effect (Coelli, 1995). It also allows for the estimation of standard errors as well as to test hypotheses. The stochastic production frontier decomposes the error term into a two-sided random error that captures random effects outside the control of the firm (farmer) and the one-sided inefficiency component. According to Coelli *et al*. (1998), it is called a stochastic function because the output values are bounded by the stochastic (random) variable $exp(x_i\beta + v_i)$. Furthermore, the random error v_i can be positive or negative and therefore, the stochastic frontier outputs vary about the deterministic part of the model, $exp(x_i\beta)$.

The general stochastic model is given as:

$$y_i = f(x_i; \beta)\exp(v_i - u_i) \qquad (5.2)$$

where y_i is the output of the ith farmer; x_i is a vector of farm inputs; β is a vector of parameters to be estimated; while v_i measures the random variation in output (y_i) due to factors outside the control of the farm, u_i are factors within the control of the farm that account for its inefficiency. v_i is assumed to be identically and independently distributed as $N(0, \sigma_v^2)$ and independent of u_i which has a half normal non-negative distribution. u_i is independently, but not identically distributed. The composed error term, ε_i is defined as:

$$\varepsilon_i = v_i - u_i \qquad (5.3)$$

Jondrow *et al.* (1982) specified a decomposition method from the conditional distribution of u given ε. Assuming a normal distribution of v, and the half-normal distribution of u, the farm specific conditional inefficiency ($u/_{\varepsilon}$) for each observation is derived from the conditional distribution of u, where $u = \varepsilon + v$. Therefore, the conditional mean u is:

$$E(u/_{\varepsilon}) = \sigma^2 \left[\frac{f\left(\varepsilon\lambda/_{\sigma}\right)}{1-F\left(\varepsilon\lambda/_{\sigma}\right)} - \frac{\varepsilon\lambda}{\sigma} \right] \tag{5.4}$$

where *f* and *F* represent the standard normal density and cumulative distribution functions, respectively and λ is given as:

$$\lambda = \sigma_u/\sigma_v \tag{5.5}$$

Equation (5.5) is the ratio of the two standard errors as used by Jondrow *et al.* (1982) and it measures the total variation of output from the frontier that can be attributed to technical efficiency. The estimation of γ which is the ratio of the variance of u to the total variance is given as:

$$\gamma = \sigma_u^2/\sigma_v^2 \tag{5.6}$$

σ_v^2 and σ_u^2 are variances of the stochastic model and the inefficiency model respectively. Technical efficiency is measured as a ratio of actual to potential output (Aigner *et al.*, 1977; Meeusen and van den Broeck, 1977). Therefore, the technical efficiency (TE) of a firm is defined as, $TE = \exp(-u_i)$, that is.

$$TE = \frac{y_i^*}{y_i} = \frac{f(x_i\beta)\exp(v_i - u_i)}{f(x_i\beta)\exp(v_i)} = \exp(-u_i) \tag{5.7}$$

Following Battese and Coelli (1995), the technical inefficiency, TI effects are defined by:

$$u_i = z_i\delta + w_i \tag{5.8}$$

where, z_i is a $(1 \times m)$ vector of explanatory variables associated with the TI effects; δ is a $(m \times 1)$ vector of unknown parameters to be estimated; and w_i is an unobservable random variable. The parameters indicate the impacts of variables in z on TE. A negative value suggests a positive influence on TE and vice versa.

5.4 Selection bias in stochastic frontier analysis

The purpose of many agricultural interventions particularly in developing countries is to improve the incomes of poor farmers through increased farm output and better management practices (Bravo-Ureta, 2014; Cavatassi *et al*., 2011). Technological improvements such as adoption of improved rice varieties can lead to upward adjustment of the production frontier, which together with efficient farm practices can close the difference between achievable and actual farm output (Bravo-Ureta, 2014). Nonetheless, participation in most agricultural development projects is mostly not random (Duflo, Glennerster and Kremer, 2008; Winters, Salazar and Maffioli, 2010) leading to selection bias, observed and unobserved endogeneity (Bravo-Ureta, 2014). In interventions such as the dissemination and adoption of improved rice varieties, the challenge is often how to separate the upward shifts of the production frontier and improved farm practices of adopters of improved rice varieties and the counterfactual non-adopter control group (Ravallion, 2008).

To correct selectivity bias in stochastic frontier estimation, approaches such as the Heckman (1979) two-step procedure using the inverse-mills ratio (Solís, Bravo-Ureta and Quiroga, 2007) has been criticized by Greene (2010) as inappropriate for the non-linear stochastic frontier model. Propensity score matching has also been used to correct bias from observable characteristics (Mayen, Balagtas, and Alexander, 2010; Bravo-Ureta, Greene and Solís, 2012) for the stochastic production frontier. Lai, Polachek, and Wang (2009) have proposed the inclusion of selection bias in the composed error (ε_i) of the stochastic frontier model. Kumbhakar, Tsionas, and Sipilainen (2009) also proposed a framework that incorporates selectivity bias in the inefficiency component (in the u_i rather than v_i) of the stochastic frontier model. Kumbhakar *et al.* (2009) used the full information maximum likelihood to simultaneously estimate the stochastic frontiers[21] and adoption with inefficiency as an additional regressor. The authors argued that adoption was likely to influence farmer technical inefficiency by way of output and vice versa.

5.4.1 Greene approach to selection bias in stochastic frontier analysis

Kumbhakar *et al.* (2009) approach incorporates selectivity bias in the inefficiency component (u_i) whereas Lai *et al.* (2009) attributes selection bias to the composed error (ε_i) of the stochastic frontier model. Greene (2010) described the log likelihood in the proposition by Kumbhakar *et al.* (2009) and Lai *et al.* (2009) as difficult to compute. Instead, he suggested a model that accounts for selection bias due to unobservable characteristics in the noise component (v_i) of the stochastic frontier, stressing that farmers do not self-select into programme participation based on their being inefficient. Therefore, selectivity bias existed because of the correlation of unobserved factors in the noise component of the composed error term of the stochastic frontier model,v_i, with the error term from the probit selection equation (w_i). The probit model (equation 5.9) is applied in estimating the determinants of adoption of improved rice varieties and the predicted values are used in computing the inverse mills ratio ($\theta\lambda_i$) in equation (5.11). The $\theta\lambda_i$ is added to the

[21] The authors assumed different stochastic production frontiers for conventional and organic dairy farmers and estimated them separately.

substantive stochastic frontier model (equation 5.10) in correcting selection bias due to differences in unobservable characteristics, where there is correlation between w_i and v_i. This is a typical two-stage sample selection correction procedure which addresses the peculiar composed error term ($\varepsilon_i = v_i - u_i$) of the non-linear stochastic frontier model. The probit model is also applied in section 5.4.2 to address selection bias due to differences in observable factors using the propensity score matching procedure.

Unlike many studies, the original contribution of this present study is the recognition of the fact that technology exposure comes before adoption. Therefore, the stochastic frontier with sample selection is estimated conditional on technology exposure which controls technology non-exposure bias. This follows from section 4.2.2 which provided an extensive discussion of the approach to assessing technology adoption with correction for technology exposure which yields unbiased and consistent estimates of adoption (Diagne and Demont, 2007).

The probit sample selection and stochastic frontier equations by Greene (2010) are given by:

$$d_i = 1[\alpha' z_i + w_i > 0] \qquad (5.9)$$

$$y_i = \beta' x_i + v_i - u_i \qquad (5.10)$$

$$E[\, y_i | x_i, d_i = 1 \,] = \beta' x_i + E[\varepsilon_i | d_i = 1] = \beta' x_i + \frac{\rho\sigma_\varepsilon \phi(\alpha' z_i)}{\Phi(\alpha' z_i)} = \beta' x_i + \theta\lambda_i \quad (5.11)$$

where, $\varepsilon_i = v_i - u_i$; $u_i = |\sigma_u U_i|$; $v_i = |\sigma_u V_i|$; $w_i \sim N|0{,}1|$

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

Thus, the error terms of both the selection and stochastic frontier models have a bivariate normal distribution (Greene, 2006 & 2010). Following Greene, a maximum simulated likelihood is used to integrate out the unobserved random variable $|U_{ir}|$ from R draws for a standard normal population since there is no closed form as:

$$f(y_i|x_i) =\approx \frac{1}{R}\sum_{r=1}^{R} \frac{exp\left[-\dfrac{\frac{1}{2}(y_i-\beta' x_i+\sigma_u|U_{ir}|)^2}{\sigma_v^2}\right]}{\sigma_u\sqrt{2\pi}} \tag{5.12}$$

Greene (2010) also stated that where $d_i > 0$, $a_i = \alpha' z_i$ and therefore, $d_i = 0$ observations do not influence the parameters of the simulated log likelihood. In that case, the maximized function can be expressed as:

$$logL_{S,C}(\beta,\sigma_u,\sigma_v,\rho)$$
$$= \sum_{d_i=1} log\frac{1}{R}\sum_{r=1}^{R}\left[\frac{-\frac{1}{2}(y_i-\beta' x_i+\sigma_u|U_{ir}|)^2/\sigma_v^2}{\sigma_u\sqrt{2\pi}}\right.$$
$$\left.\times\,\Phi\left(\frac{\rho(y_i-\beta' x_i+\sigma_u|U_{ir}|)/\sigma_\varepsilon+a_i}{\sqrt{1-p^2}}\right)\right] \tag{5.13}$$

When ρ equals zero[22], it means v_i and w_i are not correlated and the maximand reduces to the maximum simulated likelihood estimator of the basic stochastic frontier model. Using Jondrow *et al*. (1982) conditional expectation, Greene (2010) specified farm specific estimates of technical inefficiency as:

$$E[\,u_i|\varepsilon_i\,] = \frac{\sigma\lambda}{1+\lambda^2}\left[\mu_i+\frac{\phi(\mu_i)}{\Phi(\mu_i)}\right]\ ,\quad \mu_i=\frac{-\lambda\varepsilon_i}{\sigma}\qquad \varepsilon_i = y_i-\beta' x_i \tag{5.14}$$

Alternatively, technical inefficiency (u_i) can be estimated using simulated maximum likelihood (Greene, 2010) as:

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[22] This is used to test the specification of the selection model using LR test, where $H_0 : \rho = 0$.

$$p[\, u_i|\varepsilon_i \,] = \frac{p(u_i,\varepsilon_i)}{p(\varepsilon_i)} = \frac{p(\sigma_u|U_i|),\varepsilon_i)}{p(\varepsilon_i)} \;, \quad u_i = \sigma_u|U_i| \tag{5.15}$$

Notwithstanding, Greene (2010) approach fails to account for selection bias arising from observable characteristics (Bravo-Ureta, 2014). Given the stand-alone inherent weaknesses of both the propensity score matching (PSM) and Greene (2010), Bravo-Ureta *et al.* (2012) applied both the PSM and Greene (2010) model to resolve selection biases arising from observable and unobservable attributes respectively. Bravo-Ureta *et al.* (2012) first estimated the PSM to correct observable biases. Secondly, the authors used the matched propensity scores to estimate separate stochastic frontier functions for both the treated and the counterfactual using Greene (2010) approach which frees the estimates from unobserved endogeneity.

5.4.2 Correcting observable bias using PSM in stochastic frontier model

In estimating the causal impact of adoption of improved rice varieties on rice output, two sources of selection bias (observable and unobservable factors) arise (Bravo-Ureta *et al.*, 2012; Bravo-Ureta, 2014). This is because farmers who choose to cultivate improved rice varieties may be systematically different from their non-adopter counterparts in both observable and unobservable factors (Bravo-Ureta *et al*., 2012). As a result, estimating a stochastic production frontier without controlling for these factors produces biased estimates (Villano *et al*., 2015).

Selection bias due to observable factors in the stochastic frontier can be controlled using propensity score matching [PSM] (Dehejia and Wahba, 2002; Smith and Todd, 2005; Bravo-Ureta *et al*., 2012). Selection bias resulting from unobservable factors in the stochastic frontier is addressed following Greene (2006 and 2010) procedure.

The PSM performs counterfactual analysis by matching treatment (adopters) with control groups (non-adopters) under the assumption of conditional independence where the decision to cultivate improved rice varieties is based only on observed covariates X and should jointly affect rice output and technical efficiency with or without treatment (Rubin, 1978; Wooldridge, 2002). Applying the conditional independence assumption also known as the 'ignorability' or 'uncounfoundness' assumption (Rosenbaum and Rubin, 1983; Wooldridge, 2002; Imbens, 2004; Cameron and Trivedi, 2005), the improved rice variety adoption outcomes (y_1, y_0) and farmer efficiency can be independent once the observed covariates of adoption are controlled (Bravo-Ureta *et al*., 2012). The conditional independence assumption (CIA) is written as:

$$y_1, y_0 \perp D|z \Rightarrow y_1, y_0 \perp D|p(z) \tag{5.16}$$

$$\begin{aligned} Pr[D_i = 1|y_1, y_0, p(z)] &= E[D_i = 1|y_1, y_0, p(z)] \\ &= E[E[D|z]|y_1, y_0, p(z)] \\ &= [E[p(Z)|y_1, y_0, p(z)] \\ &= p(z) \end{aligned} \tag{5.17}$$

Therefore, by conditioning on $p(z)$, the decision to adopt improved rice varieties can be independent and uncorrelated with the technical inefficiency component of the composed error term of the stochastic production frontier (Bravo-Ureta *et al*., 2012; Bravo-Ureta, 2014). This implies that when the unconfoundedness assumption is fulfilled, it eliminates all observable bias (Imbens, 2004; Cameron and Trivedi, 2005).

Although, the PSM is unable to eliminate hidden or unobservable bias, the severity of hidden bias can be tested using Rosenbaum bounds sensitivity analysis (Rosenbaum, 2002; DiPrete and Gangl, 2004; Becker and Caliendo, 2007; Caliendo and Kopeinig, 2008; Faltermeier and Abdulai, 2009).

The matching is carried out using *psmatch2*, a STATA user-written code developed by Leuven and Sianesi (2003). The first step of the PSM involves regressing the adoption of improved rice varieties decision on all the covariates including those of the stochastic production frontier as well as the determinants of technical inefficiency for both adopters and non-adopters using a probit model (Dehejia and Wahba, 2002; Leuven and Sianesi, 2003).

The probit model is expressed as:

$$D_i = \beta z_i + w_i > 0 \tag{5.18}$$

where D_i is the binary (1, 0) improved rice variety adoption outcome, β is the estimated parameter, z_i is the vector of observable characteristics of both adopters and non-adopters most likely to affect adoption decision and technical inefficiency, and w_i is the error term. Assuming the absence of hidden bias, the probability of adoption based on observable characteristics, z_i becomes $\Pr(D_i = 1|z_i) \equiv p(z)$.

Secondly, the propensity scores, $p(z)$ of both adopters and non-adopters of improved rice varieties are predicted from the results of the probit estimation. Thirdly, by imposing a common support condition (Leuven and Sianesi, 2003), and following Villano *et al*. (2015), the propensity scores are matched using nearest- neighbour[23] with replacement approach to control observable bias (Cameron and Trivedi, 2005; Smith and Todd, 2005). The nearest neighbour matching with replacement pairs up to four matches per adopter with the counterfactual non-adopters of improved rice varieties based on similar observable characteristics within a caliper distance of 0.025 (Dehejia and Wahba, 2002, Faltermeier

[23] Other methods are kernel-based matching, stratified matching, radius and Mahalanobis matching and produce comparable results asymptotically.

and Abdulai, 2009). The caliper distance is the maximum distance of a propensity score to find a nearest matched neighbour within the common support region. Matching with replacement improves the quality of the matching procedure by allowing a given non-adopter counterfactual to be matched to more than one adopter which further reduces observable bias by avoiding bad matches (Smith and Todd, 2005).

The propensity scores of adopters of improved rice varieties outside the common support interval (the extreme tails of the propensity score distribution, i.e., 0 and 1) are excluded from the matching procedure (Leuven and Sianesi, 2003). The common support condition ensures the overlapping of the propensity scores of both adopters and non-adopters of improved rice varieties based on observable characteristics (Heckman, Ichimura and Todd, 1997).

The nearest-neighbour matching with replacement improves the quality of the matching procedure by reducing bias at the expense of variance (Smith and Todd, 2005). Faltermeier and Abdulai (2009) explained that because matching with replacement pairs more than one adopter with the counterfactual non-adopter, it reduces the distinct number of non-adopters used in calculating the counterfactual mean, giving it a higher variance. Nonetheless, the quality of the matching procedure in eliminating bias due to observable characteristics between adopters and non-adopters is assessed using a balancing test (Caliendo and Kopeinig, 2008; Lee, 2008). The balancing test is performed using the standardized mean difference between the adopter and non-adopter samples (Rosenbaum and Rubin, 1985).

The standardized mean and corresponding variance of each covariate before and after matching are used to estimate its bias, $B(Z)$ as:

$$B(Z) = 100 \frac{\bar{Z}_T - \bar{Z}_C}{\sqrt{\frac{V_T(Z) + V_C(Z)}{2}}} \quad (5.19)$$

where $\bar{Z}_T$ and $\bar{Z}_C$ are the sample means of a covariate for the adopters and non-adopters of improved rice varieties; $V_T(Z)$ and $V_C(Z)$ are their respective sample variances. The percentage total bias (BR) is then estimated as an unweighted average of all covariates before and after matching as:

$$BR = 100 \left(1 - \frac{B_{\text{after}}}{B_{\text{before}}}\right) \quad (5.20)$$

The amount of bias after matching for a given covariate should be less than the critical level of 20% (Rosenbaum and Rubin, 1985). As further proof of the elimination of observable bias, the joint significance of the regressors (the pseudo R^2 statistic) after matching should not be statistically significant (Sianesi, 2004).

The matched sample is then used in estimating separate stochastic production frontiers for the pooled as well as for the adopters and non-adopters which does not account for sample selection bias due to unobservables.

Nonetheless, there is often considerable interest in measuring the performance of rice farms across groups (e.g., comparing efficiency levels in rice production across adopters and non-adopters of improved rice varieties). A comparison can be made by measuring efficiency relative to a common metafrontier, defined as a smooth envelope of the group frontiers.

5.5 Theoretical framework of the stochastic metafrontier model

Hayami (1969) first proposed the metafrontier production function in the examination of the causes of agricultural productivity differences among developed and less developed countries. Hayami and Ruttan (1970 and 1971) made an assumption that the technological possibilities available to all agricultural producers in different countries could be characterized by the same production function known as the meta-production function. Battese and Rao (2002), Battese, Rao and O'Donnell (2004) and by O'Donnell, Rao and Battese (2008) who did further work on the metafrontier approach argue that the metafrontier model is an envelope of individual stochastic frontiers for different groups. The meta-production frontier efficiency score of a rice farm reflects how well it performs relative to the predicted performance of the best-practice rice farms that exploit the best technology available for all groups to produce a given output mix. Moreover, the metafrontier is able to disentangle output differences due to technological differences across groups from that which results from output shortfalls due to technical inefficiency of rice farmers (O'Donnell *et al.*, 2008 and Villano *et al.*, 2015).

The metafrontier estimation proposed by Battese *et al.* (2004) and O'Donnell *et al.* (2008) is constructed deterministically by solving a linear programming problem, which minimises the distance between a group stochastic production frontier and the metafrontier. Nonetheless, estimating the metafrontier using mathematical programming has been criticized as being inconsistent with the stochastic frontier methodology (Huang, Huang and Liu, 2014; Amsler, O'Donnell and Schmidt, 2017). This is because if the individual group frontiers are stochastic, then the metafrontier should also be stochastic by incorporating v_i in the estimation.

The stochastic metafrontier proposed by Asmler *et al.* (2017) is an umbrella of the stochastic production frontiers estimated for adopters and non-adopters of improved rice varieties operating under different technology sets within the rice farming population.

Following Asmler *et al.* (2017), the stochastic production frontier for an individual farm unit i is expressed as:

$$y_i = x_i'\beta_{d_i} + v_i d_i - u_i d_i \tag{5.21}$$

where d_i is the group (adopter or non-adopter of improved rice varieties) to which the farm unit i belongs, $v_i d_i$ is a normal random error term, or noise, and $u_i d_i \geq 0$ represents technical inefficiency. Relative to the metafrontier, the class, s to which the groups ($s = d_i$) belong is observed as $y_i d_i$. Thus for $s = d_i$, y_{is} is observed for the group frontier and is expressed as:

$$y_{is} = x_i'\beta_s + v_{is} - u_{is} \tag{5.22}$$

The individual frontiers from the groups that comprise the metafrontier is given as:

$$f_{is} = x_i'\beta_s + v_{is} \tag{5.23}$$

where $s = 1, \ldots S$ with $y_{is} \leq f_{is}$

The metafrontier, f_i is given as:

$$f_i = \max[f_{i1}, \ldots . f_{iS}\ ] \tag{5.24}$$

where $y_{is} = y_i d_i \leq f_i d_i \leq f_i$ because the stochastic metafrontier is an envelope function of the stochastic group frontiers.

Following Amsler *et al*. (2017), the metafrontier can be decomposed as:

$$(f_i - y_i) = (f_i d_i - y_i\ ) + (f_i - \ f_i d_i) \text{ or } \ U_i = U_i d_i + M_i d_i \tag{5.25}$$

$U_i d_i = f_i d_i - y_i = u_i d_i$ is the one-sided technical inefficiency term for unit i in the stochastic frontier model for group d_i and $M_i d_i = f_i - \ f_i d_i$ is the metafrontier distance. The metafrontier distance captures the random error component, v_i thus making the metafrontier a stochastic metafrontier. Empirically, the stochastic metafrontier is calculated as follows:

$$1 = \frac{exp(x_i'\beta_{d_i})}{exp(x_i'\beta_s)} \times \frac{exp(v_i d_i)}{exp(v_{is})} \times \frac{exp(u_i d_i)}{exp(u_{is})} \qquad (5.26)$$

[MTR] [TER]

The metatechnology ratio, MTR measures the ratio of the output for the group production frontier relative to the potential output that is defined by the metafrontier function, given the observed inputs (Battese and Rao, 2002; Battese *et al.*, 2004). The technical efficiency, TE_i^* of farm i relative to the metafrontier is at least lower than that relative to the group frontier, TE_i . Thus, the technical efficiency ratio (TER) is written as:

$$TER_i = \frac{exp(u_i d_i)}{exp(u_{is})} = \frac{TE_i}{TE_i^*} \qquad (5.27)$$

The technical efficiency, TE_i^* of a rice farm with respect to the metafrontier is given as:

$$TE_i^* = TE_i \times MTR_i \qquad (5.28)$$

Technical efficiency of the metafrontier, TE_i^* is equal to the product of technical efficiency of the group frontier and the metatechnology ratio for the group. It is between zero and one, but less than the technical efficiency relative to the stochastic frontier for the group. For instance, if technical efficiency with respect to the group frontier is 0.8 and its technical efficiency with respect to the metafrontier is 0.7, this means that the output of the farm is at 80% of potential output as represented by the specific group technology and 70% of potential output as represented by the metafrontier. This gives a technology gap ratio (MTR) of $\frac{0.7}{0.8} = 0.875$. Thus, the potential output from the group technology is 87.5% of that of the metafrontier. The MTR is between zero and one and values closer to one imply the rice farms are producing nearer to the maximum potential output (metafrontier) given the technology available for the rice farming population as a whole.

Previous studies (such as Battese and Rao, 2002; Battese *et al.*, 2004; O'Donnell *et al.*, 2008) estimated a metatechnology ratio, MTR (also known as metafrontier distance) which does not consider the stochastic nature of production although the group frontiers are stochastic. The metafrontier distance (naïve[24] metafrontier distance) proposed by O'Donnell *et al.* (2008) is expressed as:

$$1 = \underbrace{\frac{exp(x_i'\beta_{d_i})}{exp(x_i'\beta_s)}}_{[MTR]} \times \underbrace{\frac{exp(u_i d_i)}{exp(u_{is})}}_{[TER]} \tag{5.29}$$

The naïve metafrontier envelopes the deterministic component of the group frontiers of adopters and non-adopters of improved rice varieties and excludes the random error ratio.

5.6 Review of empirical studies on stochastic frontier with sample selection and metafrontier

In agricultural technology dissemination such as the adoption of improved crop varieties, farmers are likely to self-select into treatment (World Bank, 2006). More so, farmers who self-select into adoption may be systematically different from the non-adopter control group in terms of both observable and unobservable characteristics (Bravo-Ureta *et al*., 2012). Thus, proceeding with econometric estimation such as the stochastic frontier produces biased estimates. The issue of selection bias in stochastic frontier analysis has been raised in the literature (Kaparakis *et al*., 1994; Solís *et al*., 2007; Rahman *et al*., 2009; Kumbhakar

[24] Amsler *et al*. (2017) referred to the metafrontier obtained using linear programming as the naïve metafrontier.

et al., 2009; Greene, 2006 & 2010) with further analytical improvement by Bravo-Ureta *et al* (2012).

Bravo-Ureta, Greene and Solís (2012) compared the technical efficiency of farmers who participated in an agricultural programme (2004-2009) with their control group in Honduras. The authors addressed selection bias in the stochastic frontier model using Greene (2010) probit selection model to correct unobservable factors and PSM to deal with observable characteristics. Bravo-Ureta *et al.* (2012) first estimated the probability of participation in the agricultural programme using a probit model. Secondly, the nearest neighbour matching without replacement[25] and under common support assumption was used to match treated against their counterfactual based on observable characteristics[26]. The matched sub-samples from the PSM were then used to estimate separate stochastic production frontiers[27] for both treated and control groups with correction for selection bias following Greene (2010).

Separate probit selection estimations were carried out for the matched and unmatched sub-samples. The age of farmer had negative effect on the probability of participation in the agricultural intervention for both matched and unmatched groups. Additionally, education and family size had positive and statistically significant effect on the programme participation for the unmatched sub-sample only. The dependent variable for the translog stochastic production function was total value of agricultural output with cost of purchased production inputs, value of hired and family labour, farm altitude as well as farm size as

[25] Nearest neighbour matching without replacement was used for ease of computation.

[26] Bravo-Ureta *et al.* (2012) also used the t-test to establish similarity of mean values of the observable characteristics before and after matching to reinforce the balancing property of observed variables.

[27] The translog functional form was specified for the production function after Cobb-Douglas was rejected following an LR test.

explanatory variables. The correlation coefficient, (ρ) after matching was statistically different from zero (indicating the presence of selection bias) for the stochastic frontier with correction for sample selection in both the beneficiary and control groups. Bravo-Ureta *et al.* (2012) argued that the statistical significance of ρ gave credence to the application of stochastic frontier with sample selection which produces unbiased estimates unlike the traditional stochastic frontier model where selection bias yields biased frontier estimates and technical efficiency scores.

The cost of purchased inputs and farm size had positive effect on value of agricultural output relative to the stochastic frontier with sample selection for matched beneficiaries. However, the cost of purchased inputs and farm altitude positively influenced the value of output for the stochastic frontier with sample selection in the matched non-beneficiaries. The mean technical efficiency estimates were 70% and 67%[28] respectively for beneficiaries with correction for selectivity bias and conventional frontier model without correcting for unobservable bias. Similarly, mean efficiency scores were 59% and 40% respectively for the counterfactual with and without correcting for unobservable differences. The results also indicated that ignoring selection bias led to the under-estimation of efficiency score for both beneficiaries and the control groups.

The authors concluded that beneficiaries had higher mean technical efficiency scores (70%) than the control group (59%) after accounting for both observable and unobservable heterogeneity. Nonetheless, a shortcoming of the Bravo-Ureta *et al.* (2012) study is the direct comparison of the technical efficiency estimates of beneficiaries with non-beneficiaries without recourse to the stochastic metafrontier. This is because the

[28] Bravo-Ureta *et al.* (2012) used the t-test which showed the mean scores were statistically different from each other.

beneficiaries and non-beneficiaries operate using different technologies and a direct comparison can only be made using a common production frontier through the stochastic metafrontier.

Villano, Bravo-Ureta, Solıs, and Fleming (2015) assessed the impact of adoption of certified rice seeds on farm productivity while accounting for technology gaps between adopters and non-adopters using the metafrontier approach. The study involved 3,164 rice farming households in the Philippines for the 2006/7 cultivation year. The authors applied Battese *et al.* (2012) approach to control both observable and non-observable bias in the stochastic production frontier. Secondly, they estimated a metafrontier that provided a common production frontier in order to compare the results of adopters with non-adopters operating under different production frontiers. A translog stochastic production frontier with correction for sample selection was estimated with farm size, seed, fertilizer quantity, labour, herbicide, machinery rental cost and dummy variables for use of fertilizer, cultivation of certified rice seed, cultivation season (wet or dry season), source of power for farm operations (mechanized or manual). With the exception of seed quantity, all the first order coefficients for both the adopters and non-adopters of certified rice seeds had positive and statistically significant effect on output after correcting for observable and non-observable bias. Nonetheless, the results indicated a higher yield for adopters of certified rice seeds than the non-adopters which also translated into higher net farm returns.

The mean technical efficiency estimates for the adopters and non-adopters within their own groups were 0.73 and 0.69 for the stochastic frontier with sample selection. Regarding the results of metafrontier, the meta-technology ratio for adopters (0.90) was higher than that of the non-adopters of certified rice seeds (0.54). Similarly, the mean technical efficiency relative to the meta-frontier were 0.61 and 0.37 for the adopters and non-adopters respectively. The authors explained that without correcting for sample selection biases, the technical efficiency scores were over-estimated. Meanwhile, the estimation of the metafrontier revealed a gap in production technology for the respective adopter and non-adopter groups in relation to the metafrontier. The authors concluded that the adoption of certified rice seeds had a positive impact on the net returns of rice farmers through increased yield and thus recommended the cultivation of certified rice seed. Although, Villano *et al.* (2015) accounted for selection bias and estimated a metafrontier to allow for direct comparison of the technical efficiency results, they failed to account for technology exposure. Technology exposure precedes technology adoption and this should have been accounted before proceeding to estimate the determinants of adoption which serves as the selection model to the substantive stochastic frontier model in correcting selection bias for the stochastic frontier. Moreover, they estimated a metafrontier using linear programming which is non-parametric unlike the preferred stochastic metafrontier. This is because if the individual group frontiers are stochastic, then the metafrontier should also be stochastic by incorporating random error in the estimation.

Azumah, Donkoh and Awuni (2019) applied the stochastic frontier with correction for selection bias to analyse the technical efficiency of 543 rain-fed and irrigated rice farmers in northern Ghana. The authors estimated a translog stochastic production function using farm size, seed, fertilizer, labour and herbicide with rice output as the dependent variable. Relative to the first order coefficients, farm size and fertilizer had positive effect whereas seed quantity and herbicide had negative effect on irrigated rice output whereas none had any statistically significant effect on rain-fed rice output. Nonetheless, their findings indicated increasing returns to scale in rice cultivation for both groups of farmers. The age, sex, FBO membership, farm location, commercial motives for rice cultivation reduced the technical inefficiency of irrigated rice farmers. On the other hand, experience, education and input subsidy reduced technical inefficiency for the rain-fed farmers.

The mean technical efficiency estimates from the stochastic frontier with sample selection were 68% and 63.4% respectively for irrigated and rain-fed farmers. Relative to the conventional stochastic frontier, the mean efficiency estimates were 74.4% and 60% for irrigated and rain-fed, implying that without accounting for selection bias, the efficiency estimates would be over-estimated. The authors recommended the construction of small village-dams by government to support irrigated rice cultivation and targeted input subsidies to young and experienced farmers who have commercial motive to rice cultivation. Azumah *et al*. (2019) study is criticized for making a direct comparison of rain-fed and irrigated rice producers with different production technologies without estimating a stochastic metafrontier. Secondly, rice technology exposure was not considered in their analysis, given that it is only when farmers are aware of a technology that they can make an adoption decision.

Asravor et al. (2020) analysed the production efficiency and environmental-technology gaps of 768 rice-producing households in the forest-savannah transition and guinea savannah agro-ecological zones of Ghana. Their results revealed farms in the forest zone had higher mean environmental-technology gap ratio (0.95) than those in the guinea savannah zone (0.50). Similarly, the mean metafrontier technical efficiency estimate was higher in the forest zone (0.50) than the guinea savannah zone (0.42). Nonetheless, farms in both zones experienced decreasing returns to scale in rice production. The first order coefficients of the translog revealed fertilizer and land statistically increased the rice output of farms in the forest zone whereas labour, land and fertilizer had positive effect on the output of farms in the guinea savannah zone.

Mono-cropping rice and selling at farm gate reduced the technical inefficiency of farmers in both zones whereas bund construction and engaging in off-farm wage activities increased technical inefficiency in both zones. Training in rice cultivation, access to improved rice varieties and ownership of farmland decreased the inefficiency of farmers in the forest zone only. However, relying solely on own rice cultivation knowledge, and access to improved varieties and longer distance to guinea savannah farms increased the technical inefficiency of farmers in the forest zone and guinea savannah zone respectively. The authors recommended training in rice cultivation, expanding access to improved rice varieties and output markets, and facilitating land ownership will further increase the efficiency of farmers in these zones. Although, the authors estimated a stochastic metafrontier to allow for comparison of production across agroecological zones, the specific rice cultivation technologies espoused in their study was not evident. Moreover, observable and unobservable factors that affect production decisions were not accounted for before estimating the metafrontier.

5.7 Conclusion

This chapter provided the theoretical background and reviewed literature on the application of the stochastic production frontier with correction for sample selection. The stochastic frontier with correction for sample selection is applied in assessing the effect of adoption of improved rice varieties on farmers' physical rice output and technical efficiency, which is the second objective of this study.

Unlike the empirical studies reviewed in this chapter, the original contribution of this study is correcting for technology exposure in the stochastic frontier with sample selection and the metafrontier. This is done by estimating the stochastic frontier with correction for sample selection conditional on technology exposure. It is followed by a stochastic metafrontier estimation that allows for a direct comparison of the technical efficiency scores of different group frontiers relative to a common production frontier using the sub-sample of only households with exposure to the improved rice varieties. The stochastic metafrontier makes it possible to separate productivity differences due to technology gaps from technical inefficiency.

CHAPTER SIX

THEORETICAL FRAMEWORK AND LITERATURE REVIEW- EFFECT OF TECHNOLOGY ADOPTION ON HOUSEHOLD NET RICE INCOME

6.1 Introduction

This chapter presents the theoretical background of the application of the switching regression model in assessing the effect of adoption of improved rice varieties on household net rice income per ha. It also lays the methodological justification for the empirical estimation of the third objective of this study which broadly examines the effect of adoption of improved rice varieties on household net rice income per ha. The second major sub-section presents a review of empirical studies and how this study is situated in the context of existing literature.

6.2 Analysing the effect of agricultural technology adoption on household welfare

Household welfare can be measured by household income or consumption expenditure or both (Deaton, 1997; Deaton and Zaidi, 2002; Moratti and Natali, 2012; Tambo and Wünscher, 2014). Households that are aware of and adopt output enhancing farm technologies such as improved crop varieties *ceteris paribus* would mostly likely benefit from increase in yield or output and therefore would have more farm produce for home consumption and or for sale and that income can be used to purchase other goods for household consumption (Tambo and Wünscher, 2014).

Deaton (1997) argue consumption expenditure is mostly preferred to household income in measuring household well-being because it is less prone to seasonal fluctuations and measurement errors. Deaton and Zaidi (2002) further explain that consumption gives a good picture of long-term income. More so, consumption is more stable particularly in agricultural settings and therefore is a good indicator of the real living standard of a household (Asfaw *et al*., 2012; Moratti and Natali, 2012). Thus, consumption expenditure shows a household's ability to provide its basic life needs, which is an indicator of its welfare status.

On the other hand, total household income usually comprises farm and off-farm income. Gross farm income is the revenue obtained from the sale of crops produce, livestock and livestock products as well as home consumption of farm produce valued at local market prices (Tambo and Wünscher, 2014). All agricultural production related costs (such as seed, fertilizer, herbicide, pesticide, hired labour, animal feed, veterinary services, etc.) incurred by households over a 12-month period is then subtracted from the gross farm income to obtain the net farm income. Off-farm income includes wages and salaries from non-agricultural activities, profits from off-farm self-employment, pensions, remittances, rental income, and income from other off-farm sources.

Nonetheless, this study acknowledges the concerns of estimating household welfare using household income and consumption expenditure alone without including other factors such as leisure, good health, and dietary diversity amongst others that contribute to improved welfare or standard of living. Moreover, there are limitations to the secondary data relative to its application in estimating household welfare. For instance, the questionnaire was designed to collect production and input data on rice, hence it does not have production information on other crops cultivated by the household, animals and many of the components that constitute household income and expenditure such as food, education, housing, energy, transportation, communication, purchases of consumer durables and non-durables and transfer payments made by households which affect its welfare.

Therefore, to assess the monetary gains of adoption of improved rice varieties, this study examines the direct effect of adoption on household net rice income per ha amongst those who have been exposed to the improved varieties, which is a sub-component of total household income.

In estimating the causal impact of technology adoption on household welfare, the propensity score matching (explained in section 5.4.2) and switching regression methods are usually used (Maddala and Nelson, 1975; Angrist, 2001; Amare *et al*., 2012; Asfaw *et al*., 2012; Noltze *et al*., 2013; Tambo and Wünscher, 2014). Measuring the effect of adoption of improved rice varieties on household net rice income per ha has potential endogeneity because adoption is non-randomly assigned (farmers choose to adopt) leading to self-selection and biased estimates (Ravallion and Wodon, 1998; Baker, 2000; Diagne and Demont, 2007; Phillips *et al*., 2014). More so, adopters may be systematically different from non-adopters and may mask the true effect of adoption of improved rice varieties on household well-being (Burtless, 1995; Duflo *et al*., 2007; Banerjee and Duflo, 2009; Del Carpio and Maredia, 2010; Asfaw *et al*., 2012). As a result, estimation using ordinary least squares yields biased results, and approaches such as Heckman selection, instrumental variable (IV) and propensity score matching (PSM) have sought to correct such inherent biases. Nonetheless, both Heckman selection and IV methods impose functional form restrictions by assuming common slope coefficients (intercept shift) of technology adoption for adopters and non-adopters and not a slope shift in welfare due to increased productivity of factors of production arising out of technology adoption (Alene and Manyong, 2007; Asfaw *et al*., 2012). The PSM fails to correct for unobservable bias in the adoption behaviour and net rice income per ha of households and therefore, the switching regression is preferred (Maddala and Nelson, 1975; Laure, 2007).

6.2.1 The switching regression approach

Having pointed out the limitations of the PSM, the preferred switching regression methodology which corrects for both observable and unobservable bias is applied in this study. Unlike many studies, the switching regression is analysed using only households who knew of the existence of the improved rice varieties since varietal exposure usually precedes adoption. Most studies incorrectly treat households without exposure as non-adopters although they could have adopted upon exposure leading to biased results. Let household welfare indicated by net rice income per ha be Y_1 for adopters and Y_0 for non-adopters. Similarly, X_1 and X_0 are the $1 \times n_1$ and $1 \times n_0$ vectors of explanatory variables relevant to each group. Let β_1 and β_0 be $n_1 \times 1$ and $n_0 \times 1$ individual specific parameter vectors and γ and $m \times 1$ parameter vectors of the adoption equation, P is a latent variable determining which group applies, and z_i a $1 \times m$ vector of explanatory variables assumed to explain the probability of adoption of improved rice varieties. Finally, let u_i, μ_1, and μ_0 be error terms. The selection equation analyses the determinants of adoption. Separate outcome equations are specified for each household's net rice income per ha, conditional on a selection equation (adoption decision) amongst the exposed as follows:

$$P_i = 1(z_i\gamma) + u_i > 0 \tag{6.1}$$

$$Y_1 = X_1\beta_1 + \mu_1 \qquad \text{If } P = 1 \tag{6.2}$$

$$Y_0 = X_0\beta_0 + \mu_0 \qquad \text{If } P = 0 \tag{6.3}$$

According to Lee (1978) and Fuglie and Bosch (1995), the error terms u, μ_1 and μ_0 are also assumed to have a trivariate-normal distribution with mean vector 0, and a covariance matrix specified as:

$$cov(u, \mu_1, \mu_0) = \begin{bmatrix} \sigma_u^2 & \sigma_{\mu_1 u} & \sigma_{\mu_0 u} \\ \sigma_{\mu_1 u} & \sigma_{\mu_1}^2 & \sigma_{\mu_1 \mu_0} \\ \sigma_{\mu_0 u} & \sigma_{\mu_1 \mu_0} & \sigma_{\mu_0}^2 \end{bmatrix} \quad (6.4)$$

where, $(u) = \sigma_u^2$, is 1 because γ can only be estimated up to a scale factor (Maddala 1983). Likewise, $var(\mu_1) = \sigma_{\mu_1}^2$, $var(\mu_0) = \sigma_{\mu_0}^2$, $cov(u, \mu_1) = \sigma_{\mu_1 u}$, $cov(u, \mu_0) = \sigma_{\mu_0 u}$ and $cov(\mu_1, \mu_0) = \sigma_{\mu_1 \mu_0}$.

Selection bias exists when the error term of the selection equation is correlated with the error terms of the net rice income per ha functions. Following Fuglie and Bosch (1995), the expected values of the error terms μ_1 *and* μ_0 are expressed as:

$$E(\mu_1 | P_i = 1) = \sigma_{\mu_1 u} \lambda_1 \quad (6.5)$$

$$E(\mu_0 | P_i = 0) = \sigma_{\mu_0 u} \lambda_0 \quad (6.6)$$

where, λ_1 and λ_0 are the inverse mills ratios (IMR) evaluated at γz_i as:

$$\lambda_1 = \frac{\phi(z_i \gamma)}{\Phi(z_i \gamma)} \text{ for positive observations } (P_i = 1) \quad (6.7)$$

and $\lambda_0 = -\frac{\phi(z_i \gamma)}{1 - \Phi(z_i \gamma)}$ for the zero observations $(P_i = 0)$ (6.8)

where ϕ and Φ are the probability density functions and cumulative distribution functions respectively of the standard normal variable. Consequently, estimates from the selection equation are used to compute λ_1 and λ_0 which are then included in the outcome equations to correct for selection bias (Maddala, 1983) as follows:

$$Y_1 = X_1\beta_1 + \sigma_{\mu_1 u}\lambda_1 + \xi_1 \;\; if \; P_i = 1 \tag{6.9}$$

$$Y_0 = X_0\beta_0 + \sigma_{\mu_0 u}\lambda_0 + \xi_0 \;\; if \; P_i = 0 \tag{6.10}$$

The outcome equations can be estimated using a two-stage method (such as Lee, 1978; Freeman *et al*., 1998) or an efficient one-step procedure such as the full information maximum likelihood (FIML) which estimates the selection and outcome equations simultaneously (Lee and Trost, 1978; Greene, 2000; Lokshin and Sajaia, 2004 & 2011; Alene and Manyong, 2007; Di Falco *et al*., 2011). When the estimated covariance $\sigma_{\mu_1 u}$ and $\sigma_{\mu_0 u}$ in the two outcome equations are statistically significant, then the adoption decisions and net rice income per ha outcomes are correlated, thus an endogenous switching model and, exogenous switching regression when they are statistically not significant ($\sigma_{\mu_1 u} = \sigma_{\mu_0 u} = 0$).

The FIML switching regression model can be identified through non-linearities of λ_1 and λ_0 (Lokshin and Sajaia, 2004 and 2011; Di Falco *et al*., 2011). Nonetheless, a better and preferred identification requires an exclusion restriction (Asfaw *et al*., 2012; Tambo and Wünscher, 2014) where an instrumental variable that determines a household's decision to adopt improved rice varieties, but has no direct impact on household net rice income per ha is used. The validity of the instrument is ascertained using a falsification test (Di Falco *et al*., 2011) and if appropriate, it will only affect adoption decision and not affect the net rice income per ha outcome of non-adopters. The log likelihood function is expressed as:

$$\ln(L) = \sum_{i=1}^{N} P_i \left[ln\Phi\left(\frac{\mu_1}{\sigma_{\mu_1}}\right) - ln\sigma_{\mu_1} + ln\Phi(\varphi_{i1}) \right] + 1 - P_i \left[ln\Phi\left(\frac{\mu_0}{\sigma_{\mu_0}}\right) - ln\sigma_{\mu_0} + \ln(1 - \Phi(\varphi_{i0})) \right] \tag{6.11}$$

where, $\varphi_{ij} = \frac{z_i\gamma + \gamma_i \, \mu_{i\,/\,\sigma_i}}{\sqrt{1} = \gamma_i^2}$ with γ_i denoting the correlation coefficient between the error term u_i of the selection equation and the error terms, μ_1, μ_0 of the outcome equations respectively. The predicted values of net rice income per ha (wellbeing indicator) from the switching regression are used to estimate both the ATT and ATU. The ATT estimates the difference in net rice income per ha of adopters of improved rice varieties and what their wellbeing would have been if they had not adopted. On the other hand, the ATU reveals the difference in net rice income per ha for non-adopters of improved rice varieties and what would have pertained had they adopted (Heckman *et al*., 2001; Di Falco *et al*., 2011). Given a household with characteristics X, the expected value of net rice income per ha for choosing to adopt and the counterfactual had it chosen not to adopt are:

$$E(Y_1|P_i = 1) = X\beta_1 + \sigma_{\mu_1 u}\lambda_1 \tag{6.12}$$

$$E(Y_0|P_i = 1) = X\beta_0 + \sigma_{\mu_0 u}\lambda_1 \tag{6.13}$$

Therefore, the change in net rice income per ha resulting from adoption is:

$$ATT = E(Y_1|P_i = 1) - E(Y_0|P_i = 1) = X(\beta_1 - \beta_0) + \lambda_1(\sigma_{\mu_1 u} - \sigma_{\mu_0 u}) \tag{6.14}$$

Likewise, for a household with characteristics X, the expected value of net rice income per ha for choosing not to adopt and the counterfactual had it chosen to adopt are expressed by:

$$E(Y_1|P_i = 0) = X\beta_0 + \sigma_{\mu_1 u}\lambda_0 \tag{6.15}$$

$$E(Y_0|P_i = 0) = X\beta_1 + \sigma_{\mu_0 u}\lambda_0 \tag{6.16}$$

The change in net rice income per ha for non-adoption and its counterfactual are:

$$ATU = E(Y_0|P_i = 0) - E(Y_1|P_i = 0) = X(\beta_1 - \beta_0) + \lambda_0(\sigma_{\mu_1 u} - \sigma_{\mu_0 u}) \tag{6.17}$$

This study also estimates what is known in literature as the effect of base heterogeneity (Carter and Milon, 2005; Di Falco *et al*., 2011) which is the mean difference in net rice income per ha between actual adopter households ($E(Y_1|P_i = 1) = X\beta_1 + \sigma_{\mu_1 u}\lambda_1$) and the counterfactual hypothetical adopters ($E(Y_1|P_i = 0) = X\beta_0 + \sigma_{\mu_1 u}\lambda_0$) in the non-adopter households as:

$$E(Y_1|P_i = 1) - E(Y_1|P_i = 0) = X(\beta_1 - \beta_0) + \sigma_{\mu_1 u}(\lambda_1 - \lambda_0) = BH_1 \qquad (6.18)$$

Similarly, the base heterogeneity (BH) for the actual non-adopters ($E(Y_1|P_i = 0) = X\beta_0 + \sigma_{\mu_0 u}\lambda_1$) and their counterfactual hypothetical non-adopters ($E(Y_0|P_i = 0) = X\beta_1 + \sigma_{\mu_0 u}\lambda_0$) in the adopter households:

$$E(Y_1|P_i = 0) - E(Y_0|P_i = 0) = X(\beta_1 - \beta_0) - \sigma_{\mu_0 u}(\lambda_1 - \lambda_0) = BH_2 \qquad (6.19)$$

Another estimation is the difference in net rice income per ha between ATT and ATU known as the transitional heterogeneity. It assesses whether the effect of adoption of improved rice varieties is larger or smaller for actual adopter households or for counterfactual adopters in the non-adopter households.

6.3 Review of empirical studies on effect of technology adoption on farmer welfare

The propensity score matching (PSM) and switching regression methods are normally applied (Maddala and Nelson, 1975; Angrist, 2001; Alene and Manyong, 2007; Amare *et al*., 2012) to assess the effect of agricultural technology adoption on household welfare.

For instance, Faltermeier and Abdulai (2009) applied the PSM to assess the impact of water and intensification technologies amongst 342 rice farmers during the 2006 cultivation season in the Northern Region of Ghana. Specifically, the authors analysed the effect of adoption of bund construction for water conservation and seed dibbling on demand for nitrogen fertilizer, output, and net returns to household income. Faltermeier and Abdulai (2009) explained that under risk neutrality, the choice of bund construction as well as dibbling seed and fertilizer should trigger the purchase of fertilizer to increase rice output because farmers seek to maximize expected net revenue[29] rather than expected utility.

The authors used the Mahalanobis metric matching with replacement[30] because of its ability to include other variables[31] in addition to the propensity scores that strongly influence an outcome. Matching with replacement pairs a given non-adopter to more than one adopter using observable characteristics. The standardized mean difference test between treatment and control variables proposed by Rosenbaum and Rubin (1985) was used to measure observable bias between treatment and control samples before and after matching. The probit model was used to estimate the propensity scores and the method of treatment effect used to calculate the effect of adoption of the cultivation practices on rice output, net revenue and nitrogen fertilizer demand.

Results of their analysis after controlling for observable bias, revealed rice farmers who adopted bund construction increased their nitrogen fertilizer demand by 3.05kg/acre and this was statistically significant at 10%. The standardized bias reduced from 20.1% to 7.8% after matching indicating a substantial reduction in bias through balanced distribution of

[29] Technology adoption is expected to help increase output, whiles higher output through income effect may affect technology adoption.

[30] According to Dehejia and Wahba (2002), matching without replacement may yield bad matches because adopters are matched with non-adopters who may have different propensity scores. Nonetheless, it has a high variance due to the use of fewer non-adopters in calculating the counterfactual mean.

[31] Where many variables are included, the Mahalanobis does not produce good matches (Guo *et al*., 2006).

covariates between adopters and non-adopters of bund construction. Nonetheless, there was no significant difference between adoption of bund construction on rice output and net revenue. After controlling bias, adopters of seed dibbling increased their rice output by nearly 2bags/acre, with no significant effect of adoption on neither demand for nitrogen fertilizer nor net revenue. Similarly, the combined adoption of dibbling seed and fertilizer statistically increased demand for nitrogen fertilizer by 5.37kg/acre at 1% level. More so, dibbling seed and fertilizer as well as manually weeding two times increased rice output by 1.7 bags/acre and net revenue by GH¢22 per acre after reducing bias by 73.8% and 84.6% respectively through matching. Results of Rosenbaum bound sensitivity analysis to hidden bias showed no significant effect of unobservable characteristics on the estimates. Faltermeier and Abdulai (2009) concluded that the significant effect of adoption of both seed and fertilizer dibbling on rice output as well as the demand for nitrogen fertilizer required access to credit to purchase inputs to boost rice production.

Amare, Asfaw and Shiferaw (2012) employed both the propensity score matching and two-stage switching regression to analyse the welfare impacts (using income and expenditure) of improved pigeon pea and maize adoption in Tanzania. Results of the PSM obtained using the kernel based matching and nearest neighbour matching revealed higher income (about 30% more) for improved maize adopters than non-adopters. The consumption expenditure of improved maize adopters was also 15% higher than non-adopters. To control for the unobserved heterogeneities, the PSM results were complemented by estimates from the two-stage switching regression. The authors used the predicted values of income and consumption expenditure per capita from the endogenous switching regression to estimate the mean income and consumption expenditure gap between adopters and if they had not adopted as well as for the non-adopters and their counterfactual had they adopted. Their results indicated adopter maize farmers attained 150% higher mean income per capita for adopting and thus were better off with cultivation of improved maize. Non-adopter maize farmers would have increased their mean income by 36% had they adopted. On the other hand, adopter maize farmers increased their expenditure per capita by 120% whereas the non-adopter maize farmers would have raised their per capita consumption expenditure by 163% had they adopted. Amare *et al*. (2012) concluded that even though both the PSM and two-stage switching regression results showed improvement in household well-being from adoption, after controlling for unobserved characteristics, the endogenous switching regression produced much better estimates of household welfare by way of higher household income and consumption expenditure per capita.

Given the relative superiority of the switching regression model to the PSM, Asfaw, Shiferaw, Simtowe and Lipper (2012) applied the full information maximum likelihood switching regression to assess the impact of adoption of pigeon pea and chick pea on the welfare of 1313 rural farmers in Ethiopia and Tanzania using household consumption expenditure per adult equivalent unit[32]. The authors argued that the adoption of improved varieties of pigeon pea and chick pea could help raise yield as well as consumption expenditure of households and hence translate into better wellbeing. Their results established a correlation between adoption decisions and household consumption expenditure. Therefore, adoption decisions and consumption outcomes were affected by both observed and unobserved factors, thus the consumption functions of adopters and non-adopters were significantly different. The mean consumption expenditure per adult equivalent unit for adopters of improved pigeon pea and chick pea increased by 0.71 and

[32] The adult equivalent unit is expressed as: $1 + 0.7(A - 1) + 0.5C$, where A and C are the number of adults and children in a household

0.22 respectively. If the non-adopters had adopted improved pigeon pea and chick pea, their consumption expenditure per adult equivalent unit would have increased by 0.19 and 0.69 respectively. The authors concluded that the adoption of improved pigeon pea in Tanzania and chick pea in Ethiopia increased the welfare of households through increased consumption expenditure per adult equivalent unit. Nonetheless, the level of farmer awareness of these improved crop varieties and their drivers was not explored in their analysis, given that it is only when farmers are aware of a technology that they can make an adoption decision.

Tambo and Wünscher (2014) also applied switching regression to analyse the welfare effects of farmer innovation using a sample of 409 households in the Upper East of Region of Ghana. The authors operationalised farmer innovation as the ability to generate new ideas, techniques or adaptation with no direct external support. Farmer innovation status was a binary variable. The authors used the full information maximum likelihood estimation, a one-step procedure that estimates both the innovation selection equation and welfare outcome equations simultaneously, unlike the two-stage method. From their results, off-farm activity, livestock ownership and value of household assets had positive effect on the household income of both adopters and non-adopters of innovation whereas household size had negative effect on the income of both adopters and non-adopters. Meanwhile, household dependency ratio and labour shocks had negative effect, whiles age of household head, credit access and land holding had positive effect on the household income of only non-adopters of innovation.

The authors further distinguished farm income from total household income and from the results, factors such as value of household assets, off-farm job and district dummies positively and significantly influenced only household income and not farm income. Adopters of the innovation improved their farm and households' incomes by 11% and 9% respectively. Conversely, non-adopters had they adopted would have seen their farm and household incomes appreciate by 51% and 28%.

Household size and dependency ratio negatively affected consumption expenditure of both innovators and non-innovators, with more negative impact for innovators. Meanwhile, the value of household assets increased the consumption expenditure of both adopter and non-adopter households. Pests and diseases shock also raised the expenditure of households whiles climatic shocks led to reduction in expenditure. Households that adopted innovations increased their expenditure by 5% whereas non-adopters had they innovated would have had their household expenditure decline by 13%. Tambo and Wünscher (2014) attributed the rise in consumption to increased farm revenue or reduction in production cost arising from adoption of innovations. The authors argued that the decline in consumption expenditure for the non-adopters partly explained their decision not to adopt and thus resorted to other means of attaining their consumption objectives. Tambo and Wünscher (2014) concluded that aside externally promoted technologies, farmers adopted their own cost-reducing cultivation practices which led to overall improvement in household welfare. Notwithstanding, Tambo and Wünscher (2014) study was neither crop or animal specific as their definition of farmer innovation as the ability to generate new ideas, techniques or adaptation with no direct external support was very broad and arbitrary. Moreover, their study was not technology specific and what innovation meant varied from farmer to farmer.

6.4 Conclusion

This chapter presented the theoretical framework and reviewed literature on the application of the switching regression model in addressing the third objective of this study. The original contribution of this study is using the switching regression to assess the effect of adoption of improved rice varieties on household net rice income per ha conditional on varietal exposure. This is consistent with the technology diffusion and adoption theory where rice varietal exposure precedes adoption.

CHAPTER SEVEN

RESEARCH METHODOLOGY

7.1 Introduction

This chapter contains a description of the study area, sampling and data collection and the empirical models explaining exposure and adoption of improved rice varieties. It also includes the empirical models explaining the effect of adoption on rice output and technical efficiency of farmers and how adoption influences household net rice income per hectare. It ends with a method of analysis of qualitative data.

7.2 Description of the study area

The study area covers eight out of a total of sixteen[33] regions in Ghana. The regions are Northern, Upper East, and Upper West (all three are in the northern part of the country) and the remaining five in the southern part of Ghana are Ashanti, Greater Accra, Volta, Western, and Eastern Regions (refer to map in Figure 7.1 for location). It is important to note that these 16 regions are political administrative regions as part of a unitary central government. Geographically, the country is divided into north and south. The north comprises 5 regions and the remaining 11 in the south. The total land area of the country is 238,530 square kilometres of which the eight regions constitute 189,140 square kilometres or 79.29% of the total (MoFA, 2016). The Northern Region is the largest region of Ghana with an area of

[33] Until late 2019, Ghana had 10 regions when the data were collected in late 2012 to early 2013.

about 70,383 square kilometres (29.5% of total land area of Ghana) whereas the Greater Accra Region is the smallest with 3,240 square kilometres [1.36% of the country's land area] (MoFA, 2016). The climate of Ghana is tropical and rainfall distribution in the north of the country is unimodal giving a single growing season of 180-200 days between May and October (MoFA, 2011). However, southern Ghana has a bimodal rainfall distribution from March to July and from September to October (MoFA, 2016). Soils in Ghana are generally loam, sandy loam and sandy clay and deficient in nutrients such as phosphorus with average pH of 5.2 (Buri *et al*., 2010).

Ghana as a whole is regarded the study area without recourse to the individual 16 regions. Nonetheless, in order of higher output, the main regional producers are Volta (34.48%), Northern (31.51%), Upper East (21.46%), Ashanti (6.5%), and Eastern (6.05%) regions (MoFA, 2016). For the purposes of this study, the country is divided into 3 main agroecological zones namely the Savannah zone in north, the forest and coastal zones in the south (details in Table 7.2). The mean annual rainfall figures are 800mm, 1,100mm and about 1500mm for the coastal, savannah and forest agroecological zones (MoFA, 2011). There are no regional peculiarities in method of rice production and all rice varieties can be grown in all the regions, although the savannah agroecological zone under lowland rain-fed conditions produces 53% of the national output (MoFA, 2016). The main production methods for rice in Ghana are lowland rain-fed cultivation that constitutes 78%, upland rain-fed at 6% and irrigated land cultivation representing 16% of the national output (MoFA, 2009). Although, data on rice production relative to other household crops are not readily available across all the regions, Table 7.1 indicates rice is the second most important staple cereal crop after maize in Ghana (MoFA, 2018).

Smallholder dry season irrigated rice production takes place in irrigation sites at the Tono and Vea irrigation schemes in the Upper East Region, the Kpong, and Afife irrigation schemes in Greater Accra Region, Bontanga and Golinga irrigation schemes in Northern Region (CARD, 2010).

Table 7.1: Production of Selected Food Crops ('000 Mt) in Ghana, 2012 - 2016

	2012		2013		2014		2015		2016	
Crop	Freq	%	Freq	%	Freq	%	Freq	%	Freq	%
Maize	1950	59.7	1764	57.2	1769	56.5	1692	54.6	1723	54.7
Rice	**481**	**14.7**	**570**	**18.5**	**604**	**19.3**	**641**	**20.7**	**688**	**21.8**
Millet	180	5.5	155	5.0	155	5.0	157	5.1	159	5.0
Sorghum	280	8.6	257	8.3	259	8.3	263	8.5	230	7.3
Soybean	152	4.7	139	4.5	141	4.5	142	4.6	143	4.5
Cowpea	223	6.8	200	6.5	201	6.4	203	6.6	206	6.5
Total	3266	100.0	3085	100.0	3129	100.0	3098	100.0	3149	100.0

Source: MoFA, 2016 and 2018.

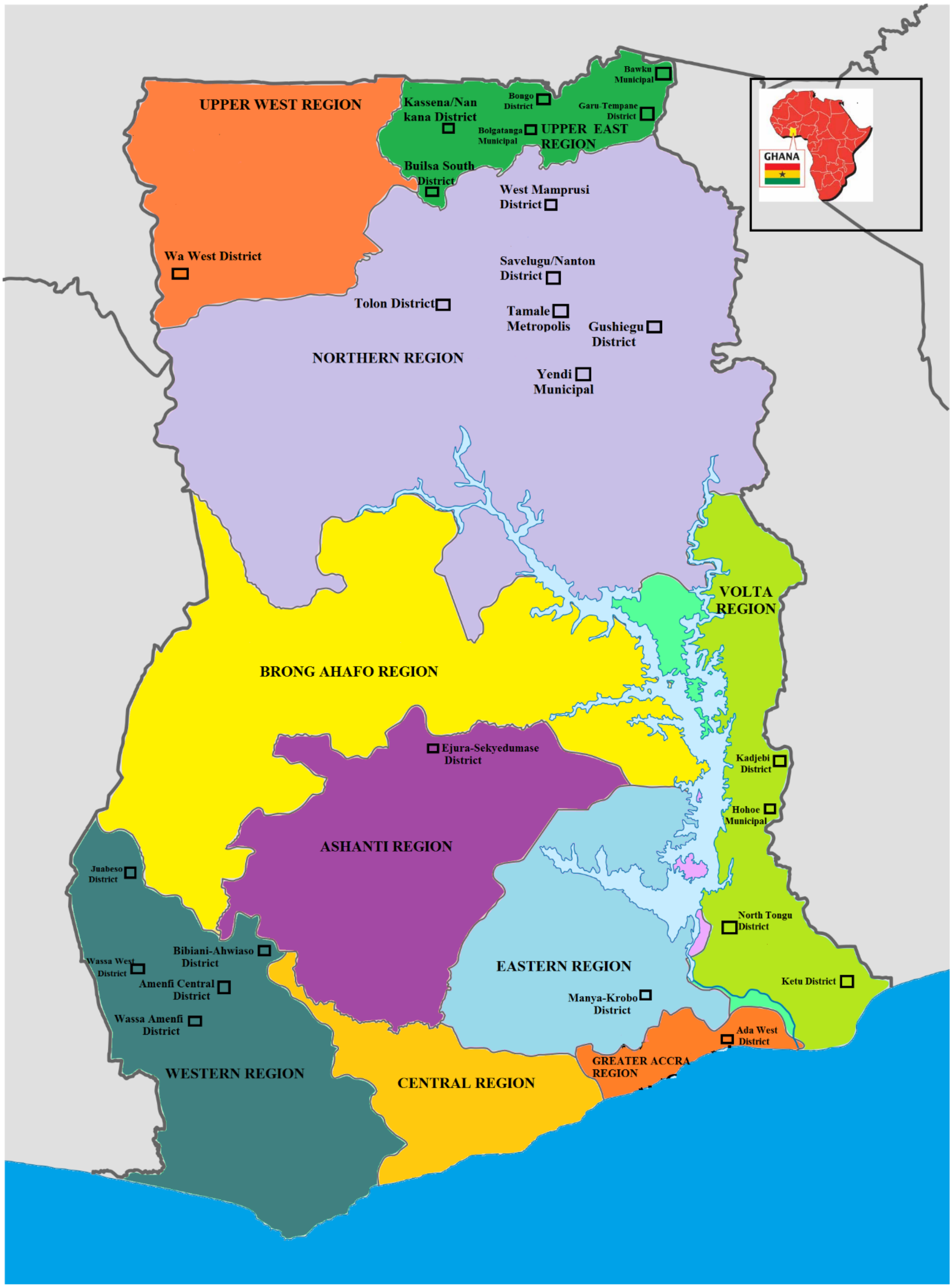

Figure 7.1: A Map of Ghana showing the Study Area

7.3 Sampling and data collection

This thesis used a mix of quantitative and qualitative methods. The qualitative data was collected at the end of the quantitative analysis to elicit further insights into the quantitative results. Qualitative primary data collection mainly focus group discussions and personal interviews with rice farmers, improved seed suppliers and agricultural extension agents were collected between January and February 2020 in the Upper East Region of northern Ghana and Volta Region in southern Ghana.

Two focus group discussions involving men and women were organized with rice farmers, one in each region. Four in-depth personal interviews with rice farmers were conducted in each region with a total of eight for the two regions. For instance, farmers were asked to list the characteristics/traits that they liked, did not like and wished the rice varieties they cultivated possessed as well as the constraints in adopting improved rice varieties among others. The inclusion criterion for participating in the personal interviews and focus group discussions was rice farmers who have been cultivating rice since 2012[34] up to the 2019 cropping year. With the help of a community focal person, invitations were sent out to rice farming households who met this criterion, and those willing to participate were identified. Finally, simple random sampling through balloting was employed to select participants where many were eligible after the inclusion criterion. Two agricultural extension agents and one improved seed supplier respectively were also interviewed in each region to identify constraints regarding dissemination and access to improved varieties, and what measures need to be put in place to improve adoption rates. The detailed interview guides for the farmers, agricultural extension agents and improved seed suppliers are found in appendices A1 to A5.

[34] This is because the IFPRI data was collected for the 2012 cropping season.

The secondary data used in this study was provided by the International Food Policy Research Institute country office in Ghana. The survey was carried out between November 2012 to February 2013 to collect data on both rice and maize production during the 2012/2013 cropping season by the Ghana Strategy Support Programme of the International Food Policy Research Institute in collaboration with two national agricultural research institutes namely the Crops Research Institute in Kumasi and the Savannah Agricultural Research Institute in Nyankpala (Ragasa and Chapoto, 2017). Multi-stage sampling methods were used to sample a total of 576 rice farming households from 25 rice producing districts[35] across eight regions. The survey first applied a proportional probability sampling method that gave more sampling weight[36] to districts with higher rice production output[37], whilst random sampling was employed in the final selection of sampled districts. Random sampling was also used to sample enumeration areas in each district as well as rice farming households amongst the selected enumeration areas or communities.

Table 7.2: Sample distribution across regions, districts and communities

Agro-ecological zone	Region	District	Number of respondents	Communities/enumeration areas
Savannah	Northern	[38]West Mamprusi	21	Kpasenkpe, Loagri, Yamma
		Tolon-Kumbungu	42	Mbanaayili, Bontanga Irrigation, Kugulogu, Yoggu
		Tamale	21	Vittin, Kasaligu, Yong Dakpiemyili
		Yendi	21	Palari, Salankpang, Lamaya

[35] Districts with more than 1000 hectares of rice production annually.
[36] A higher probability of being sampled.
[37] The Northern and Upper East Regions are the biggest producers in Northern Ghana whilst the Volta Region is the leading producer in southern Ghana.
[38] West Mamprusi was added to the newly created North East Region in late 2019.

		Savelugu/Nanton	21	Tampion, Yilikpani, Jana
		Gushiegu	21	Degbela, Gaa, Nakunga
	Subtotal	*6*	*147*	
	Upper East	Kassena-Nankana	42	Tono Irrigation, Manyoro Wura, Kazugu, Korania
		Bongo	42	Zoko Kanga, Gowrie Tengre, Vea Irrigation, Samboligu Ayeopia
		Bawku	21	Kuka Natinga, Kakasiego, Kpalugu Bundari,
		Bolgatanga	21	Sumburungu Zorbogo, Yorogo Gabisi, Zuarungu Daboro,
		Builsa	21	Farinsa Aleng Yeri, Chuchuliga, Salimsa, Kanjarga Samsa
		Garu-Tempane	21	Siigure, Guri Duri, Farfar Gangkwan
	Subtotal	*6*	*168*	
	Upper West	Wa West	21	Ladayiri, Bakporanteng, Siriyiri
	Subtotal	*1*	*21*	
Forest zone	Eastern	Manya Krobo	19	Akuse, Belekope, Kpong
	Subtotal	*1*	*22*	
	Ashanti	Ejura Sekyedumase	21	Ashiakoko, Fakawa, Aframso
	Subtotal	*1*	*21*	
		Bibiani Ahwiaso	21	Lineso, Degede, Adupri

	[39]Western	Juabeso	21	Benkyemaa Nkwanta, Juabeso, Afere
		Wassa West	11	Pensanom, Obeng
		Wassa Amenfi	3	Wuratrem
		Amenfi Central	7	Obeng, Kwabena Amaosa
	Subtotal	*5*	*63*	
Coastal zone	Greater Accra	Ada West	20	Kpong Irrigation
	Subtotal	*1*	*20*	
	Volta	Ketu	41	Dekpor-Yia, Lave, Todome, Koryia, Tsiaveme,
		North Tongu	36	Aveyime, Alagbornu, Benkasa, Tutukope
		Kadjebi	21	Dapaa-Kukurantumi, Asato, Dodo-Tamale
		Hohoe	19	Alavanyo Wudidi, Lipke Agbozume, Gbi-Atabu,
	Subtotal	*4*	*118*	
	Total	**25**	**576**	

Source: Author's construction based on IFPRI 2013 data set.

According to the 2010 Population and Housing Census[40] (GSS, 2012), Ghana had an estimated crop farmer population N, of 1,896,055. Adapting a sample size determination formula proposed by Yamane (1967) and assuming a margin of error, e of 5%, the sample size, n is calculated as follows:

$$n = \frac{N}{1+N(e^2)} \qquad (7.1)$$

[39] The sampled districts in this region became part of the newly created Western North Region in late 2019.
[40] Population and housing census is conducted in Ghana every 10 years and the next is expected in 2020.

$$n = \frac{1896055}{1+1896055(0.05)^2} = 400 \text{ rice farming household for the eight regions}$$

where, n = sample size, N = population size and e =level of precision.

The data were collected using semi-structured questionnaires. It included both socioeconomic and demographic characteristics of rice farmers such as age, educational level, household income and expenditures, household assets, household size etc; social and community engagements such as membership of farmer based organizations, participation in rice projects, participation in block farming, engagement as a model rice farmer, community membership status and number of years stayed in community, as well as those directly related to rice production and output such as rice varieties known and cultivated by farmers, land preparation and weed control practices, seeds priming and method of planting, type of fertilizer applied, adoption of bund construction, farrowing, puddling, levelling, farm size in hectares, seeds quantity used in sowing (kg), quantity of fertilizer applied (kg), labour quantity (in man days), use of herbicide and weeding times, rice cultivation system (such as upland rainfed, lowland rainfed, irrigated), agro-ecological zone of rice production (coastal, forest, savannah), access to agricultural extension service, method of harvesting, amongst others.

7.4 Empirical models of exposure and adoption of improved rice varieties

One of the objectives of this study is to assess the exposure and adoption of improved rice varieties by Ghanaian farmers. Following Diagne and Demont (2007), this study defines exposure to improved rice varieties as a farmer being aware of the existence of or having knowledge of any of these improved varieties (FARO 15, GR varieties [GR 17 to GR 22], GRUG7, Digang, NERICA varieties, Jasmine 85, Togo Marshall, WITA 7, Jet 3, Aromatic Short, Sikamo, Bumbaz, Bodia, IR20, Sakai). A detailed description of the distinctive characteristics of each of the improved varieties is found in Table 2.1. Exposure to improved rice varieties precedes adoption, and therefore, adoption of improved rice varieties is estimated using the subsample of farmers with knowledge about these varieties. Households that planted any of the improved rice varieties in Table 2.1 during the 2012/2013 cropping season were regarded as adopters whereas those who cultivated any of these traditional varieties (Mandii, Mr. Moore, Mr. Harry, Anyofula, Paul/Adongadonga, Salma saa, Muikpong, Wariwari) were treated as non-adopters. A summary definition of variables used in the empirical analyses is presented in Table 7.3.

Table 7.3: Summary definition of variables used in empirical analyses

Variable	Notation	Description
Exposure model	ω_i	Dummy; 1, household is exposed to improved rice variety, 0, otherwise
Community participation in rice projects	K_1	Dummy; 1, community participated in rice project, 0, otherwise
Presence of agro-input shop in community	K_2	Dummy; 1, agricultural input shop exists in community, 0, otherwise
Model farmer	K_3	Dummy; 1, household has been a model farmer, 0, otherwise
Block farming	K_4	Dummy; 1, household participated in block farming, 0, otherwise
Membership of farmer-based organization	K_5	Dummy; 1, household belongs to a farmer-based organization, 0, otherwise
Agricultural extension services	K_6	Dummy; 1, household accesses agricultural extension services, 0, otherwise
Adoption model		

Adoption	d_i	Dummy; 1, household cultivated improved rice variety, 0, otherwise
Community participation in rice projects	Z_1	Dummy; 1, yes, 0, otherwise
Presence of agro-input shop in community	Z_2	Dummy; 1, yes, 0, otherwise
Model farmer	Z_3	Dummy; 1, yes, 0, otherwise
Block farming	Z_4	Dummy; 1, household participated in block farming, 0, otherwise
Agricultural extension services	Z_5	Dummy; 1, yes, 0, otherwise
Sex of household head	Z_6	Dummy; 1, household head is female, 0, male
Forest zone	Z_7	Dummy; 1, agro-ecological area of rice farm is forest, 0, coastal zone
Guinea savannah zone	Z_8	Dummy; 1, agro-ecological area of rice farm is guinea savannah, 0, coastal zone
Lowland rain-fed	Z_9	Dummy; 1, rice cultivation is lowland rain-fed, 0, upland rain-fed
Irrigated production	Z_{10}	Dummy; 1, rice cultivation by irrigation, 0, upland rain-fed
Higher yield	Z_{11}	Dummy; 1, farmer seeking higher rice yield, 0, otherwise
Market demand	Z_{12}	Dummy; 1, farmer producing rice to sell, 0, otherwise.
Own consumption	Z_{13}	Dummy; 1, farmer producing rice for household consumption, 0, otherwise
Use of farm saved seed	Z_{14}	Number of years current rice variety has been continuously cultivated.
Farm size	Z_{15}	Number of hectares (ha) of cultivated rice
Stochastic Frontier		
Rice output	Y	Rice output (in kg)
Farm size	X_1	Hectares of rice plot

Rice seed	X_2	Quantity of rice seed (in kg) planted
Fertilizer	X_3	Quantity of fertilizer used (in kg)
Farm labour	X_4	Farm labour (person-days) used
Herbicides	X_5	Herbicides (in litres) used on plot
Fertilizer application	D_i	Dummy; 1, household applied fertilizer on rice farm, 0, otherwise
Technical Inefficiency		
Sex of household head	M_1	Dummy; 1, household head is female, 0, male
Age	M_2	Number of years of household head
Agricultural extension services	M_3	Dummy; 1, household has agricultural extension access, 0, otherwise
Educational Status	M_4	Number of years of formal education of household head
Rice seed priming	M_5	Dummy; 1, practising seed priming, 0, otherwise
Row planting	M_6	Dummy; 1, practising row planting, broadcasting, 0
Seedling transplanting	M_7	Dummy; 1, seedling transplanting, direct sowing, 0
Sawah system	M_8	Dummy; 1, practise sawah system, 0, otherwise
Land preparation with herbicides	M_9	Dummy; 1, land preparation using herbicides, 0, otherwise
Weeding using herbicides	M_{10}	Dummy; 1, used herbicides for weed control, 0, hand hoe weeding
Weeding frequency	M_{11}	Number of times rice plot was weeded
Actyva fertilizer use	M_{12}	Dummy, 1, applied on rice farm, 0, otherwise
Ammonia fertilizer use	M_{13}	Dummy; 1, applied on rice farm, 0, otherwise
Fertilizer rate	M_{14}	Dummy; 1 if recommended rate of at least 350kg/ha is applied, 0, otherwise
Rice harvesting method	M_{15}	Dummy; 1, combine harvester, 0, sickle

Land preparation	M_{16}	Dummy; 1, herbicide applied, 0, otherwise
Pesticide use	M_{17}	Dummy; 1, pesticide applied, 0, otherwise
Net rice income per ha		Net rice income of a household (in GH¢) divided by the rice farm area in hectares of that given household
Rice sold (tonnes) per household per year		Total tonnes of rice from harvest sold for income by household per year
Motorcycle ownership		Dummy; 1 if household owns a motorcycle, 0, otherwise
Bicycle ownership		Dummy; 1 if household owns a bicycle, 0, otherwise
Electricity		Dummy; 1 if household has access to electricity, 0, otherwise
Household size		Number of members in household

Source: Author's construction based on survey data set. Currency GH¢ = Ghana cedi. Bank of Ghana exchange rate was £1 = GH¢ 6.27 as at January 16, 2019.

7.4.1 Estimation of exposure rate, adoption rate and average treatment effect of adoption

Once the determinants of exposure to improved rice varieties are estimated using the probit model, the marginal effects and average exposure rate can be calculated for the full sample. Similarly, after estimating the determinants of adoption conditional on exposure, the average treatment effect (ATE), average treatment effect on the treated (ATT), and average treatment on the untreated (ATU) can be obtained as follows:

$$A\hat{T}E = \frac{1}{n}\sum_{i=1}^{n} g\left(z_i;\ \hat{\beta}\right) \qquad (7.2)$$

$$A\hat{T}T = \frac{1}{n_e}\sum_{i=1}^{n} \omega_i g(z_i;\ \hat{\beta}) \qquad (7.3)$$

$$A\hat{T}U = \frac{1}{n-n_e}\sum_{i=1}^{n} (1-\omega_1) g(z_i;\ \hat{\beta}) \qquad (7.4)$$

The ATE measures the average adoption of a rice farming household randomly drawn from the population when every rice farming household is exposed to the improved rice varieties.

The ATU is the average treatment for the non-adopters, and n_e is the number of rice farmers exposed to improved varieties.

On the other hand, the average joint exposure and adoption rate [JEA] (Diagne and Demont, 2007) using the full sample that contains both exposed and non-exposed rice farming households is expressed as:

$$J\hat{E}A = \frac{1}{n}\sum_{i=1}^{n} y_i \qquad (7.5)$$

Following Diagne and Demont (2007), the estimates of JEA and ATE are used to calculate the non-exposure bias (population adoption gap) which is the demand for improved rice varieties by the population hampered by incomplete diffusion is:

$$N\hat{E}B = J\hat{E}A - A\hat{T}E \qquad (7.6)$$

The population selection bias calculates the bias due to over-estimation of the true population adoption rate because of self-selection and targeting resulting from using the exposed subsample only and following Diagne and Demont (2007), it is given by:

$$P\hat{S}B = A\hat{T}T - A\hat{T}E \qquad (7.7)$$

7.5 Effect of adoption of improved rice varieties on output and technical efficiency

In assessing the effect of adoption of improved rice varieties on farm output and technical efficiency using the stochastic frontier approach, two potential sources of bias arise. Empirically, a propensity score matching is performed and the matched scores are used to estimate separate stochastic frontier functions for the adopters of improved rice varieties and the counterfactual non-adopters (Bravo-Ureta *et al.*, 2012) to correct observable biases. This is followed by Greene (2010) procedure to account for selection bias arising from unobservable characteristics.

7.5.1 Empirical estimation of the stochastic frontier with correction for sample selection

Selection bias due to unobserved factors when the error terms of the adoption selection equation, w_i and the noise component, v_i of the stochastic frontier model are correlated (Greene, 2010). The probit sample selection and stochastic frontier equations by Greene (2010) are given by:

$$d_i = \alpha_0 + \sum_{j=1}^{15} \alpha_j Z_{ji} + w_i \quad (7.8)$$

$$lnY_i = \beta_0 + \sum_{k=1}^{5} \beta_k \, lnX_{ik} + {}^{1}\!/_{2} \sum_{k=1}^{5} \sum_{j=1}^{5} \beta_{kj} \, lnX_{ik} \, lnX_{ij} + D_i + v_i + u_i \quad (7.9)$$

Equations 7.8 and 7.9 are estimated by simulated maximum likelihood (Greene, 2010), where d_i is a dichotomous variable for improved rice seeds adoption decision (1, adopter, 0, otherwise); Z is a vector of exogenous variables in the adoption model; α are the unknown parameters; and *w* is the disturbance term; ln represents logarithm to base $\boldsymbol{e}$; Y is output of rice (in kg); X_i are the five input quantities for the translog model presented in Table 7.2. Following Battese (1997), a dummy variable (D_i) is introduced to account for zero quantities of fertilizer application. This is because the natural logarithm of fertilizer is taken only when it is positive, otherwise is zero.

Similarly, the determinants of technical inefficiency for the inefficient rice farmers are estimated using Jondrow *et al*. (1982) conditional expectation procedure where u is $E[u|(\varepsilon - u)]$ with a distribution of $N(\mu^*, \sigma_*^2)$ as follows:

$$u_i = M_i\delta + w_i \quad (7.9)$$

where M_i are socioeconomic, institutional and farm-specific explanatory variables in Table 7.2 that affect technical inefficiency of rice production. δ is a vector of parameters to be estimated, and w_i is an unobservable random variable.

7.5.2 Empirical estimation of the stochastic metafrontier

To be able to make a direct comparison of the technical efficiency scores the between adopters and non-adopters of improved rice varieties, the estimation of a stochastic metafrontier is required. The stochastic metafrontier envelopes the stochastic group frontiers (adopters and non-adopters of improved rice varieties) and allows the estimation of the technology gap between the metafrontier and the individual group frontiers facing different production possibilities.

Following Amsler *et al*. (2017), the stochastic metafrontier is expressed as:

$$f_i = \max[f_{i1}, \ldots . f_{is}\ ] \qquad s = 1, \ldots S \tag{7.10}$$

Subject to $f_i d_i \leq f_i$

The metafrontier is stochastic because the group frontiers $f_{is} = x_i' \beta_s + v_{is}$ are stochastic.

$f_i d_i$ is the row vector of all inputs for each technology group, d_i ; β_s is the vector of group coefficients and β^* is the vector of meta coefficients to be estimated. Once solved, the metatechnology ratio (MTR) of a rice farm with respect to the metafrontier is estimated as:

$$MTR_i = \frac{exp(x_i' \beta_{d_i})}{exp(x_i' \beta_s\,)} \times \frac{exp(v_i d_i)}{exp(v_{is})} \tag{7.11}$$

The MTR ratio measures how close the group frontier is to the metafrontier and it depends on the input-output mix of the group frontier (Battese and Rao, 2002; Battese *et al.*, 2004).

The MTR measures the technology gap (metafrontier distance) and any increase in the MTR implies a decrease in the gap between the group frontier and the metafrontier.

Technical efficiency of farm i relative to the metafrontier, TE_i^* is calculated as the product of the technical efficiency from the group frontier, TE_i and the metatechnology ratio, MTR_i for the group as follows:

$$TE_i^* = TE_i \times MTR_i \tag{7.12}$$

The metafrontier is estimated using R econometric software following Amsler *et al*. (2017).

7.5.3 Tests of hypotheses of the stochastic production frontier

First, the appropriateness of the stochastic production function (H_A) over the average response function (H_0) by ordinary least squares (OLS) is tested. This is done following Coelli (1995) standard normal skewness statistic (M3T) and is expressed as:

$$H_0: M3T = 0$$

A negative sign of the third moment of the OLS residuals justifies the use of the stochastic frontier framework by maximum likelihood estimation procedure.

Once the skewness test justifies the stochastic frontier estimation, a number of hypotheses arise. These hypotheses are tested using the generalized likelihood ratio test expressed as:

$$k = -2\,[ln\{L(H_A)\}/ln\{L(H_0)\}] = -2\,[ln\{L(H_A)\} - ln\{L(H_0)\}] \tag{7.13}$$

The values of the log likelihood function under the alternative and null hypotheses are $L(H_A)$ and $L(H_0)$. The value of k has a Chi-square, $\chi 2$ (or mixed chi-square) distribution with the number of degrees of freedom equal to the difference between the number of parameters involved in H_0 and H_A. The following hypotheses are tested:

1. The choice of the translog functional form (H_A) is tested against the Cobb-Douglas (H_0):

$$H_0: all\ \beta_{kj} = 0$$

2. Test of presence of technical inefficiency and the influence of managerial factors (δ_i) on output variability (H_A) is tested over the H_0 of no technical inefficiency in rice cultivation:

$$H_0: all\ \delta_i = 0$$

3. Tests of fulfilment of regularity conditions of the translog functional form (Sauer *et al.*, 2006):

   (i) Monotonicity condition: the marginal products of all the inputs should be positive (non-negative production elasticities), thus $\frac{\delta y}{\delta x_i} > 0$.

   (ii) Diminishing marginal productivity for all the inputs (decreasing marginal products), $\frac{\delta^2 y}{\delta x_i^2} < 0$.

4. Test the null hypothesis [$H_0: lnL_P = lnL_{NA} = lnL_A$] that the pooled sample is not statistically different from the subsamples of adopters and non-adopters of improved rice varieties using the generalized likelihood ratio test as:

   $$LR = 2(lnL_P - (lnL_{NA} + lnL_A))$$

5. Test the existence of selection bias in the stochastic frontier ($H_A: \rho \neq 0$) against the null ($H_0: \rho = 0$)[41].

[41] When ρ equals zero, the maximand reduces to the maximum simulated likelihood estimator of the basic stochastic frontier model, i.e., no selectivity bias (Greene, 2010).

7.6 Empirical model of effect of adoption of improved rice on household rice income

Households that are aware of and cultivate improved rice varieties are more likely to benefit from increase in output for home consumption and or for sale to obtain cash income to support household expenditure. In this study, switching regression is applied in assessing the effect of adoption of improved rice varieties on household net rice income per ha amongst those exposed to the improved rice varieties. Empirically, it is estimated via full information maximum likelihood using a user-written STATA code *movestay* command (Lokshin and Sajaia, 2004), which estimates the adoption and separate net rice income per ha for adopter and non-adopter households simultaneously as:

$$P_i = 1(z_i\gamma) + u_i > 0 \quad \text{[adoption equation]} \quad (7.14)$$

$$Y_1 = X_1\beta_1 + \mu_1 \quad \text{If } P = 1 \quad \text{[outcome equation for adopters]} \quad (7.15)$$

$$Y_0 = X_0\beta_0 + \mu_0 \quad \text{If } P = 0 \quad \text{[outcome equation for non-adopters]} \quad (7.16)$$

where Y_1 and Y_0 are household net rice income per ha for adopters and non-adopters, X_1 and X_0 are the $1 \times n_1$ and $1 \times n_0$ vectors of explanatory variables contained in Table 7.2, β_1 and β_0 are $n_1 \times 1$ and $n_0 \times 1$ individual specific parameter vectors and γ and $m \times 1$ are parameter vectors of the adoption equation, P is a latent variable determining which group applies, and z_i a $1 \times m$ vector of explanatory variables that are assumed to affect the probability of adoption and u_i, μ_1, and μ_0 are error terms.

The predicted values of household net rice income per ha from the switching regression results are used to estimate the ATT and ATU. The ATT estimates the difference in net rice income per ha of adopters and what their wellbeing would have been if they had not cultivated improved rice varieties, whereas the ATU reveals the difference in net rice income per ha for non-adopters and what would have pertained had they cultivated improved rice varieties (Heckman *et al*., 2001; Di Falco *et al*., 2011). The difference between the ATT and ATU is the transitional heterogeneity, and it assesses whether the effect of adoption of improved rice varieties is larger or smaller for actual adopter households or for counterfactual adopters in the non-adopter households. A detailed discussion of the switching regression methodology is found in section 6.2.1.

7.6.1 Calculation of household net rice income per hectare

In this study, household net rice income per ha is calculated as total revenue per ha less total cost of production per ha. The total revenue is the market price of rice per bag (120kg paddy) multiplied by the total number of bags harvested per ha. The total cost incurred in rice production from land preparation, ploughing, seed, fertilizer, herbicides, pesticides, labour, and all associated costs of farm operations such as harvesting, and post-harvest handling operations including marketing and transportation cost.

Mathematically, the household net rice income per ha, NRI is expressed as:

$$NRI = TR - [TC + MC + (PL \times P_R)] \qquad (7.17)$$

$$TR = N_R \times P_R$$

where, TR is the total revenue per ha, N_R is the number of bags of rice harvested per ha, P_R is the market price of rice per bag, TC is the total production cost incurred less marketing, MC is the marketing cost incurred by farmers, PL is the physical loss (kg) of produce from harvest until it reaches the market. Physical losses in this regard rarely occur for rice.

Following Acharya and Agarwal (2001) and Sreenivasa *et al*. (2007), losses in agriculture result from field level harvesting and handling operations, post-harvest processing, wholesale and retail marketing level.

In Ghana, field level losses for rice are about 5% of total harvest mainly from manual harvesting, threshing and winnowing (MoFA, 2019). Losses arising out of harvesting, threshing and winnowing do not normally form part of the harvested produce reported by farmers and not included in total revenue. Unlike perishables such as fruits and vegetables, harvested rice (paddy) can be stored at room temperature for a long time without risk of produce loss. Marketing and transport cost are incurred where farmers have to bring the physical produce to market centres for sale and if reported, these costs are subtracted from total revenue as in equation 7.17. However, in most cases, traders and paddy aggregators contracted by milling factories visit rice farmers and handle the cost of transportation, milling and other related marketing expenses (DFID, 2015).

7.7 Method of analysis of qualitative data

The analysis of the qualitative data supports the quantitative aspect of this study. The primary qualitative data collected through focus group discussions and in-depth interviews covers aspects of this research that are not contained in the quantitative data. For instance, the focus group discussions and personal interviews with rice farmers were conducted to identify specific constraints to adoption of improved rice varieties in the study area, farmers' preferences and perceptions about varietal traits and how to facilitate their adoption. Secondly, in-depth interviews with agricultural extension agents and improved seed suppliers were undertaken to reveal constraints to the dissemination and access to improved rice varieties from their perspective as stakeholders, and what measures need to be put in place to improve adoption rates as service providers to rice farmers.

The first step in the qualitative data analysis involves a broad and an unfocused verbatim transcription of the recorded conversations (Riessman, 1993). This is followed by a more focused transcription that checks for consistency and accuracy and highlights aspects that are relevant to present and how to present them (Darlington and Scott, 2002; Gibson and Brown, 2009). Finally, the transcripts are organized into thematic areas that revolve around the importance of rice cultivation to farmers, rice varietal diffusion, access and adoption, farmers' perceptions of varietal traits, constraints to rice cultivation and how to ease these constraints.

Regarding varietal traits preferences, earlier studies such as Buah *et al*. (2011) and Coffie *et al*. (2016) revealed smallholder farmers in Ghana looked out for varietal traits such as higher yield, early maturity, disease and pest-resistance, less labour requirements, ease of threshing and milling and good taste in making their adoption decisions. Relative to rice cultivation constraints, previous studies (Kranjac-Berisavljevic' *et al*., 2003; Faltermeier and Abdulai, 2009; Ragasa *et al*., 2013; Nin-Pratt and McBride, 2014) identified erratic rainfall and floods, low soil fertility, diseases, pests, weeds infestation, high labour costs, lack of credit facilities, and declining soil fertility as major constraints to rice production in Ghana.

CHAPTER EIGHT

DEMOGRAPHIC STATISTICS OF RESPONDENTS

8.1 Introduction

This chapter contains a summary description of all the variables used in the analyses and estimations in this study. It also presents a discussion of the demographic characteristics and summary statistics of the respondent households for the full sample as well as the exposed (aware of the existence of improved rice varieties), adopter and non-adopter sub-samples.

8.2 Definition and summary statistics of variables

Table 8.1 presents the definition of variables used in this study. The explanatory factors for exposure to improved rice varieties consisted of six binary choice variables including community participation in rice projects, presence of an agro-input shop in a community, selection as a model farming household for improved varieties, participation in block farming, membership of a farmer-based organisation, and access to agricultural extension services.

In this study, 388 households stated they did not have community agro-input shops, 318 did not belong to farmer-based organizations (FBOs) and 529 households did not participate in block farming. Additionally, only 108 households indicated their communities participated in rice projects, 96 households have ever been selected as model farmers and only 160 had access to agricultural extension services as presented in Figure 8.1.

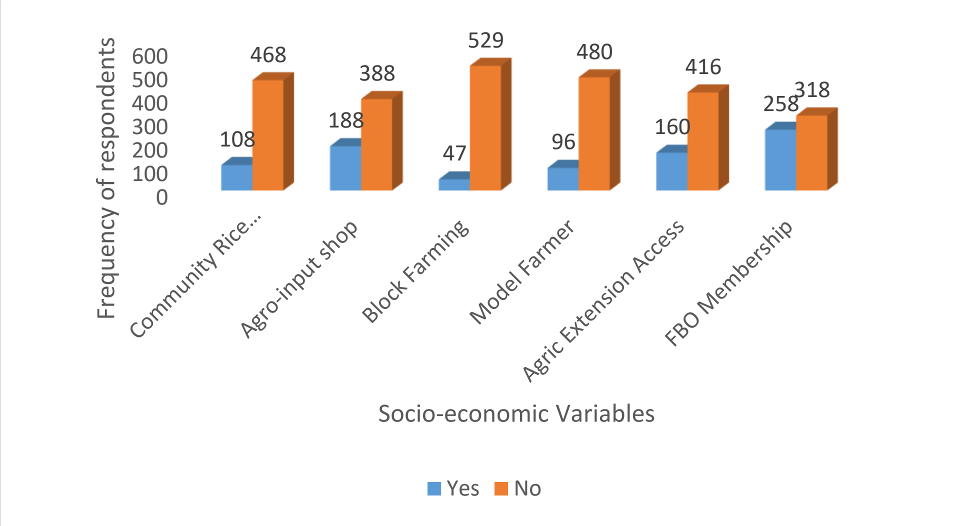

Figure 8.1: Frequency distribution of exposure variables

Table 8.1: Summary definition of variables

Variable	Description
Exposure	Dummy; 1 if a household head knows at least one improved rice variety, 0, otherwise
Adoption	Dummy; 1 if a household head cultivated at least one improved rice variety, 0, otherwise
Community participation in rice projects	Dummy; 1 if community ever participated in a rice project, 0, otherwise
Presence of agro-input shop in community	Dummy; 1 if community has agro-input shop, 0, otherwise
Being a model farmer	Dummy; 1 if household head has ever been a model farmer, 0, otherwise
Participation in block farming	Dummy; 1 if household head has ever participated in block farming, 0, otherwise
FBO membership	Dummy; 1 if household head belongs to farmer-based organization, 0, otherwise
Fertilizer application	Dummy; 1, if household applied fertilizer on rice farm, 0, otherwise
Forest zone	Dummy; 1 if agro-ecological area of rice farm is forest, 0, coastal zone

Guinea savannah zone	Dummy; 1 if agro-ecological area of rice farm is guinea savannah, 0, coastal zone
Lowland rain fed	Dummy; 1 if rice cultivation system is lowland rain fed, 0, upland rain fed
Irrigated production	Dummy; 1 if rice cultivation system is irrigation, 0, upland rain fed
Higher yield	Dummy; 1 is whether farmer seeks higher rice yield, 0, otherwise
Market demand	Dummy; 1 is whether farmer produces rice for sale in the market, 0, otherwise
Own consumption	Dummy; 1 is whether farmer produces rice for household consumption, 0, otherwise
Growing farm saved seed	Number of years farm saved seed of current rice variety was continuously cultivated by household
Agricultural extension	Dummy; 1 if household head has access to agricultural extension services, 0, otherwise
Sex of respondent	Dummy; 1 if household head is female, 0, male
Educational Status	Number of years of formal education of household head
Age	Number of years of household head
Farm size	Number of hectares (ha) of cultivated rice
Seed rate	Kilogrammes of own/purchased seeds planted per ha
Fertilizer rate	Kilogrammes of chemical fertilizer applied on rice plot per ha
Recommended fertilizer rate	Dummy; 1 if recommended rate of at least 350kg/ha is applied, 0, otherwise
Use of actyva fertilizer	Dummy; 1 if applied on rice farm, 0, otherwise. Actyva is a chemical fertilizer brand name in Ghana.
Use of ammonia fertilizer	Dummy; 1 if applied on rice farm, 0, otherwise
Farm labour	Person days of labour employed on rice farm per ha
Herbicide use	Total litres of herbicide applied on rice farm per ha
Rice yield	Tonnes of rice harvested per ha
Rice consumed	Tonnes of harvested rice consumed by household
Rice sold	Tonnes of harvested rice sold
Rice harvest	Dummy; 1 if combine harvester, 0, sickle

Land preparation	Dummy; 1 if herbicide is used, 0, otherwise
Weed control	Dummy; 1 if herbicide is used, 0, otherwise
Household size	Number of members in household
Household labour	Number of household members who work on rice farm
Seed priming	Dummy; 1 if practised, 0, otherwise
Sawah system	Dummy; 1 if practised, 0, otherwise
Weeding frequency	Number of times rice farm was weeded
Pesticide use	Dummy; 1 if pesticide was applied on rice farm, 0, otherwise
Bird infestation	Dummy; 1 if birds infested rice farm, 0, otherwise
Motorcycle	Dummy; 1 if household owns a motorcycle, 0, otherwise
Bicycle	Dummy; 1 if household owns a bicycle, 0, otherwise
Electricity	Dummy; 1 if household has access to electricity, 0, otherwise
Last season's crop income	Last season's crop income as proportion of household income (in %)

Source: Author's construction based on survey data set. Currency[42] GH¢ = Ghana cedi

The adoption of improved rice varieties was also estimated using 15 variables most of which were discrete choice in nature. In addition to the five variables in the exposure model, the other 10 in the adoption model were sex of household head (males, 459, females, 117), agro-ecological zone of the household rice farm, whether it is located in guinea savannah zone, forest zone or the base dummy variable, coastal zone. The majority of sampled households were from the guinea savannah zone, followed by the coastal zone and the forest zone as summarized in Figure 8.2. Another variable used in the analysis, was the type of rice cultivation system practised by the household such as lowland rain-fed, irrigated production, or upland; with upland rain-fed system as the base dummy variable. Figure 8.3 gives a

[42] Bank of Ghana exchange rate was £1 = GH¢ 7.30 as at July 31, 2020.

distribution of respondent households by rice cultivation system. Over half of the sampled households were into lowland rain-fed cultivation, 154 into irrigated production and 32 for upland rice producers.

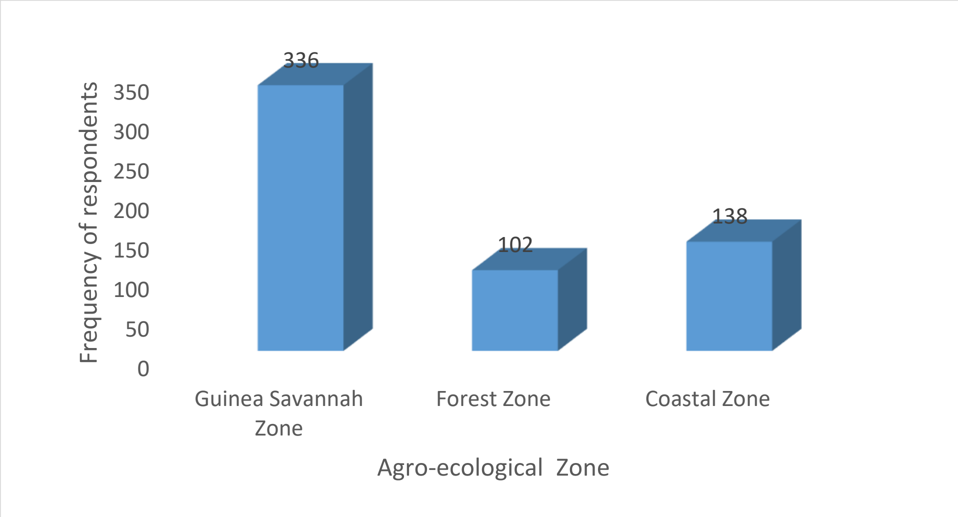

Figure 8.2: Distribution of respondents across agro-ecological zones

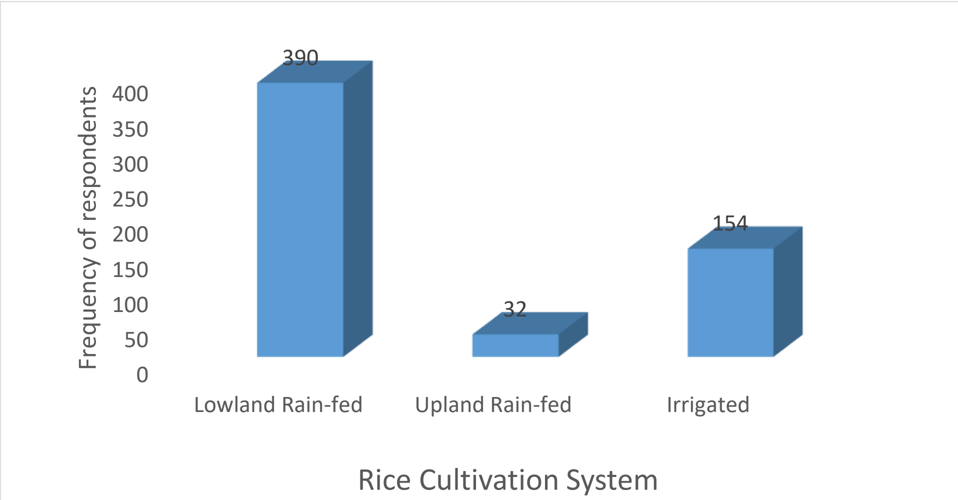

Figure 8.3: Distribution of respondents by rice cultivation system

Relative to application of rice cultural practices by households, only 185 practised seed priming as presented in Figure 8.4. It involves soaking rice seeds in clean water for 12–24 hours and drying it in the open for 24–48 hours before planting (Abdulai *et al*., 2018). Seed priming could boost yield by 25 to 40% relative to non-primed seed (Ragasa *et al.*, 2013). Adding a little potassium and phosphorus before soaking also increases rice germination rates (Bam *et al.*, 2006). Therefore, seed priming was not widely practised by rice farmers in this study.

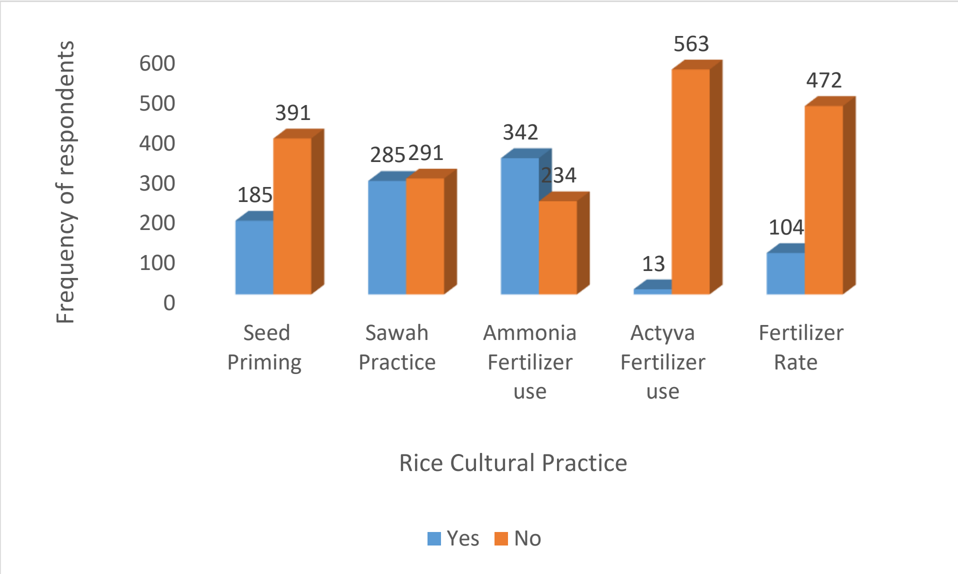

Figure 8.4: Households' application of rice cultural practices

Sawah practice was carried out by 285 households. Sawah is a water control and nutrient management practice that provides optimum growing conditions for lowland rice (Buri *et al*., 2012; Ragasa *et al.*, 2013; Abdulai *et al*., 2018). It involves bund construction, farrowing, and levelling to manage water levels on rice fields. Over half of the respondent households (342) applied ammonia fertilizer on their rice plots. However, actyva fertilizer use was significantly lower with only 13 households applying it on their rice plots. Actvya is a special fertilizer, which together with compound fertilizer, NPK boosts rice yield (Buah *et al*., 2011). Ammonia fertilizer application was relatively higher than actyva fertilizer application. Additionally, Figure 8.4 reveals that many households (472) were unable to apply the recommended rate of at least 350kg/ha of fertilizer on their rice fields.

Herbicide were widely used by rice farming households for land clearing prior to ploughing and or rice planting. Figure 8.5 also indicates that weed control after planting was done using herbicide. The mean herbicide application rate on a rice farm was 2.77litres/ha for the full sample (see Table 8.2).

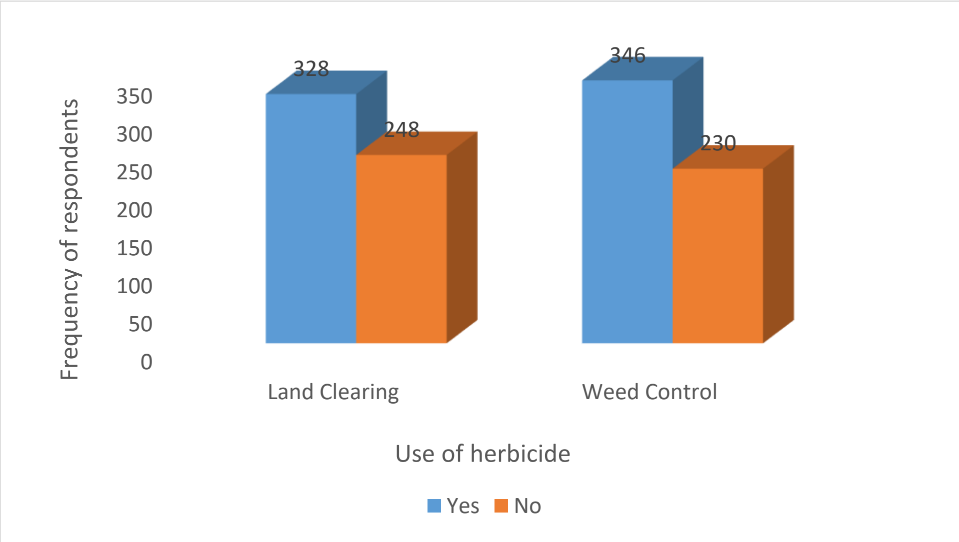

Figure 8.5: Households' application of herbicide

Herbicide are used to complement manual weeding to suppress weed growth on rice fields. The application of pre-emergence herbicide is carried out immediately after sowing before germination, whereas post-emergence herbicide is applied about 3 weeks after sowing (Ragasa *et al.*, 2013). This study also revealed farmers weeded their rice plots at least 2 times in each cultivation season (see Table 8.2).

Rice planting was mainly by sowing, although Figure 8.6 reveals a few households practised transplanting. Adinku (2013) also reported that fewer farmers practised rice transplanting in a study on the technical efficiency of rice farmers in the Greater Accra and Volta Regions of Ghana. Regarding transplanting, the recommended practice is putting two rice seedlings in a drilled hole 3-4 weeks after sowing (Ragasa *et al.*, 2013). Figure 8.7 indicates direct sowing was mostly by broadcasting, albeit some rice farmers practised row planting. The recommended practice is row planting for efficient use of seed and optimum plant density (Buah *et al*., 2011; Ragasa *et al*., 2013; Abdulai *et al*., 2018).

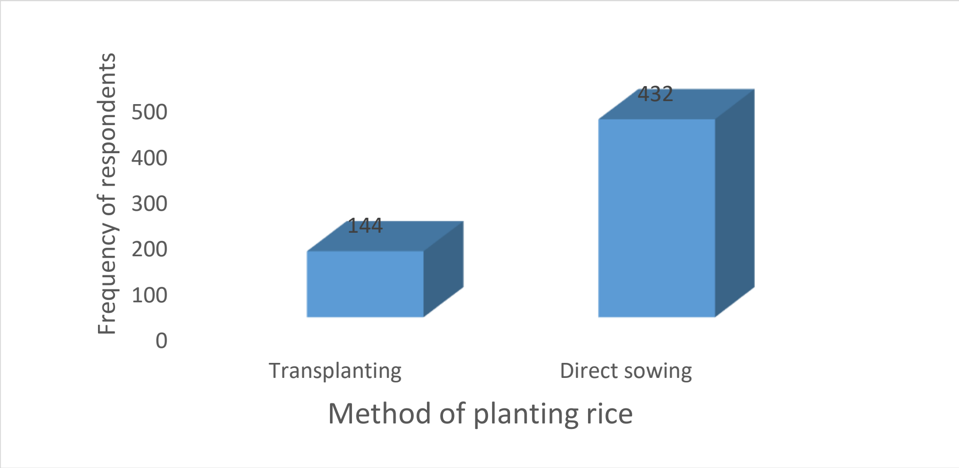

Figure 8.6: Method of planting rice by households

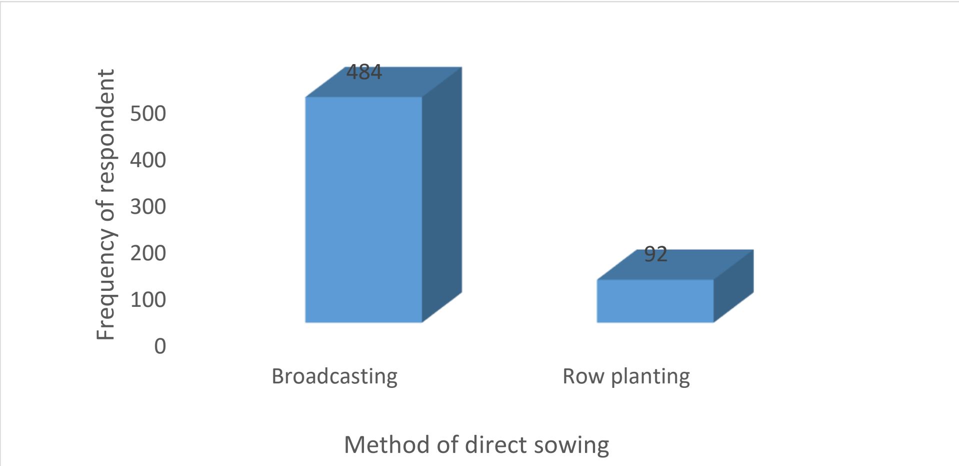

Figure 8.7: Method of direct sowing of rice by households

Bird infestation was a major challenge to rice farming households, particularly at the grain filling, ripening and drying stages before harvesting. The birds cause severe output losses by eating the rice panicles. Figure 8.8 also shows pesticides use in rice production, although not by most rice farmers.

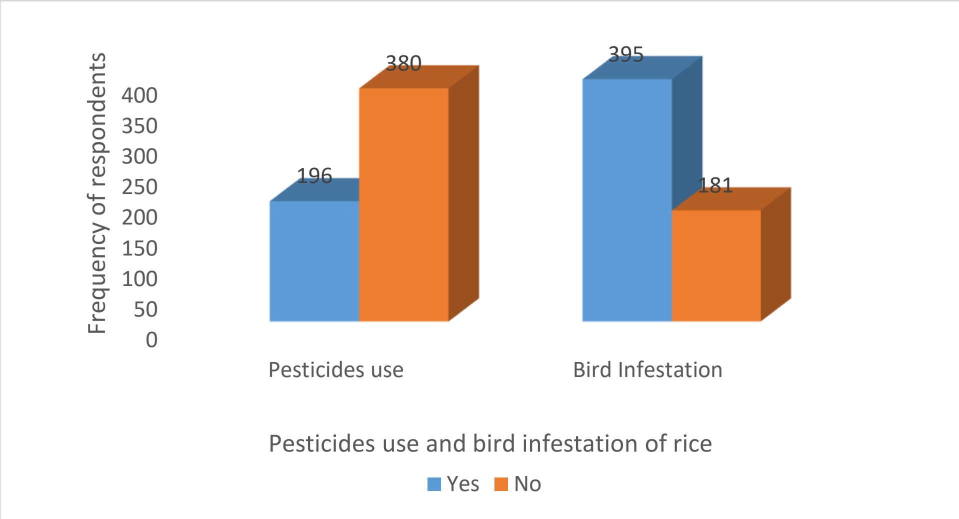

Figure 8.8: Pesticides use and bird infestation in rice cultivation

Rice harvesting was manually done using sickles in this study. From Figure 8.9, only a handful of rice farmers employed the services of combined harvesters. This is consistent with the finding by Adinku (2013) that majority of rice farmers in the Volta and Greater Regions of Ghana practised manual harvesting of rice.

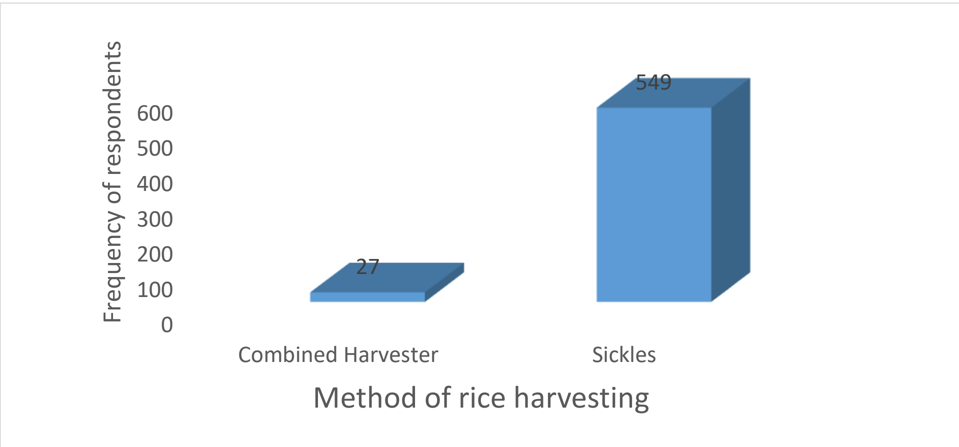

Figure 8.9: Method of rice harvesting by households

Relative to household ownership of assets, majority owned bicycles, followed by motorcycles and oxen as presented in Figure 8.10. More than half of rice farming households were not connected to the electricity grid. The ownership of durable assets reflects the wealth status of a household, hence an indicator of its welfare. Access to electricity also has a positive effect on welfare by facilitating access to information from radio, television and mobile phone on rice production including improved varieties.

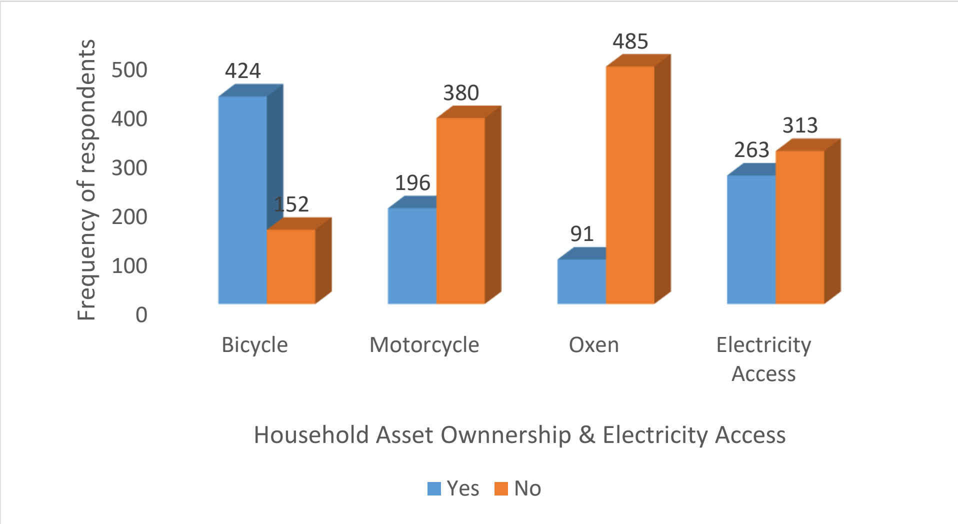

Figure 8.10: Household asset ownership and electricity access

8.3 Demographic characteristics of rice farming households

The average age of a household head was about 41 years, with a range of 19 to 78. This is consistent with Coffie *et al.* (2016) who found a similar mean age of 41 in a study on choice of rice production practices and farmers' willingness to pay in Ghana. However, a mean of 44 years was reported by Adinku (2013) for rice farmers in the Greater Accra and Volta Regions of Ghana. Alhassan (2008) also found a mean age of 42 for rice farmers in northern Ghana. The mean age of 41 years in the study area reveals that, a typical farmer was within the economically active age bracket as the national description includes people from 15 to 60 years of age (GSS, 2012). The study also found a higher mean household size of about 12 compared with the national average of 4.4 obtained in the 2010 census by the Ghana Statistical Service (GSS, 2012). Similarly, the mean household labour of 6 as presented in Table 8.2 was about equal the number of household dependants. This implies households had more dependants, at least 6 per household in the study area. The dependency ratio of 1:6 is also higher than the national mean of 1:4 recorded in the 2010 census (GSS, 2012).

Table 8.2: Descriptive statistics of household socioeconomic characteristics

Variable	Full sample	Non-exposed	Exposed subsample		
	Mean	Mean	Mean pooled	Mean non-adopters	Mean Adopters
Age (years)	41.69 (12.01)	39.94 (12.84)	42.04 (11.82)	40.49 (10.82)	42.80 (12.22)
Education (years)	4.74 (5.26)	4.49 (5.19)	4.79 (5.29)	3.23 (5.19)	5.56 (5.16)
Number of Household size	11.73 (8.26)	12.53 (8.75)	11.57 (8.16)	13.97 (8.79)	10.39 (7.57)
Number of Household labour	6.08 (3.79)	6.66 (4.46)	5.97 (3.63)	6.95 (4.07)	5.49 (3.30)
Farm size (ha)	4.53 (5.66)	4.81 (6.07)	4.48 (5.58)	5.75 (7.17)	3.85 (4.49)
Seed rate (kg/ha) per year	95.32 (58.23)	93.55 (59.60)	95.68 (58.01)	102.12 (59.99)	92.52 (56.83)
Fertilizer rate (kg/ha) per year	218.31 (343.26)	202.16 (495.56)	221.54 (304.42)	82.33 (114.15)	289.86 (343.07)

Farm labour (person- days/ha) per year	149.34 (1130.90)	83.41 (106.19)	162.53 (1237.73)	167.33 (767.88)	160.17 (1413.38)
Herbicide rate (litres/ha) per year	2.77 (4.53)	2.56 (5.54)	2.81 (4.30)	1.82 (3.30)	3.30 (4.65)
No. of years of cultivating farm saved rice seed	4.42 (3.93)	4.56 (3.69)	4.40 (3.98)	5.35 (4.94)	3.93 (3.32)
Weeding times per season	2.02 (0.80)	1.94 (0.71)	2.03 (0.81)	1.96 (0.78)	2.07 (0.83)
Rice yield (tonnes/ha) per year	2.23 (2.07)	1.89 (1.61)	2.28 (2.14)	1.31 (0.84)	2.81 (2.52)
Proportion of rice consumed (tonnes/ha) by household per year	0.34 (0.29)	0.31 (0.24)	0.34 (0.29)	0.21 (0.13)	0.41 (0.33)
Proportion of rice sold (tonnes/ha) by household per year	1.57 (1.70)	1.32 (1.23)	1.62 (1.77)	0.90 (0.69)	1.98 (2.02)
Value rice output (in GH¢) per ha per year	1385.36 (1291.26)	1184.23 (1005.12)	1425.59 (1338.44)	821.80 (521.71)	1721.86 (1507.51)
Cost of rice production (in GH¢) per ha per year	646.39 (457.87)	628.20 (568.41)	650.03 (433.01)	472.15 (224.65)	737.31 (481.55)
Net rice income (in GH¢) per ha per year	738.98 (1114.66)	556.04 (757.67)	775.56 (1170.29)	349.65 (504.61)	984.55 (1336.43)
Last season's crop income (as % of household income)	83.82 (22.41)	85.77 (20.83)	83.43 (22.72)	86.09 (20.03)	82.12 (23.85)
Number of observations	576	96	480	158	322

Source: Author's computation using survey data. Figures in brackets are the standard deviations of the mean values.

The difference between household size and household labour has implications for farm labour, especially where household heads rely on their households to provide a significant proportion of labour for most of their crop production activities (Abdulai, 2015).

The mean attainment of formal education by the rice farming household head was about 4 years. This is higher than the 2 years reported in Coffie *et al.* (2016) for rice farmers in Ghana. Figure 8.11 reveals that nearly half (47.9%) of household heads had no formal education. However, 27.8% of respondents attained basic education (primary and JHS [junior high school] education), whereas 17.9% had senior high school (SHS) education. This means that, only 52.1% of respondents were literate and 47.9% could neither read nor write in English. Human capital is an important asset for agricultural development and therefore, education plays a key role in the ability to absorb modern agricultural technology (Seini, 2002; Kibaara, 2005). Mellor (1976) proposed that investments in education should be a central ingredient in any strategy to improve agricultural productivity.

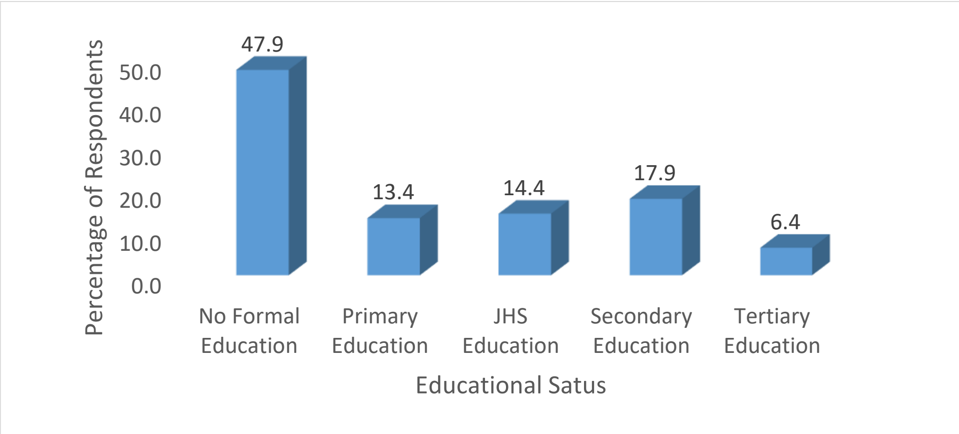

Figure 8.11: Educational level of household head

The average size of a household's rice farm was over 4 hectares (ha) for the full sample. This is higher than the 2 ha reported by Adinku (2013) for rice farmers in Volta and Greater

Regions of Ghana. It is also higher than the 1.8 ha found in Alhassan (2008) for rice farmers in northern Ghana. However, adopters of improved rice varieties had a slightly lower mean farm size of 3.85 ha compared with 5.75 ha for the non-adopters. The mean rice seed rate planted was 95.32kg/ha for the entire sample, 92.52kg/ha and 102.12kg/ha for adopters and non-adopters respectively. The seed rate in this study is lower than the 130.8 kg/ha reported in Adinku (2013). Meanwhile, the recommended practice is 100-126kg/ha for broadcasting, and 45-50kg/ha for direct sowing by dibbling or drilling (Ragasa *et al.*, 2013; Abdulai *et al*., 2018). In this study, majority of farmers resorted to broadcasting of rice seed which is inefficient in seed use and does not produce optimum plant density (Buah *et al*., 2011). Similarly, a household continuously cultivated farm saved seed of current rice variety for at least 4 years. This is not consistent with the recommendation for farmers to renew their rice seed at least once in every three planting seasons (Ragasa *et al.*, 2013).

Regarding fertilizer application rate, the mean for the full sample was 218.31kg/ha, 289.86kg/ha and 82.33kg/ha for adopter and non-adopter households. The mean fertilizer application rate across the sample is far lower than the recommended rate of at least 350 kg/ha (Ragasa *et al.*, 2013; Abdulai *et al*., 2018). The non-adopters had the least application rate of 82.33kg/ha in this study. Similar studies such as Alhassan (2008) and Adinku (2013) reported mean fertilizer application rates of 271kg/ha and 650kg/ha respectively for rice farmers in northern Ghana, and in the Volta and Greater Accra Regions.

The mean herbicide application rate was 2.77 litres/ha for the full sample, 3.3 litres/ha and 1.8 litres/ha for adopters and non-adopters respectively. The herbicide application rate in this study is slightly lower than the 3.1 litres/ha reported by Abdulai *et al.* (2018) for rice farmers in the Sagnarigu District of Ghana.

Rice cultivation is largely labour intensive. The mean labour quantity used in rice cultivation was 149.34 person-days/ha for the full sample, 167.33 person-days/ha and 160.17 person-days/ha for non-adopters and adopters respectively. The mean quantity of labour in this study is higher than the 125 person-days/ha (DFID, 2015) reported for Ghana. Except ploughing by tractor, most of the cultivation practices such as land clearing, sowing, transplanting, weeding, harvesting and post-harvest activities such as threshing, and winnowing are done manually using hired and family labour. Farm labour in this study consisted of both hired and family labour.

The mean rice yield was 2.23 tonnes/ha for the full sample, 2.81tonnes/ha and 1.31tonnes/ha for adopters and non-adopters of improved rice varieties. A mean yield of 1.9tonnes/ha was reported by Alhassan (2008) for rice farmers in northern Ghana. Meanwhile, the national average yield of rice is 2.8tonnes/ha (MoFA, 2016). Additionally, the mean yield in this study is far below the achievable and target yield of 6.0tonnes/ha under rain-fed cultivation as envisioned in the national rice development strategy (NRDS, 2009). Nonetheless, in this study, adopters of improved rice varieties had a higher mean yield of 2.81tonnes/ha compared with 1.31tonnes/ha for their non-adopter counterparts.

In Ghana, most arable crops including rice is produced for both household consumption and for sale. Regarding the full sample, the mean consumption proportion of rice produced by the households were 0.34tonnes/ha, 0.41tonnes/ha for adopters and 0.21tonnes/ha for non-adopters. Therefore, household own rice consumption was highest amongst adopters than non-adopters. Similarly, the mean proportion of rice sold was 1.57tonnes/ha for the full sample, 1.98tonnes/ha for adopter households and 0.90tonnes/ha for non-adopters. This means adopters also sold a higher proportion of rice produced than their non-adopter counterparts, due to their higher average yield.

The mean of observed net rice income per hectare were GH¢738.98, GH¢984.55 and GH¢ 349.65 respectively for the full sample, adopter and non-adopter sub-samples. Clearly, the adopter households had a higher observed net rice income per hectare than the non-adopters with a difference of GH¢634.90 per ha. This also translated into higher incomes for the adopters in comparison with the non-adopters. Regarding the cost of rice production per hectare, the mean was GH¢646.39 per ha for the full sample, GH¢737.31 per ha and GH¢ 472.15 per ha for adopters and non-adopters respectively. Thus, adopters had a higher mean cost of production per hectare than non-adopters with a difference of GH¢265.16 per ha.

Generally, except for farm size and labour, adopters recorded a higher seed planting, fertilizer and herbicide application rates than non-adopters of improved rice varieties. Although adopters obtained a higher mean yield than their non-adopter colleagues, the average yield was half of the national achievable yield.

8.4 Conclusion

This chapter discussed the demographic and socioeconomic characteristics of sampled rice farming households. Adopters of improved rice varieties were slightly older (42 years) than non-adopters (40 years). Although low, adopters had 5 years whilst non-adopters had 3 years of formal education. Mean farm size was lower amongst the adopters (3.85ha) than non-adopters (5.75ha). Regarding input use, non-adopters used more seed (102.12kg/ha) compared with adopters (92.52kg/ha). Fertilizer application rate was higher for the adopters (289.86kg/ha) than non-adopters (82.33kg/ha). Adopters used more herbicides (3.3 litres/ha) than non-adopters (1.8 litres/ha). Labour use was slightly higher amongst non-adopters (167 person-days/ha) than adopters (160 person-days/ha). Rice yield was higher for the adopters (2.8mt/ha) than non-adopters (1.3mt/ha) though lower than achievable yield of 6mt/ha. Production cost per ha was GH¢737.31 for adopters and GH¢472.15 for non-adopters. The observed net rice income per ha was higher for adopters (GH¢984.55) than non-adopters (GH¢349.65).

CHAPTER NINE

RESULTS ON EXPOSURE AND ADOPTION OF IMPROVED RICE VARIETIES

9.1 Introduction

This chapter is divided into three subsections in order to address the first objective of this study, which is to "identify the factors that influence the adoption of improved rice varieties by rice farmers". First, the determinants of exposure to improved rice varieties are estimated, followed by determinants of adoption of improved rice varieties. The third subsection contains results of exposure rate, joint exposure and adoption rate, and adoption rate (details about the methodology is found in section 7.4.3). Table 9.1 presents a summary definition of variables used in the estimation of exposure as well as adoption of improved rice varieties in this chapter.

Table 9.1: Definition of variables used in estimation of exposure and adoption

Variable	Description
Exposure	Dummy; 1 if a household head or member knows at least one improved rice variety, 0, otherwise
Adoption	Dummy; 1 if a household head cultivated at least one improved rice variety, 0, otherwise
Community participation in rice projects	Dummy; 1 if community ever participated in a rice project, 0, otherwise
Presence of agro-input shop in community	Dummy; 1 if community has agro-input shop, 0, otherwise
FBO membership	Dummy; 1 if household head belongs to farmer-based organization, 0, otherwise

Being a model farmer	Dummy; 1 if household head has ever been a model farmer, 0, otherwise
Participation in block farming	Dummy; 1 if household head has ever participated in block farming, 0, otherwise
Forest zone	Dummy; 1 if agro-ecological area of rice farm is forest, 0, coastal zone
Guinea savannah zone	Dummy; 1 if agro-ecological area of rice farm is guinea savannah, 0, coastal zone
Lowland rain fed	Dummy; 1 if rice cultivation system is lowland rain fed, 0, upland rain fed
Irrigated production	Dummy; 1 if rice cultivation system is irrigation, 0, upland rain fed
Higher yield	Dummy; 1 is whether farmer seeks higher rice yield, 0, otherwise
Market demand	Dummy; 1 is whether farmer produces rice for sale in the market, 0, otherwise. Rice characteristics such as good taste and aroma, ease of milling, long grain, parboiling and swelling properties have good market demand.
Own consumption	Dummy; 1 is whether farmer produces rice for household consumption, 0, otherwise
Farm size	Number of hectares (ha) of cultivated rice
Growing farm saved seed	Number of years farm saved seed of current rice variety was continuously cultivated by household
Agricultural extension	Dummy; 1 if household head has access to agricultural extension services, 0, otherwise
Sex of household head	Dummy; 1 if household head is female, 0, male
Educational level	Number of years of formal education of household head

Source: Author's construction based on survey data set (Nov. 2012-Feb. 2013).

9.2 Exposure rate and determinants of exposure to improved rice varieties

In this chapter, exposure to improved rice varieties is defined as a farmer having knowledge about or being aware of the existence of at least one improved rice variety (see section 4.2

for a detailed explanation). The dependent variable is exposure to improved rice varieties and the independent variables are community participation in a rice project implemented by government or non-government organization (1, yes, 0, no); existence of agro-inputs shop in the community (1, yes, 0, no); household's participation in block farming (1, participated, 0, otherwise); household's head selection as a model farmer (1, yes, 0, otherwise); farmer-based organization membership (1, member, 0, otherwise) and access to agricultural extension services (1, access, 0, no access).

Exposure to improved rice varieties is a latent variable, thus, the marginal effects of the covariates on the outcome variable are discussed. From Table 9.2, the exposure to improved rice varieties was very high at about 83%.

Table 9.2: Probit results of the determinants of exposure to improved rice varieties

Variable	Coefficient	Standard error	Marginal effect	Standard error
Constant	0.694***	0.098	-	-
Community participation in rice projects	0.407**	0.205	0.086**	0.037
Presence of agro-input shop in community	0.260*	0.148	0.060*	0.032
Being a model farmer	0.163	0.194	0.037	0.042
Participation in block farming	0.020	0.262	0.005	0.062
FBO membership	0.121	0.132	0.029	0.031
Agricultural extension	0.240	0.162	0.055	0.035
Predicted exposure rate	0.833***	0.015[a]		
Log-likelihood	-250.849			
Chi-squared test statistic	17.35**			
No. of observations	576			

***, **, *, indicate values statistically significant at 1%, 5% and 10% respectively. [a] standard error calculated using the delta method.

The participation of a community in a rice project as well as the presence of an agricultural input (agro-input) shop in a community, increased the probability of a rice farming household knowing about the existence of improved rice varieties. This finding is consistent with the *a priori* expectation. Nonetheless, variables such as being a model farmer, participation in block farming, membership of farmer-based organization (FBO), and access to agricultural extension service do not statistically influence exposure to improved rice varieties as indicated in Table 9.2.

The positive effect and statistical significance of the participation of communities in rice projects on increasing awareness of improved rice varieties is not surprising. This is because since 2003, there have been about 20 rice related projects implemented by the government of Ghana with donor support (Ragasa *et al*., 2013). These projects were mostly implemented in collaboration with the agricultural extension service of the Ministry of Food and Agriculture, and work closely with farmer groups including FBOs, and model farmers, thus generating a lot of awareness through community engagements. For instance, the Rice Sector Support Project (2008-2014) supported lowland rice production of about 6,000 ha, the NERICA Rice Dissemination Project (2005-2010) sought to increase improved rice seed production, marketing and agricultural extension, the Lowland Rice Development Project (2004-2015) focused on agricultural extension, irrigation improvement, soil fertility management, credit and post-harvest marketing. Thus, the involvement of a community in a rice project implemented by government or non-government agencies had a positive influence on a household knowing about an improved variety and making a subsequent adoption decision. Similarly, Dalton (2004) found community participation in varietal selection and seed production training programmes increased the awareness of Nerica rice promoted by Africa Rice Research Centre in Ivory Coast. Diagne (2006).

The presence of an agro-input shop in a community increased the probability of exposure to improved rice varieties by 6% at 10% significance level. Community agricultural input dealers in addition to selling inputs (chemical fertilizers, pesticides, herbicide, simple farm implements etc.), also provide informal farming advice to farmers including information on which crop varieties to cultivate. Indeed, many of the policy interventions within the agricultural sector are implemented by government working closely with community input dealers. For example, the coupon-based fertilizer subsidy programme was implemented at the community level, where farmers presented the coupons to buy fertilizer at subsidised prices.

However, as will be seen in section 12.4, the Government agricultural extension service and colleague farmers were the sources of knowledge about improved rice varieties for farmers from the qualitative interviews. Notwithstanding, improved rice varietal exposure may not lead to eventual adoption if the varieties are not easy to access. As will be explained in detail in section 12.4, the in-depth interviews with farmers, agricultural extension agents and improved seed suppliers reveal access to improved rice varieties is becoming less of a challenge due to the government's planting for food and jobs programme. Under the programme, subsidised improved rice varieties can easily be purchased from agricultural input shops.

9.3 Determinants of adoption, and joint exposure and adoption of improved rice varieties

The estimates of the joint exposure and adoption (JEA) probit model are obtained using the full sample (576) observations which contains both exposed (480) and non-exposed (96) rice farming households. The JEA model is estimated under the assumption of partial exposure because, it contains both the exposed and non-exposed households (detailed explanation is found in section 4.2). Thus, it treats farmers not aware of the existence of improved rice varieties as non-adopters, although they could have adopted if they had knowledge of the existence of such varieties, leading to non-exposure bias (further explanation can be found in page 42). On the other hand, the $ATE(x)$ corrected probit model recognises non-exposure bias by estimating the adoption of improved rice varieties using the sub-sample of households (480 observations) who were aware of the existence of improved varieties. The exposed sub-sample consists of 158 non-adopters and 322 adopter households. Both the joint exposure and adoption model as well as the ATE corrected adoption model are estimated separately using a probit model. A detailed discussion of the methodology is found in section 4.2.2.

It is important to state that for a typical two-stage probit sample selection model, the issue of selectivity bias has to be addressed. In this study, a probit sample selection was estimated. The first stage involved the estimation of the determinants of exposure to improved rice varieties for the full sample of 576, followed by the estimation of the classical joint exposure and adoption also using the full sample in the second stage. However, the results (see appendice Tables A1 & A2) of the Heckman probit selection model did not reject the null hypothesis of the non-existence of selectivity bias in this study. Relative to the $ATE\ (x)$ corrected adoption model, the average treatment effect of adoption is estimated using the subsample of only farmers with exposure to improved rice varieties, which in this study determines treatment. Therefore, the untreated (non-exposed) farmers who are also non-adopters of improved rice varieties are not included in the estimation of the $ATE\ (x)$ corrected probit model (for an extended explanation of the methodology, refer to section 4.2.2). Moreover, under the conditional independence assumption (Wooldridge, 2002;

Imbens, 2004), potential adoption is independent of the observed factors that explain exposure once we control for the factors that affect adoption. Similarly, exposure to improved rice varieties is independent of the observed factors that determine adoption outcomes, once the factors that influence exposure are controlled by estimating the propensity scores (a detailed explanation can be found in paragraph 2 of page 42). Nonetheless, the ATE corrected probit accounts for selection and or targeting bias post-estimation through the calculation of the population selection bias (Diagne and Demont, 2007; Simtowe *et al*., 2016) as will be discussed in section 9.4 of this chapter (for further explanation on the methodology, refer to equations 4.5 and 4.6 in Chapter 4). The dependent variable in each case is improved rice variety adoption status of a household (1, adopter, 0, non-adopter) and the independent variables are as defined in Table 9.1.

The marginal effects of many of the explanatory variables statistically influenced adoption decisions in both the joint exposure and adoption model (under partial exposure) as well as the $ATE(x)$ corrected adoption model (under full exposure). For instance, community participation in a rice project, not only increased awareness about improved rice varieties, as was the case in Table 9.2. It also increased the probability of adoption in the $ATE(x)$ adoption model by over 13% and in the joint exposure and adoption model by about 20% at the 5% and 1% levels of significance respectively as presented in Table 9.3. Community participation in rice projects implemented by government and non-government organizations had positive effect on a farmer's decision to adopt improved rice varieties at 10% significance level before and after matching. This was largely due to the over 20 rice related projects implemented across the country in nearly two decades (Ragasa *et al*., 2013). These projects helped in creating awareness about the existence of improved rice varieties as well as encouraged their cultivation by farmers. Diagne and Demont (2007) also found community participation in agricultural development projects such as participatory varietal selection had positive and significant effect on the adoption of Nerica rice varieties in Ivory Coast.

Table 9.3: Results of adoption, joint exposure and adoption of improved rice varieties

	Classical probit joint exposure & adoption model		ATE(x) probit adoption model	
Variable	Coefficient	Marginal effect	Coefficient	Marginal effect
Constant	-0.478	-	0.176	-
	(0.331)		(0.392)	
Community participation in rice projects	0.566***	0.203***	0.512*	0.132**
	(0.208)	(0.068)	(0.273)	(0.060)
Presence of agro-input shop in community	0.062	0.024	0.179	0.051
	(0.145)	(0.056)	(0.171)	(0.048)
Being a model farmer	0.553***	0.198***	0.852***	0.194***
	(0.202)	(0.065)	(0.277)	(0.046)
Participation in block farming	0.399	0.145*	0.597*	0.140**
	(0.256)	(0.085)	(0.357)	(0.064)
Agricultural extension	0.573***	0.210***	0.656***	0.171***
	(0.154)	(0.053)	(0.194)	(0.045)
Sex of household head	0.038	0.015	0.059	0.017
	(0.163)	(0.063)	(0.194)	(0.055)
Forest zone	-0.248	-0.097	-0.624**	-0.208**
	(0.218)	(0.086)	(0.297)	(0.106)
Guinea savannah zone	-0.458**	-0.174*	0.898***	-0.247***
	(0.185)	(0.068)	(0.257)	(0.063)

Lowland rain-fed production	0.385	0.150	0.395	0.121
	(0.256)	(0.100)	(0.288)	(0.091)
Irrigated production	1.409***	0.450***	1.567***	0.346***
	(0.292)	(0.068)	(0.343)	(0.057)
Higher rice yield	0.413***	0.160***	0.399**	0.121**
	(0.152)	(0.059)	(0.183)	(0.057)
Rice market demand	0.118	0.046	0.067	0.020
	(0.153)	(0.059)	(0.182)	(0.053)
Own consumption of rice	0.145	0.055	0.107	0.031
	(0.164)	(0.062)	(0.190)	(0.053)
Planting farm saved seed	-0.055***	-0.021***	-0.060***	-0.018***
	(0.017)	(0.007)	(0.019)	(0.006)
Farm size	-0.022*	-0.008*	-0.025*	-0.007*
	(0.012)	(0.005)	(0.014)	(0.004)
Average joint exposure & adoption rate	0.559***			
	(0.017[a])			
Average adoption rate			0.672***	
			(0.017[a])	
Log-likelihood	-283.931		-199.166	
Chi-squared test statistic	222.60***		209.91***	
No. of observations	576		480	

***, **, * indicate values statistically significant at 1%, 5% and 10% respectively. Figures in brackets are the standard errors. [a] standard error calculated using the delta method.

Although, community agro-input shops increased the probability of being aware of improved rice varieties in this study, they did not statistically influence adoption decisions of households. This is because being aware is distinct from the decision to cultivate improved rice varieties. More so, the zeal to cultivate improved rice is dampened if there are constraints to adoption such as access to improved seed. Where access is a challenge as it has been the case in recent past in Ghana (Tripp and Mensah-Bonsu, 2013), community agro-input shops cannot do much beyond awareness creation, as they do not have the improved varieties in stock for farmers to purchase.

Selection as a model farming household and participation in block farming increased substantially, the probability of making a positive adoption decision by 19.4% and 14% each in the $ATE(x)$ corrected model for the exposed sub-sample at 1% and 5% significance levels respectively. This is particularly due to the close working relationship between rice project implementers and farmers, some of whom took part in varietal trials and demonstrations, which eventually influenced their adoption of the improved rice varieties. Participation in block farming and model farming also had positive influence relative to the joint exposure and adoption (classical probit) model. This finding is in line with *a priori* expectation. It is important to note that most of the rice projects implemented in many rice growing communities across the country worked closely with farmers. Some of the farmers in beneficiary communities were selected as model farmers to take part in on-farm varietal trials and demonstrations, and also help garner support for the adoption of these improved varieties. The block farming system was an ad hoc intervention introduced by the government of Ghana in 2009, in the wake of the 2008 food crisis. It supported farmers with production input credit in the form of subsidised mechanisation services, fertilizers, improved seed varieties, pesticides and agricultural extension services to increase the cultivation of arable crops including rice (Benin *et al*., 2011).

Access to agricultural extension service positively influenced the adoption of improved rice varieties by 21% and 17% for the classical probit model and the $ATE(x)$ probit model

Access to agricultural extension service had a positive effect on the choice of households to adopt improved rice varieties at 1% level of statistical significance in both models respectively. Agricultural extension service is widely known in literature as an important determinant of the adoption of improved production technologies (Kalirajan, 1981; Doss and Morris, 2001; Bhasin, 2002; Ransom, Pandyal and Adhikari, 2003; Al-hassan, 2008; Villano *et al*., 2015). It is the means by which information on better and new technologies of farming can be disseminated to farmers. More importantly, it also serves as the major link by which research on new ways of farming and crop cultivation gets to farmers and the challenges of farmers that require research are put to researchers. Doss and Morris (2001) found agricultural extension significant and argued that the adoption of new technologies was facilitated by farmers' contact with agricultural extension agents.

The sex of the household head did not significantly affect neither the adoption of improved rice varieties in the classical probit nor the $ATE(x)$ probit model. This is contrary to the *a priori* expectation, which hypothesised male-headed households would have a higher likelihood of being exposed to and adopt improved rice varieties relative to their female counterparts. This is because male farmers are mostly the first point of contact relative to dissemination of new agricultural technologies given the cultural setting of the study area. Similar studies by Diagne (2006) as well as Diagne, and Dermont (2007) did not find sex of rice farmer statistically significant in influencing the adoption decisions of Nerica rice in Ivory Coast.

As regards adoption decisions across agro-ecological zones, the probability of adopting improved varieties by rice farming households in the guinea savannah zone was lower in comparison with those in the coastal zone for the $ATE(x)$ probit as well as the classical probit model. The probability of adoption by farmers in the guinea savannah zone *vis-a-vis* those in the coastal zone reduced by 24.7% for the $ATE(x)$ probit, and by 17.4% relative to the joint exposure and adoption model at 1% and 10% levels of significance respectively. Theis is contrary to the *a priori* expectation, particularly in the guinea savannah (comprising Northern, Upper East and Upper West Regions) agro-ecological zone, which has been the leading rice-producing zone in Ghana (Ragasa *et al.,* 2013; MoFA, 2016). More so, many of the rice projects were implemented in the guinea savannah zone. For instance, the Northern Rural Growth Programme and Ghana Commercial Agriculture Project supported out-grower schemes, invested in infrastructure and improved access to credit. The Rice Sector Support Project also worked with lowland rice farmers in the Northern, Upper East, Upper West and northern parts of the Volta Region. Nonetheless, the Volta Region classified as a coastal zone in this study, is the single largest rice-producing region (MoFA, 2016). Although the guinea savannah zone produces 53% of national output (MoFA, 2016), many farmers still cultivate traditional varieties. Similarly, the probability of adopting improved rice varieties decreased by 20.8% in the forest zone in comparison with farmers in the coastal zone at 5% level of significance for the $ATE(x)$ probit model only. The forest zone is the third largest producing zone after the coastal zone (Kranjac-Berisavljevic' *et al.*, 2003; MoFA, 2016).

The cultivation of lowland rice as opposed to upland rice did not statistically affect the adoption of improved rice varieties. This is not consistent with *a priori* expectation given that 78% of the national production is lowland rain-fed (NRDS, 2009; DFID, 2015). Moreover, majority of the improved rice are lowland varieties, except for NERICA and otoomu, which are upland varieties (Ragasa *et al.,* 2013). Additionally, lowland rain-fed cultivation that constitutes 84% of national production is the most profitable, albeit irrigated production gives the highest yield (NRDS, 2009; CARD, 2010). The cultivation of irrigated rice increased the probability of adoption of improved rice relative to upland rice by 45% for the classical probit and by 34.6% for the $ATE(x)$ probit model at 1% level of statistical significance. Thus, irrigated rice farmers were more likely to adopt improved varieties than the upland rice farmers. Irrigated rice production apart from giving the highest mean yield of 4.5mt/ha (CARD, 2010), it also accounts for 16% of national output whereas upland rain-fed is 6% (NRDS, 2009). Nonetheless, Ghana's irrigation potential remains untapped (Osei-Asare, 2010) with irrigated land representing 3.44% of total land area under cultivation (MoFA, 2016). The few irrigation schemes are the Tono and Vea irrigation schemes in the Upper East Region, Kpong, and Afife irrigation schemes in Greater Accra Region, Bontanga and Golinga irrigation schemes in Northern Region that are mostly used for rice and vegetable production during the dry season (CARD, 2010).

One of the reasons farmers would choose to cultivate improved rice varieties is to achieve higher yield. In this study, seeking higher yield increased the probability of adopting improved rice by 16% and 12.1% for the classical probit and ATE probit at 1% and 5% levels of significance respectively. Many of the rice breeding programmes incorporated desirable traits including higher yield (Ragasa *et al*., 2013). This is consistent with Adesina and Forson (1995) who found higher yield to be the motivation for farmers choosing to cultivate improved sorghum over local varieties in Burkina Faso. Another study by Buah *et al*. (2011) on enhancing access to improved rice seed by farmers in Ghana identified higher yield, early maturity, ease of threshing and milling as well as good taste as reasons for adoption. A similar study by Coffie *et al*. (2016) on choice of rice production practices and farmers' willingness to pay in Ghana, revealed that farmers preferred high yielding and early maturing rice varieties with less labour requirements. Singh *et al.* (2011) argued that a technology's inability to meet farmer expectations such as yield and other characteristics creates doubt and risk rejection. In the same vein, a study by Kijima *et al*. (2011) revealed over 50% of farmers who adopted Nerica rice variety in Uganda abandoned the variety within two years.

Although producing to meet market demand and for household consumption, had positive signs on adoption, they did not statistically affect improved rice adoption decisions. Until recently, many of the interventions in the rice sub-sector over the years, have concentrated more on producing high yielding varieties with little attention to post-harvest processing and marketing (Angelucci *et al*., 2013). Nonetheless, Ghana's rice development strategy now seeks to facilitate the establishment of mills equipped with pre-cleaners, de-stoners, hullers, polishers, paddy separators, aspirators, and graders to process paddy to meet premium-marketing standards (NRDS, 2009). The handling of the post-harvest processing and marketing by non-farm entities relieves farmers of the burden of marketing their own produce. For example, Avnash, the largest privately owned rice-processing factory in Ghana, relies heavily on out-growers and paddy aggregators to feed its factory (DFID, 2015). With this arrangement, rice farmers can focus more attention on increasing production, given the comparative advantage Ghana enjoys in rice production (Asuming-Brempong, 1998).

On the other hand, the continuous planting of farm saved seed of current rice variety by a household reduced the probability of adopting improved rice varieties. The probability of choosing to cultivate another rice variety decreased by 2.1% and 1.8% per cultivation year respectively for the classical probit and $ATE(x)$ probit models. The planting of seeds from harvest reduces genetic purity. In this study, the average number of years a rice-farming household continuously cultivated a particular variety was over 4 years for both adopters and non-adopters. Indeed, 73.5% of the rice plots in this study were planted with farmer saved seeds from previous harvest. This implies the planting of farm saved seed was rife even within the adopters who selected rice seed from harvest for cultivation in the next season. In a situation where access to improved seed varieties is hampered by the lack of a well-developed commercial seed production industry as has been in recent past in Ghana (Tripp and Mensah-Bonsu, 2013), growing farm saved rice seed is common. This is finding is contrary to the recommended practice that encourages farmers to renew their rice seeds at least once every three years (Ragasa *et al.*, 2013).

Likewise, the probability of cultivating improved varieties reduced marginally by 0.8% and 0.7% with increasing farm size for both the joint exposure and adoption as well as the $ATE(x)$ probit adoption model at 10% level of statistical significance. The average rice plot sizes in this study were 5.75 ha and 3.85 ha respectively for non-adopter and adopter households. This corroborates the finding by DFID (2015) that rice cultivation is mainly by smallholders. Even though Ghana has vast unexploited lowland rain-fed rice fields, access is hampered by land tenure system that limits acreage expansion and investments (NRDS, 2009). This has led to majority of farmers in Ghana continuously cultivating rice on the same lowland fields spanning decades (Ragasa *et al*., 2013). Access to land can also facilitate experimentation with new agricultural technologies (Pingali *et al.,* 1987; Carletto *et al*., 2007), and thus determine the pace of adoption (de Janvry *et al*., 2011).

Although, there was little difference in terms of the signs and statistical significance of the factors that influenced joint exposure and adoption model as well as the $ATE(x)$ corrected adoption model, the JEA had slightly higher values than the $ATE(x)$ adoption model. Moreover, there was inherent non-exposure bias in the JEA estimates that automatically considered the non-exposed within the sample as non-adopters. However, the $ATE(x)$ corrected adoption model addressed non-exposure bias by using only the exposed sample in its estimation. Thus, the $ATE(x)$ corrected estimates are preferred because they are consistent and unbiased.

9.4 Exposure rate, joint exposure and adoption rate, and adoption rate

There was a relatively high awareness of the existence of improved rice varieties with a predicted exposure rate of 83.3% as presented in Table 9.4. The exposure rate reported here is obtained from the results in Table 9.2 under section 9.2, which discussed the exposure rate and the determinants of exposure to improved rice varieties. Clearly, the high exposure rate indicated widespread diffusion of the improved rice varieties amongst the population, especially the varieties that were introduced a few decades ago (Ragasa *et al.*, 2013).

Moreover, many of the improved rice varieties had been widely promoted through rice projects that were implemented in many communities across the country. Exposure, facilitated by diffusion within a population is a necessary step in the technology adoption process. This is because it is only after knowing about an improved rice variety that a household chooses to adopt it or not to adopt (Diagne and Demont, 2007). Nonetheless, the efforts of awareness would not be able to achieve the desired impact if adoption is impeded by lack of access to improved rice varieties. Tripp and Mensah-Bonsu (2013) as well as Ragasa *et al.* (2013) emphasized the importance of the existence of a thriving commercial seed industry to provide farmers with certified seeds of higher uniformity and genetic purity. A well-developed commercial seed supply system makes it possible for farmers to access improved rice varieties, rather than relying on own seeds selected from harvest. The recommended practice is for farmers to renew their rice seeds at least once every three years (Ragasa *et al.,* 2013).

Table 9.4: Predicted estimates of exposure and adoption of improved rice varieties

Description of estimation	Estimate	Std error
Predicted population exposure rate	0.833***	0.015
Predicted adoption rate within the unexposed[43]	0.429***	0.021
Predicted population joint exposure and adoption rate (JEA)[44]	0.559***	0.017
Predicted average population adoption rate (ATE)	0.672***	0.017
Predicted adoption rate for adopters in the exposed subpopulation (ATE1)	0.797***	0.014
Predicted adoption rate for exposed non-adopters (ATE0)	0.416***	0.027
Estimated population adoption gap:		
Non-exposure bias, $N\hat{E}B = J\hat{E}A - A\hat{T}E$	-0.113***	0.003
Population selection bias, $P\hat{S}B = A\hat{T}E1 - A\hat{T}E$	0.125***	0.010

***, **, *, indicate values statistically significant at 1%, 5% and 10%. Standard errors are calculated using the delta method (Wooldridge, 2002, p. 44).

The predicted probability of adoption within the non-exposed population in Table 9.4 was 0.429. The predicted adoption rate within the unexposed was calculated using only the unexposed subsample from the joint exposure and adoption estimation results in Table 9.3 and previously discussed in section 9.3. The joint exposure and adoption estimation was obtained using the full sample which includes households with exposure to improved rice

[43] The predicted adoption rate within the unexposed is calculated using only the unexposed subsample from the joint exposure and adoption estimation which includes households with exposure to improved rice varieties and those without exposure from which the predicted adoption rate of 0.429 for the unexposed is obtained.

[44] This is the 'ATE' of the joint exposure and adoption estimation which includes households with and without exposure to improved rice varieties. It is predicted from the classical joint exposure and adoption estimation in Table 8.3.

varieties and those without exposure from which the predicted adoption rate of 42.9% for the unexposed is obtained. This means the adoption rate for the non-exposed population would have been 42.9% if those rice farming households were aware of the improved rice varieties.

Similarly, the population joint exposure and adoption (JEA) rate of 55.9% was predicted using the classical joint exposure and adoption estimation in Table 9.3. This estimate is higher than the 4% reported by Diagne (2006) as well as Diagne and Dermont (2007) respectively in their study on Nerica rice adoption in Ivory Coast involving a sample of 1,500 rice farmers. The higher JEA rate was partly as a result of the widespread diffusion (83.3% exposure rate) of the improved rice varieties in this study. The JEA is the classical adoption rate which treats the non-exposed as non-adopters although, they have the potential to adopt under complete diffusion. Thus, the JEA, which was previously discussed in section 9.3, gives a biased result by under-estimating the adoption rate.

Relative to the exposed population, the consistent and unbiased average treatment effect (ATE) of adoption of improved rice varieties is 67.2%. This estimate is higher than the 37% adoption rate for the exposed sample in Diagne and Dermont (2007) study on improved rice variety adoption in Ivory Coast. The predicted ATE[45] obtained from the $ATE(x)$ corrected probit adoption estimation in Table 9.3 in section 9.3 measures the adoption outcome of a rice farming household randomly drawn from the population when every rice farmer is exposed to the improved varieties. Therefore, under complete diffusion, the average adoption rate (ATE) would have been 67.2%, instead of the adoption rate (JEA) of 55.9% under partial exposure. This produces a non-exposure bias, also known as the population

[45] This is the average treatment effect of the ATE corrected adoption estimation which includes both adopters and non-adopters, although they both have exposure to improved rice varieties. It is predicted from the $ATE(x)$ corrected adoption estimation in Table 8.3. Refer to pages 40-42 for details on the methodology.

adoption gap (the difference between the estimates of 55.9% for the JEA and 67.2% for the ATE) of -11.3%. The negative value (-11.3%) implies a gap in adoption due to incomplete diffusion of the improved rice varieties. Thus, there is the possibility of increasing the adoption rate further by about 11% within the rice farming population by intensifying awareness about improved rice varieties.

The predicted average treatment effect on the treated[46] (ATE1), which is an estimation of the adoption rate for only the households who knew about the improved rice varieties and cultivated at least one variety was 79.7%. This is also higher than the 46% and 37% respectively found in Diagne (2006) and in Diagne and Demont, (2007) for a sample of rice farmers in Ivory Coast. The predicted ATE1 obtained from the $ATE(x)$ corrected probit adoption results in Table 9.3 under section 9.3 tends to over-estimate the true adoption rate due to self-selection and targeting bias, as rice farmers most likely to adopt improved varieties are those who get exposed (Diagne and Demont, 2007). Moreover, the results of the $ATE(x)$ corrected probit in Table 9.3 were obtained using only the subsample of farmers who were exposed to the improved rice varieties and not the full sample which contained both the exposed and unexposed farmers.

Meanwhile, the predicted average treatment effect for households who chose not to adopt (ATE0) despite being aware of the improved rice varieties was 41.6%. This means constraints other than exposure, significantly influenced the non-adoption decisions of those households who chose not to adopt despite being aware. The predicted ATE0 is calculated for the non-adopters of improved rice varieties from the $ATE(x)$ corrected probit results in Table 9.3. On the other hand, the predicted probability of adoption within the non-exposed

[46] In this chapter, exposure to improved rice varieties determines treatment.

was 42.9%. This means there was a higher probability of adoption within the non-exposed which consisted of potential adopters than those who were already aware and decided not to adopt (41.6%). The predicted adoption rate within the unexposed was calculated using only the unexposed subsample from the joint exposure and adoption results in Table 9.3 which included households with exposure and without exposure to improved rice varieties. The average treatment effect on the exposed non-adopters is higher in this study than the 25% and 17% in Diagne (2006) and Diagne and Demont (2007) respectively.

The non-exposure bias, $N\hat{E}B = J\hat{E}A - A\hat{T}E$ which is the potential additional adoption for improved rice varieties by the population hampered by non-exposure was -11.3%. It is the difference between the classical JEA average adoption rate and the ATE of the $ATE(x)$ corrected probit results in Table 9.3. As more rice farming households become aware of the improved rice varieties, the population adoption gap is expected to narrow.

Lastly, there was a population selection bias ($A\hat{T}E1 - A\hat{T}E$) of 12.5%. The population selection bias which is the difference between the predicted ATE1 and ATE is estimated from the $ATE(x)$ corrected probit in Table 9.3 under section 9.3. This positive population selection bias stems from the over-estimation of the true population adoption rate because of self-selection and targeting resulting from using the exposed subsample only. The population selection bias of 12.5% in this study is lower than the 19% and 18% found in Diagne (2006) and Diagne and Demont (2007) respectively for Nerica rice adoption in Ivory Coast.

9.5 Key findings and policy implications

This chapter addressed the first objective of this study that “identify the factors that influence the adoption of improved rice varieties by rice farmers”. First, the determinants of exposure to improved rice varieties was estimated using a probit model, followed by determinants of adoption of improved rice varieties.

The results revealed a higher level of awareness within communities, and widespread diffusion of the improved rice varieties within the rice farming population. The average exposure rate in this study was 83.3%. Nonetheless, there is room for improvement and further strengthening of dissemination efforts to reach those rice farming households yet to be exposed. Awareness creation and exposure to the improved rice varieties were largely enhanced by community participation in rice projects implemented by government and non-government organizations over the years and community agrochemical input dealers. These projects involved the agricultural extension service of the Ministry of Food and Agriculture, and farmer groups, thus creating a lot of community awareness.

Although, adoption can be impeded by lack of access to improved rice varieties even upon exposure, the in-depth interviews in section 12.4 will reveal access is becoming less of a challenge due to conscious government policy. For instance, the planting for food and jobs programme is coordinating the production of certified seeds by trained growers in line with national rice development strategy (MoFA, 2019). For instance, a total of 577,000 farmers benefitted from subsidised fertilizer and seed in 2019 nationwide.

Adoption under incomplete exposure under-estimated the adoption rate as 55.9%, producing a non-exposure bias of 11.3%. The average adoption rate (ATE) assuming complete exposure was 67.2%. This average adoption rate of 67.2% within the exposed population, gives an indication of the effectiveness of diffusion efforts on adoption of these improved rice varieties. The average treatment effect on the treated (ATE1) was 79.8%. The variables that had positive and statistically significant influence on the adoption of improved rice varieties were community participation in rice projects, selection of a household as a model farming unit for the improved rice varieties, participation of a household in block farming, household's access to agricultural extension services, seeking higher rice yield, and irrigated rice producing households had a higher likelihood of adopting improved varieties than upland rice producers. However, increasing rice plot size, and growing farm saved seed had negative effect on adoption. Farmers in the guinea savannah zone also had a lower probability relative to those in the coastal zone in adopting improved rice varieties.

The results thus provide evidence on how to increase diffusion, as well as improve and sustain adoption rates of improved rice varieties within the population as outlined in Ghana's National Rice Development Strategy. The strategy aims to double domestic rice output by working with upland, lowland and irrigated land growers[47] as well as promote its consumption. It tackles constraints relating to access to improved rice seed varieties and fertilizer, access to agricultural mechanization services, promoting agricultural research and technology dissemination amongst others. Secondly, the results of this study will aid effective planning of future rice projects, and the dissemination efforts on improved rice varieties by the agricultural extension service department of the Ministry of Food and Agriculture in Ghana.

Meanwhile, the in-depth interviews in section 12.5 will indicate that farmers who cultivate traditional varieties do so to meet the demand of their local markets and taste preferences, because of their longer maturity periods, and perceived resistance to bird infestation. These

[47] The policy targets yield of 2.5mt/ha for upland, 3.5mt/ha for lowland and 6.0mt/ha for irrigated and overall average yield of 4.0mt/ha.

reasons will have to be considered when persuading farmers to adopt improved rice varieties.

9.6 Conclusion

This chapter addressed the first objective of this study by the identifying the factors that influenced adoption of improved rice varieties. First, the determinants of exposure to improved rice varieties were estimated using a probit model, followed by determinants of adoption of improved rice varieties using the method of treatment effect. There was widespread diffusion of the improved rice varieties within the rice farming population with an average exposure rate of 83.3%. Awareness about the improved rice varieties were enhanced by community participation in rice projects implemented by government and non-government organizations and the presence of agricultural input shops in communities.

Adoption under incomplete exposure under-estimated the adoption rate as 55.9%, producing a non-exposure bias of 11.3%. The average adoption rate of the improved rice varieties within the exposed population was 67.2% whereas the average treatment effect on the treated was 79.8%. Adoption of improved rice varieties was largely influenced by community participation in rice projects, household participating as a model farming unit for improved rice varieties, participation of a household in block farming, access to agricultural extension services, household’s quest to achieving higher rice yield, and cultivating rice under irrigation. Nonetheless, the size of rice farm and growing farmer saved seed had negative effect on adoption of improved rice varieties. These findings provide empirical evidence to aid effective planning of agricultural extension dissemination efforts to promote adoption of improved rice varieties.

CHAPTER TEN

ADOPTION OF IMPROVED RICE VARIETIES ON OUTPUT AND EFFICIENCY

10.1 Introduction

This chapter addresses the second objective of this study that seeks to "analyse the effect of adoption of improved rice varieties on farmers' output and technical efficiency". This was done using the stochastic frontier approach with correction for selectivity bias due to unobservable and observable characteristics (for a detailed discussion of the methodology, refer to section 7.3). Lastly, a metafrontier was estimated to differentiate production technology gap (between the group frontiers and the metafrontier) from managerial gaps due to farmers' technical inefficiencies.

In this chapter, the estimations are performed using data from 496 individual farmer rice plots reported by the 480 rice-farming households who had knowledge of the existence of improved rice varieties. Therefore, the results and discussion in this chapter refer to the individual farmer plots and not households. This is done in order to be able to assess the farmer plot specific input-output relationships as well as the determinants of production inefficiency (efficiency), rather than lump up the production data for all rice plots for a given household. Farmer plot specific estimations make it possible for a given household to assess and compare its production efficiency per plot with other plots within the household, and how to improve efficiency for each plot.

Table 10.1 presents a summary definition of variables used in the estimation of the conventional stochastic production frontier (SPF) as well as the SPF with adoption sample selection. The sample selection involves estimating the determinants of adoption of improved rice varieties using a probit model using the same variables in Table 9.1.

Table 10.1: Definition of variables used in the SPF estimation

Variable	Description
Adoption	Same variables as in Table 9.1
Stochastic frontier	
Rice output	Rice output (in kg) harvested from farm
Farm size	Number of hectares (ha) of rice plot
Rice seed	Quantity of rice seed (in kg) planted
Fertilizer	Quantity of fertilizer used (in kg)
Farm labour	Farm labour (person-days) used
Herbicides	Herbicides (in litres) used on plot
Fertilizer application	Dummy; 1, if household applied fertilizer on rice farm, 0, otherwise
Technical Inefficiency	
Sex of household head	Dummy; 1, household head is female, 0, male
Age	Number of years of household head
Agricultural extension services	Dummy; 1, household has agricultural extension access, 0, otherwise
Educational Status	Number of years of formal education of household head
Rice seed priming	Dummy; 1, practising seed priming, 0, otherwise
Row planting	Dummy; 1, practising row planting, broadcasting, 0
Seedling transplanting	Dummy; 1, seedling transplanting, direct sowing, 0
Sawah system	Dummy; 1, practise sawah system, 0, otherwise
Land preparation with herbicides	Dummy; 1, land preparation using herbicides, 0, otherwise
Weeding using herbicides	Dummy; 1, used herbicides for weed control, 0, hand hoe weeding
Weeding frequency	Number of times rice plot was weeded
Actyva fertilizer use	Dummy, 1, applied on rice farm, 0, otherwise

Ammonia fertilizer use	Dummy; 1, applied on rice farm, 0, otherwise
Fertilizer rate	Dummy; 1 if recommended rate of at least 350kg/ha is applied, 0, otherwise
Rice harvesting method	Dummy; 1, used combine harvester, 0, sickle
Land preparation	Dummy; 1, herbicide applied, 0, otherwise
Pesticide use	Dummy; 1, pesticide applied, 0, otherwise

Source: Author's construction based on survey data set.

10.2 Controlling observable bias in stochastic production frontier estimation

The propensity score matching is applied to eliminate selection bias due to differences in observable characteristics between adopters and non-adopters of improved rice varieties. Imposing a common support condition (Leuven and Sianesi, 2003), and following Villano *et al*. (2015), the propensity scores were matched using nearest neighbour with replacement of up to 4 matches per adopter to the counterfactual non-adopter within a caliper distance of 0.025[48]. Matching with replacement improves the quality of matches by allowing a given non-adopter counterfactual to be matched to more than one adopter which further reduces observable bias by avoiding bad matches (Smith and Todd, 2005). The distribution of the region of common support of the propensity scores ranged from 0.015 to 0.948 as presented in Figure 10.1. The propensity scores of adopters of improved rice varieties outside the common support interval were excluded from the matching procedure (Leuven and Sianesi, 2003).

The results of the standardized mean difference (Rosenbaum and Rubin, 1985) in Table 10.2 reveal significant levels of observable bias in the mean values of covariates between adopters and non-adopters before matching. However, there was no statistically significant

[48] The maximum distance of a propensity score to find a nearest matched neighbour within the common support region.

difference in the observable characteristics between adopters and non-adopters after matching, hence the matched comparison group is an appropriate counterfactual (Lee, 2008). This is also indicative of the quality of the matching procedure to balance the distribution of observable factors between adopters and non-adopters under the region of common support (Leuven and Sianesi, 2003; Caliendo and Kopeinig, 2008).

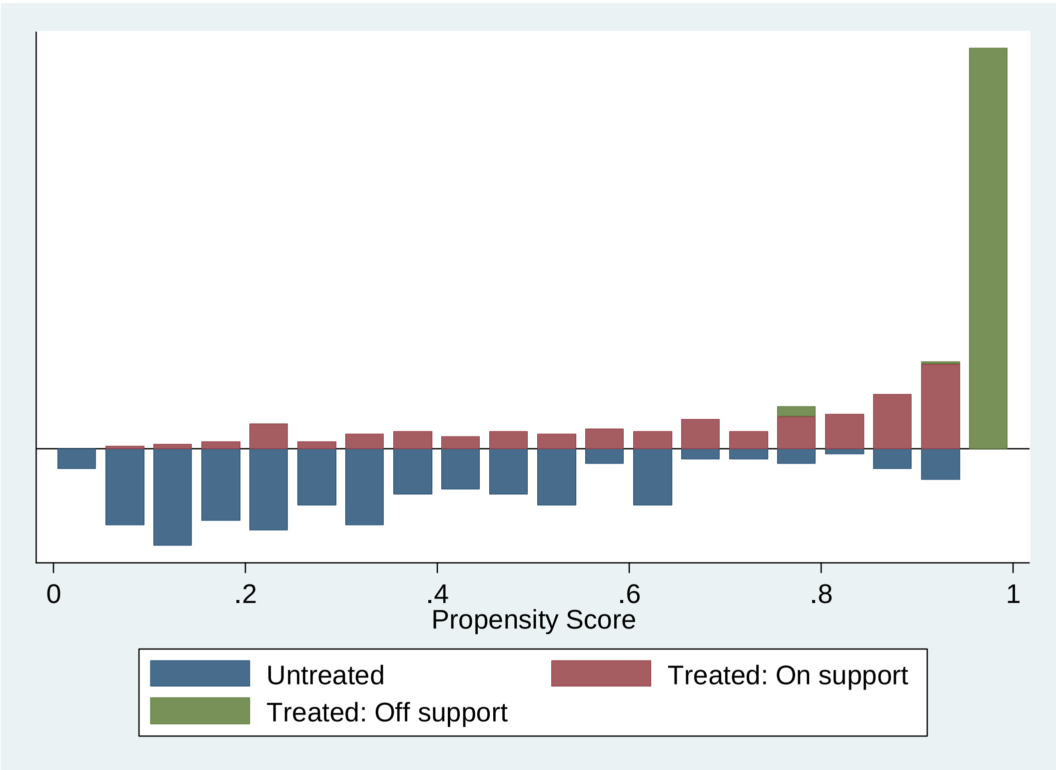

Figure 10.1: Distribution of propensity scores and region of common support

Additionally, from column 5 in Table 10.2, the amount of bias of the covariates before matching between adopters and non-adopters ranged from 98.7% to -76.9%. On the other hand, after matching the bias was significantly reduced and within 17% to -21.5% interval, which is well below the 20% critical level proposed by Rosenbaum and Rubin (1985). Furthermore, at the bottom of Table 9.2, the pseudo R^2 and the corresponding *p*-values of the likelihood ratio test of the joint significance of all the covariates used in estimating the propensity scores from the probit model was statistically different from zero at 1% level of significance before matching. As a further demonstration of the quality of the matching procedure, the joint significance of the regressors after matching was rejected (found in the last row of Table 10.2). The lower value of the pseudo R^2 after matching means all systematic differences in the distribution of the covariates between adopters and non-adopters of improved rice varieties was eliminated (Faltermeier and Abdulai, 2009).

Table 10.2: Standardized mean difference of covariates between adopters and non-adopters before and after matching

Variable	Unmatched (U) Matched (M)	Sample mean: Adopters	Sample mean: Non-adopters	% bias	(Total) % |bias | reduction	t-test t value	V(T)/ V(C)
Community participation in rice projects	U	0.291	0.049	68.0	91.1	6.44***	-
	M	0.168	0.189	-6.0		-0.51	-
Presence of agro-input shop in community	U	0.393	0.251	30.6	56.7	3.14**	-
	M	0.287	0.349	-13.3		-1.20	-
Model farmer	U	0.246	0.037	62.9	94.3	5.92***	-
	M	0.120	0.108	3.6		0.34	-
Participation in block farming	U	0.129	0.018	43.3	97.3	4.05***	-
	M	0.072	0.069	1.2		0.11	-
FBO membership	U	0.480	0.423	11.5	59.0	1.20	-
	M	0.461	0.485	-4.7		-0.43	-
Forest agro-ecological zone	U	0.195	0.135	16.2	66.0	1.66*	-
	M	0.204	0.183	5.5		0.47	-
Guinea savannah agro-ecological zone	U	0.456	0.804	-76.9	83.9	-7.76***	-
	M	0.645	0.703	-12.4		-1.09	-

Lowland rain fed production system	U	0.541	0.859	-73.9	77.0	-7.31***	-
	M	0.719	0.645	17.0		1.44	-
Irrigated production system	U	0.426	0.049	98.7	78.2	9.30***	-
	M	0.222	0.304	-21.5		-1.71*	-
Higher yield	U	0.688	0.479	43.3	61.4	4.59***	-
	M	0.587	0.668	-16.7		-1.53	-
Market demand	U	0.559	0.282	58.2	91.5	5.99***	-
	M	0.437	0.414	4.9		0.43	-
Own consumption	U	0.237	0.196	9.9	67.1	1.03	-
	M	0.252	0.265	-3.3		-0.28	-
Growing farm saved seed (years)	U	3.961	5.282	-31.4	55.4	-3.53***	0.45*
	M	4.255	4.844	-14.0		-1.49	0.78
Agricultural extension access	U	0.372	0.123	60.3	97.5	5.94***	-
	M	0.236	0..242	-1.5		-0.13	-
Sex of respondent	U	0.216	0.184	8.0	90.3	0.83	-
	M	0.205	0.202	0.8		0.07	-
Education (years)	U	5.592	3.239	45.1	67.7	4.73***	0.97
	M	4.435	3.673	14.6		1.37	1.13
Age (years)	U	42.802	40.331	21.5	63.9	2.20**	1.27*
	M	40.981	40.090	7.7		0.69	1.30
Farm size (ha)	U	3.812	5.697	-31.9	99.5	-3.62***	0.39*
	M	4.182	4.191	-0.2		-0.02	1.80*
Seed quantity (kg)	U	313.670	584.060	-39.6	68.6	-4.62***	0.28*
	M	349.690	434.690	-12.5		-1.39	1.30
Fertilizer quantity (kg)	U	612.530	265.690	88.1	96.6	8.62***	2.39*
	M	386.860	375.120	3.0		0.32	0.84
Farm labour (person- days)	U	1171.6	592.13	4.8	85.7	0.44	44.87*
	M	239.14	322.25	-0.7		-0.62	0.28*
Herbicide use (litres)	U	6.860	5.244	25.0	18.0	2.60**	1.06
	M	6.118	7.444	-20.5		-1.51	0.72

Rice output (kg)	U	9538.50	6919.20	17.3	54.4	1.64	4.70*
	M	6122.70	7317.10	-7.9		-1.28	2.28*
Fertilizer rate use	U	0.267	0.043	65.1	99.5	6.15***	-
	M	0.081	0.080	0.3		0.03	-
Actyva fertilizer use	U	0.024	0.018	3.9	44.7	0.40	-
	M	0.031	0.028	2.2		0.16	-
Ammonia fertilizer use	U	0.712	0.429	59.4	79.1	6.31***	-
	M	0.615	0.556	12.4		1.07	-
Rice harvesting method	U	0.075	0.006	35.4	93.2	3.26**	-
	M	0.006	0.002	2.4		0.67	-
Land clearing herbicide	U	0.655	0.270	39.8	90.2	4.20***	-
	M	0.534	0.515	3.9		0.34	-
Weed control herbicide	U	0.667	0.521	29.8	52.9	3.12**	-
	M	0.584	0.652	-14.0		-1.26	-
Weeding times	U	2.084	1.957	16.0	38.8	1.66*	1.12
	M	1.919	1.997	-9.8		-0.93	1.05
Pesticide use	U	0.489	0.135	82.6	91.2	8.15***	-
	M	0.286	0.317	-7.2		-0.61	-
Rice seed priming	U	0.438	0.110	78.9	83.7	7.70***	-
	M	0.335	0.389	-12.8		-0.99	-
Seedling transplanting	U	0.360	0.080	71.9	79.5	6.93***	-
	M	0.255	0.312	-14.7		-1.14	-
Row planting	U	0.228	0.098	35.7	79.3	3.54***	-
	M	0.174	0.147	7.4		0.66	-

Sample	Pseudo R^2	LR chi^2	p value
Unmatched	0.435	273.36	0.000***
Matched	0.088	40.82	0.196

***, **, *, indicate values statistically significant at 1%, 5% and 10% respectively.

Generally, the total amount of bias reduction in column 6 of Table 10.2 after matching ranged from 18% to 99.5%. The 8th column of Table 10.2 is the variance ratio, V(T)/V(C) of treated over non-treated relative to continuous covariates only. A ratio of 1 implies a perfect balance, whilst an asterisk is displayed for variables that have variance ratios outside (0.81; 1.24) for the unmatched and (0.73; 1.36) for the matched.

The matching procedure successfully produced 167 adopter rice plots against 163 counterfactual non-adopter rice plots and used in estimating separate stochastic production frontiers with correction for sample selection bias due to unobservable factors.

10.3 Determinants of adoption of improved rice varieties sample selection model

The first stage of the stochastic frontier with sample selection (Greene, 2010) involves the estimation of determinants of adoption of improved rice varieties using a probit model. The results of the adoption selection model are similar to those of the $ATE(x)$ in Table 9.3 discussed in section 9.3. Nonetheless, the results before and after the propensity score matching are presented in appendix Table A3.

10.4 Tests of hypotheses

The generalized likelihood ratio test was used in determining the appropriate functional form for the conventional stochastic production frontier by testing the translog functional form (H_A) against the Cobb-Douglas (H_0). For instance, the translog was appropriate for the pooled data in both the unmatched and matched samples as presented in Table 10.3. Similarly, the translog functional form was also maintained after matching for the non-adopters. In the case of adopters of improved rice varieties, the functional form changed from Cobb-Douglas in the unmatched to the more flexible translog in the matched sample.

Table 10.3: Test of choice of functional form

Sample	Null Hypothesis	Log Likelihood Function (H_0)	Test Statistic	Critical Value	Decision
Unmatched sample					
Pooled	$H_0: \beta_{ij} = 0$	-480.340	32.94**	24.996 (15)	Reject H_0: Translog appropriate
Adopters		-309.907	20.54		Do not reject H_0: Cobb-Douglas appropriate
Non-adopters		-78.744	109.214***		Reject H_0: Translog appropriate
Matched sample					
Pooled	$H_0: \beta_{ij} = 0$	-300.557	34.75**	24.996 (15)	Reject H_0: Translog appropriate
Adopters		-136.313	38.76**		Reject H_0: Translog appropriate
Non-adopters		-78.744	109.086***		Reject H_0: Translog appropriate

Critical values are at 5% and 1% significance level and obtained from χ^2 distribution table. Figures in brackets are number of restrictions.

The second hypothesis tests the sign of the third moment ($M3T$) and skewness of the ordinary least squares (OLS) residuals. A negative skewness test statistic implies a rejection of the null hypothesis, $H_0: M3T = 0$ and provides justification for the estimation of stochastic production frontier by maximum likelihood (Coelli, 1995). As presented in Table 10.4, the skewness test rejected the estimation of OLS in favour of the stochastic frontier for both the unmatched and matched samples.

A third hypothesis was tested to establish the role of socio-economic factors in explaining technical inefficiency in rice production. From Table 10.5, the null hypothesis ($H_0: all\ \delta_i = 0$) that the socioeconomic variables (δ_i) did not explain the presence of technical inefficiency were all rejected. This means socioeconomic factors played a significant role in explaining observed output variability in rice production.

Table 10.4: Test of stochastic frontier estimation

Frontier Test	Skewness Test Statistic	Decision
Unmatched Sample		
Pooled	-2.003***	Reject H_0: frontier not OLS appropriate
Adopters	-4.059***	Reject H_0: frontier not OLS appropriate
Non-adopters	-3.558***	Reject H_0: frontier not OLS appropriate
Matched Sample		
Pooled	-4.682 ***	Reject H_0: frontier not OLS appropriate
Adopters	-4.242 ***	Reject H_0: frontier not OLS appropriate
Non-adopters	-3.558***	Reject H_0: frontier not OLS appropriate

*** means 1% significance level.

Table 10.5: Test of presence of technical inefficiency

Sample	Null Hypothesis	Log Likelihood Function (H_0)	Test Statistic	Critical Value	Decision
Unmatched sample					
Pooled	$H_0: all\ \delta_i = 0$	-499.423	71.10**	26.296 (16)	Reject H_0: technical inefficiency present
Adopters		-351.398	82.983**		Reject H_0: technical inefficiency present
Non-adopters		-146.688	26.672**	26.296 (16)	Reject H_0: technical inefficiency present
Matched sample					
Pooled	$H_0: all\ \delta_i = 0$	-303.603	40.84**	26.296 (16)	Reject H_0: technical inefficiency present
Adopters		-143.559	53.248**		Reject H_0: technical inefficiency present
Non-adopters		-146.560	26.544**	26.296 (16)	Reject H_0: technical inefficiency present

Critical values are at 5% significance level and obtained from χ^2 distribution table. Figures in brackets are number of restrictions.

The fourth hypothesis tests the estimation of separate stochastic production frontiers for adopters and non-adopters of improved rice varieties as opposed to the pooled (Greene, 2007). The null hypothesis, [$H_0: lnL_P = lnL_{NA} = lnL_A$] posits the pooled sample is not statistically different from the subsamples of adopters and non-adopters of improved rice varieties. The values of log likelihood functions are L_P , lnL_{NA} and lnL_A respectively for the pooled, non-adopters and adopters obtained from the conventional stochastic production frontier estimations. The results in Table 10.6 reject the null hypothesis in favour of the estimation of separate and different SPF for adopters and non-adopters in both the unmatched and matched samples.

Table 10.6: Test of estimation of separate SPF for adopters and non-adopters

Null Hypothesis	Log Likelihood Function (H_0)	Test Statistic	Critical Value	Decision
Unmatched sample				
$H_0: lnL_P = lnL_{NA} = lnL_A$	-463.871[a]	41.352**	26.296 (16)	Reject H_0: separate SPF appropriate
Matched sample				
$H_0: lnL_P = lnL_{NA} = lnL_A$	-283.182[b]	65.918**	26.296 (16)	Reject H_0: separate SPF appropriate

Critical values are at 5% significance level and obtained from χ^2 distribution table. Figures in brackets are number of restrictions. [a] and [b] are the log likelihood values for the pooled.

10.5 Determinants of rice output

This section discusses the determinants of rice output for the pooled, adopters and non-adopters in both the unmatched and matched samples using the conventional stochastic production frontier. It also includes a discussion of results of the estimation of sample selection stochastic production frontier (Greene, 2006 & 2010) in both the unmatched and matched samples. There were twenty-one variables in the determinants of rice output for the translog functional form and six variables for the Cobb-Douglas. The input variables used in the translog functional form were normalized against their geometric mean values preceding estimation, and therefore the first order coefficients could be interpreted as partial production elasticities (Coelli *et al*., 2003).

The results of the unmatched sample (in Table 10.7) which has both observable and unobservable bias relative to the conventional stochastic production frontier are presented vis-à-vis the results of the stochastic frontier with sample selection which only corrects unobservable bias. The results of the hypothesis test in Table 10.6 found the estimation of separate production frontiers appropriate as opposed to the pooled, which assumes a common production frontier for both adopters and non-adopters of improved rice varieties. Nonetheless, the results of the stochastic frontier with sample selection (in columns 5 and 6 of Table 10.7) reveal the existence of selectivity bias (the significance of $\rho(w, v)$ at 1%) in both the adopters and non-adopters of improved rice varieties. Therefore, the results of the stochastic frontier with sample selection for adopters and non-adopters respectively in the unmatched sample found in columns 5 and 6 of Table 10.7 are discussed.

For instance, conventional production inputs such as the size of rice farm, quantity of fertilizer applied, as well as the application of herbicide had positive and statistically significant effect on the output of non-adopters of the improved rice varieties. The first terms coefficients of the parameters of the translog non-adopter stochastic frontier with sample selection model can be interpreted as partial production elasticities. For instance, the coefficient of 0.766 for farm size in column 6 of Table 10.7, means that when farm size is increased by 100%, holding all other inputs constant, output would also increase by about 76.6%. Similarly, the partial production elasticities of fertilizer application and herbicide on the rice output of the non-adopting households were 0.449 and 0.268 respectively at 1% level of statistical significance each. As regards the translog for the adopters of improved rice varieties, the first term coefficients of farm size, seed and fertilizer had positive and statistically significant effect on rice output. Specifically, in column 5 the partial production elasticities of 0.623, 0.159 and 0.631 respectively for farm size, seed and fertilizer imply increasing any of these inputs by 100%, whilst holding all the other inputs constant, would increase rice output by about 62%, 16% and 63% resulting from an increase in farm size, seed and fertilizer.

Table 10.7: Results of the stochastic production frontier for the unmatched sample

	Conventional SPF			Sample selection SPF	
Variable	Pooled	Adopters	Non-adopters	Adopters	Non-adopters
Constant	8.785***	9.064***	8.814***	9.280***	8.594***
	(0.095)	(0.083)	(0.100)	(0.093)	(0.071)
Farm size (ha)	0.566***	0.629***	0.691***	0.623***	0.766***
	(0.058)	(0.060)	(0.130)	(0.077)	(0.084)
Seed (kg)	0.153***	0.077	0.098	0.159**	0.096
	(0.053)	(0.048)	(0.109)	(0.073)	(0.070)
Fertilizer (kg)	0.533***	0.589***	0.505***	0.631***	0.449***
	(0.056)	(0.056)	(0.166)	(0.078)	(0.054)
Labour (person days)	0.065	0.042	-0.018	0.083	0.013
	(0.041)	(0.042)	(0.069)	(0.062)	(0.054)
Herbicide (litres)	0.088*	0.018	0.302***	0.095	0.268***
	(0.047)	(0.050)	(0.095)	(0.072)	(0.076)
Farm size squared	0.192		-0.204	0.376	0.194

	(0.131)	(0.253)	(0.255)	(0.171)
Seed squared	0.118***	0.164**	0.092	0.120***
	(0.043)	(0.064)	(0.170)	(0.045)
Fertilizer squared	0.294***	0.353	0.251	0.432**
	(0.092)	(0.250)	(0.164)	(0.184)
Labour squared	-0.034	-0.030	-0.051	-0.037
	(0.023)	(0.052)	(0.068)	(0.057)
Herbicide squared	0.148**	-0.024	0.183	0.003
	(0.066)	(0.149)	(0.119)	(0.103)
Farm size*seed	-0.136**	-0.012	-0.119	-0.126
	(0.066)	(0.113)	(0.176)	(0.085)
Farm size*fertilizer	-0.007	-0.119	0.265*	-0.053
	(0.088)	(0.169)	(0.140)	(0.158)
Farm size*labour	-0.056	0.123	-0.132	0.055
	(0.046)	(0.087)	(0.107)	(0.081)
Farm size*herbicide	0.069	0.043	-0.009	0.138
	(0.067)	(0.177)	(0.126)	(0.105)
Seed* fertilizer	-0.115*	-0.094	-0.195	-0.148
	(0.062)	(0.122)	(0.136)	(0.123)
Seed* labour	0.006	0.009	0.041	-0.003
	(0.028)	(0.042)	(0.090)	(0.041)
Seed* herbicide	-0.062	-0.087	-0.067	-0.131*
	(0.054)	(0.101)	(0.136)	(0.069)
Fertilizer*labour	0.093	0.094	0.007	0.039
	(0.064)	(0.132)	(0.110)	(0.091)

Fertilizer*herbicide	-0.001		0.079	-0.057	0.066
	(0.081)		(0.176)	(0.128)	(0.123)
Labour*herbicide	-0.028		0.057	0.049	-0.043
	(0.051)		(0.800)	(0.092)	(0.058)
Fertilizer use (0,1)	0.392***	0.395***	0.210*	0.423***	0.307***
	(0.093)	(0.131)	(0.118)	(0.114)	(0.099)
Adoption	0.204***				
	(0.074)				
Lambda (λ)	2.343***	1.709***	3.782***		
	(0.109)	(0.149)	(0.142)		
Variance (σ^2)	0.999***	0.938***	0.979***		
	(0.106)	(0.136)	(0.159)		
Sigma-u				0.831***	0.999***
				(0.105)	(0.041)
Sigma-v				0.463***	0.354***
				(0.078)	(0.036)
Selectivity bias $\rho(w, v)$				-0.850***	0.999***
				(0.128)	(0.002)
Mean efficiency	0.646	0.702	0.582	0.552	0.523
Returns to scale	1.405	1.355	1.578	1.591	1.590
Log-likelihood function	-463.871	-309.907	-133.288	-415.601	-249.627
No. of observations	496	333	163	333	163

***, **, *, indicate values statistically significant at 1%, 5% and 10% respectively. Figures in brackets are the standard errors.

The coefficients of fertilizer use in columns 5 and 6 of Table 10.7 revealed output gains for applying fertilizer against non-application for both adopters and non-adopters of improved rice varieties. However, the effect of fertilizer application on output is higher for adopters (0.423) than the non-adopters (0.307).

Meanwhile, the returns to scale value was positive and above unity respectively in both the adopter and non-adopter translog stochastic production frontiers, implying increasing returns to scale. Therefore, an increase in the use of the variable inputs in the production process would lead to a more than proportionate increase in rice output.

Notwithstanding the discussion of the stochastic frontier with sample selection in Table 10.7, the results failed to eliminate bias emanating from observable characteristics between adopters and non-adopters of improved rice varieties. Bias due to observable factors was controlled using nearest neighbour matching with replacement. The matched sample was used to estimate separate stochastic production frontiers with correction for selection bias resulting from unobservable bias for both adopters and non-adopters of improved rice varieties. The significance of $\rho(w, v)$, the correlation coefficient between the error term of the adoption of improved rice varieties selection model and the stochastic production frontier at 1% for both the adopters and non-adopters of improved rice varieties in Table 10.8 clearly indicate the presence of selection bias due to unobservable characteristics.

Therefore, the existence of selection bias validates the application of a stochastic frontier with sample selection to estimate separate stochastic production frontiers for the adopters and non-adopters of improved rice varieties in this study (Greene 2006 & 2010; Bravo-Ureta *et al.*, 2012). Additionally, the statistical significance of $\rho(w, v)$ means the estimation of separate production frontiers each for adopters and non-adopters using the conventional stochastic frontier approach gives biased results, which in turn leads to biased technical efficiency scores (Rahman *et al*., 2009; Bravo-Ureta *et al*., 2012; Villano *et al*., 2015). In this regard, columns 5 and 6 in Table 10.8 are discussed.

The coefficients of farm size and fertilizer had positive and statistically significant effect on the rice output of non-adopters at 1% and 5% significance level. Farm size had the highest partial production elasticity of 0.805 on rice output, followed by quantity of fertilizer with 0.463. Although, the quantity of rice seed and labour had positive signs, they did not statistically influence rice output for the non-adopters of improved rice varieties.

Table 10.8: Results of the stochastic production frontier for the matched sample

	Conventional SPF			Sample selection SPF	
Variable	Pooled	Adopters	Non-adopters	Adopters	Non-adopters
Constant	8.885***	9.078***	8.814***	9.452***	8.685***
	(0.075)	(0.094)	(0.100)	(0.016)	(0.110)
Farm size (ha)	0.653***	0.757***	0.691***	0.803***	0.805***
	(0.072)	(0.081)	(0.130)	(0.016)	(0.127)
Seed (kg)	0.127**	0.105*	0.098	0.043***	0.088
	(0.059)	(0.063)	(0.109)	(0.012)	(0.107)
Fertilizer (kg)	0.227**	0.127	0.505***	0.057***	0.463**
	(0.099)	(0.123)	(0.166)	(0.020)	(0.199)
Labour (person days)	0.009	0.020	-0.018	0.038***	-0.023
	(0.044)	(0.054)	(0.069)	(0.010)	(0.070)
Herbicide (litres)	0.149***	0.118**	0.302***	0.195***	0.206
	(0.049)	(0.057)	(0.095)	(0.013)	(0.126)
Farm size squared	-0.263*	-0.423**	-0.204	-0.839***	0.027

	(0.148)	(0.207)	(0.253)	(0.043)	(0.279)
Seed squared	0.150***	0.068	0.164**	-0.142***	0.133
	(0.049)	(0.155)	(0.064)	(0.024)	(0.096)
Fertilizer squared	-0.002	-0.327	0.353	-0.481***	0.431
	(0.150)	(0.199)	(0.250)	(0.043)	(0.290)
Labour squared	-0.080***	-0.130*	-0.030	-0.112***	-0.014
	(0.030)	(0.074)	(0.052)	(0.018)	(0.074)
Herbicide squared	0.100	0.079	-0.024	0.056**	0.016
	(0.069)	(0.086)	(0.149)	(0.028)	(0.152)
Farm size*seed	0.026	0.123	-0.012	0.478***	-0.034
	(0.068)	(0.152)	(0.113)	(0.019)	(0.153)
Farm size*fertilizer	-0.043	0.414**	-0.119	0.437***	0.112
	(0.112)	(0.165)	(0.169)	(0.049)	(0.239)
Farm size*labour	0.140**	0.158	0.123	0.027	0.006
	(0.057)	(0.113)	(0.087)	(0.018)	(0.101)
Farm size*herbicide	-0.048	-0.240**	0.043	-0.525***	0.270
	(0.087)	(0.104)	(0.177)	(0.027)	(0.212)
Seed* fertilizer	-0.033	-0.138	-0.094	-0.221***	-0.192
	(0.086)	(0.136)	(0.122)	(0.037)	(0.188)
Seed* labour	-0.026	-0.083	0.009	-0.062***	-0.010
	(0.031)	(0.113)	(0.042)	(0.020)	(0.068)
Seed* herbicide	0.047	0.036	-0.087	0.368***	-0.114
	(0.068)	(0.088)	(0.101)	(0.023)	(0.160)
Fertilizer*labour	0.171**	0.156*	0.094	0.180***	0.005
	(0.076)	(0.091)	(0.132)	(0.023)	(0.142)

Fertilizer*herbicide	0.037	0.104	0.079	-0.133***	-0.117
	(0.113)	(0.118)	(0.176)	(0.036)	(0.223)
Labour*herbicide	0.043	0.214**	0.057	0.421***	-0.011
	(0.054)	(0.077)	(0.800)	(0.016)	(0.083)
Fertilizer Use (0,1)	0.267***	0.322**	0.210*	0.158***	0.285***
	(0.086)	(0.139)	(0.118)	(0.009)	(0.116)
Adoption	0.653**				
	(0.064)				
Lambda (λ)	4.212***	5.593***	3.782***		
	(0.089)	(0.120)	(0.142)		
Variance (σ^2)	1.056***	1.050***	0.979***		
	(0.112)	(0.149)	(0.159)		
Sigma-u				1.259***	1.005***
				(0.009)	(0.064)
Sigma-v				0.030***	0.279***
				(0.006)	(0.061)
Selectivity bias $\rho(w, v)$				-0.749***	0.997***
				(0.243)	(0.031)
Mean efficiency	0.551	0.579	0.582	0.467	0.518
Returns to scale	1.165	1.127	1.578	1.136	1.360
Log-likelihood function	-283.182	-116.935	-133.288	-227.001	-236.215
No. of observations	330	167	163	167	163

***, **, * indicate values statistically significant at 1%, 5% and 10% respectively. Figures in brackets are the standard errors.

The first term variables of the translog stochastic production frontier (in column 5 of Table 10.8) for the adopters of improved rice varieties were all statistically significant at 1%. In fulfilment of the monotonicity condition (Sauer *et al.,* 2006), the coefficients of these variables were also positive and thus had significant effect on rice output at the initial stage. For example, in column 5 of Table 10.8, the partial elasticity of farm size on rice output was 0.803. This means that when farm size is increased by 100%, holding all other inputs constant, output would also increase by about 80%. The coefficient of 0.043 for seed, implies a 100% increase in quantity of seed *ceteris paribus*, leads to a 4.3% increase in rice output at 1% significance level. Similar interpretation applies to the quantity of fertilizer, labour and herbicide with coefficients of 0.057, 0.038 and 0.195 respectively.

The lower partial elasticity of improved rice seed (0.043) in comparison with farm size (0.803) does not imply farmers do not consider it important in rice cultivation, given the average adoption rate of 67.2%. It is important to note that apart from farm size, the other conventional inputs are variable in the short term and farmers decide the quantities applied which can be sub-optimal and below recommended practices. This can in turn affect the partial elasticities of these variable inputs on rice output. For instance, instead of the recommended direct sowing by dibbling, most farmers (adopters and non-adopters) resorted to broadcasting that does not produce optimum plant density. Moreover, 73.5% of rice plots (adopters and non-adopters) were continuously planted with farmer saved seeds contrary to the recommended practice to acquire new seed at least once every three years. The fertilizer application rate of adopters (289.86kg/ha) and non-adopters (82.33kg/ha) were below the recommended 350kg/ha (Abdulai *et al*., 2018). This explains the partial elasticities of fertilizer on the output of both adopters and non-adopters of improved rice varieties. Adopters of improved rice varieties weeded their plots twice with herbicides at 3.3 litres/ha.

In keeping with regularity conditions (Sauer *et al.*, 2006), the coefficients of the square of the conventional inputs such as seed, fertilizer, labour and farm size were negative and statistically significant at 1%, thus fulfilling the diminishing marginal productivity condition for these inputs relative to the adopters of improved rice varieties. For example, the squared of variables for farm size, seed, fertilizer and labour had negative signs of -0.839, -0.142, -0.481, and -0.112 respectively. This implies that continuously increasing the quantities of these production inputs by 100% would in the long run decrease output by 83.9%, 14.2%, 48.1%, and 11.2% respectively for farm size, seed, fertilizer and labour respectively.

Some of the interaction terms were statistically significant and had both positive and negative signs. The interaction terms explain whether the production inputs were substitutes or complements. For instance, the interaction terms of farm size and seed; farm size and fertilizer; seed and herbicide; fertilizer and labour; and labour and herbicide were all statistically significant with positive coefficients of 0.478, 0.437, 0.368, 0.180, and 0.421 respectively. This means farm size and seed; farm size and fertilizer; seed and herbicide; fertilizer and labour; as well as labour and herbicide were complements to each other in rice production for adopters of improved rice varieties in the study area. Likewise, the interaction terms of variables such as farm size and herbicide; seed and fertilizer; seed and labour; fertilizer and herbicide had negative signs of -0.525, -0.221, -0.062 and -0.133 respectively and were each statistically significant at 1%. Therefore, farm size and herbicide[49]; seed and fertilizer; seed and labour; fertilizer and herbicide were substitutes to each other.

[49] This is interpreted with caution and does not imply "total" substitution of land. Herbicide application can control weed growth which competes with rice plants for nutrients and can reduce output. A smaller farm

The returns to scale value was positive and above unity for the translog stochastic production frontier for both the adopters and non-adopters of improved rice varieties respectively in the matched sample. This means the existence of increasing returns to scale for rice production in the study area. Therefore, an increase in the use of variable inputs such as seed, fertilizer, labour, herbicide and farm size in the production process would lead to a more than proportionate increase in the rice output of adopters of improved rice varieties. On the other hand, increasing the use of fertilizer and expanding farm size led to a more than proportionate increase in the rice output of non-adopters of improved rice varieties.

Moreover, the mean technical efficiency estimates (at the bottom of columns 5 and 6 in Table 10.8) of 47% amongst the adopters and 52% within the non-adopters indicated that for the individual group production frontiers, non-adopters of improved rice varieties performed well by producing closer to the frontier output amongst their own peers than the adopters of improved rice varieties. Therefore, this study estimated the determinants of technical inefficiency to explain the inability of rice farmers to produce very close to the frontier output.

10.5 Determinants of technical inefficiency in rice production

The determinants of technical inefficiency in rice production are discussed using the estimated coefficients associated with the inefficiency effects in Table 10.9. Variables with negative coefficients have negative relationship with technical inefficiency. The opposite is the case for variables with positive coefficients. The socio-economic variables employed to

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size with effective weed control is a better substitute than a larger farm infested with weeds giving a lower output.

explain technical inefficiency were sex of household head, age of household head, access to agricultural extension, number of years of formal education attained by household head, practising rice seed priming (soaking seeds in water for 12-24 hours before planting), rice seedling transplanting, row planting of rice, practising sawah system (levelling or bunding to manage water level on rice plot), land preparation using herbicide, weeding using herbicide, weeding frequency, application of ammonia fertilizer, application of actyva fertilizer, fertilizer application rate, method of rice harvesting, and pesticides application.

The unbiased results in columns 6 and 7 of the matched sample in Table 10.9 are discussed. The results in the unmatched columns are biased as they have not been corrected for observable characteristics that are likely to influence both the determinants of rice output and technical inefficiency. Following Greene (2006 & 2010), selectivity bias due to unobservable characteristics result from the correlation of the error term (w) of the adoption of improved rice varieties model and the unobservable factors from the random error component (v) and not the inefficiency component (u) of the stochastic production frontier. Additionally, the likelihood ratio test results in Table 10.6 reject the estimation of a common (pooled) production frontier in favour of the estimation of separate production frontiers for adopters and non-adopters in both the unmatched and matched samples.

Regarding the adopters of improved rice varieties, the sex of household head (0, male, 1, female), access to agricultural extension services (1, access, 0, no access), practice of sawah system (1, practised, 0, not practised), weeding using herbicide (1, herbicide, 0, manual hoe), and weeding frequency statistically influenced technical inefficiency in rice production.

Table 10.9: Results of the determinants of technical inefficiency in rice production

	Inefficiency term estimated using conventional SPF					
	Unmatched sample			Matched sample		
Variable	Pooled	Adopters	Non-adopters	Pooled	Adopters	Non-adopters
Constant	0.526	1.493**	-0.577	0.526	1.728**	-0.577
	(0.459)	(0.763)	(0.782)	(0.459)	(0.716)	(0.782)
Sex of household head	0.485**	0.821**	0.013	0.485**	0.633*	0.013
	(0.240)	(0.381)	(0.409)	(0.240)	(0.351)	(0.409)
Age of household head	0.001	0.005	9.561E-04	0.001	0.003	9.561E-04
	(0.008)	(0.013)	(0.014)	(0.001)	(0.011)	(0.014)
Agricultural extension	-0.307	-0.977**	0.237	-0.307	-1.011**	0.237
	(0.257)	(0.508)	(0.466)	(0.257)	(0.370)	(0.466)
Education of household head	0.000	-0.022	-0.010	0.000	-0.020	-0.010
	(0.017)	(0.033)	(0.026)	(0.017)	(0.031)	(0.026)
Rice seed priming	0.229	-0.352	-0.407	0.229	-0.048	-0.407
	(0.289)	(0.421)	(0.675)	(0.289)	(0.344)	(0.675)
Seedling transplanting	-0.392	-0.564	-0.487	-0.392	-0.041	-0.487
	(0.328)	(0.462)	(1.091)	(0.328)	(0.397)	(1.091)
Row planting	0.059	-0.254	-0.577	0.059	0.115	-0.577
	(0.285)	(0.421)	(0.563)	(0.285)	(0.392)	(0.563)
Sawah system	-0.436**	-0.920**	-0.288	-0.436**	-0.964**	-0.288
	(0.212)	(0.371)	(0.408)	(0.012)	(0.318)	(0.408)
Land preparation using herbicide	-0.425**	-0.497	0.057	-0.425**	-0.397	0.057
	(0.208)	(0.343)	(0.362)	(0.208)	(0.311)	(0.362)

Weeding using herbicide	-0.365*	-0.727**	-0.423	-0.365*	-0.671**	-0.423
	(0.206)	(0.358)	(0.335)	(0.026)	(0.306)	(0.335)
Weeding frequency	-0.061	-0.505**	0.462*	-0.061	-0.469**	0.462*
	(0.130)	(0.220)	(0.252)	(0.130)	(0.182)	(0.252)
Use of Actyva fertilizer	0.759	0.843	0.063	0.759	0.637	0.063
	(0.582)	(0.919)	(1.173)	(0.582)	(0.791)	(1.173)
Use of ammonia fertilizer	-0.384*	-0.152	-1.006***	-0.384*	-0.095	-1.006***
	(0.200)	(0.323)	(0.340)	(0.200)	(0.301)	(0.340)
Fertilizer rate	0.597	0.291	-0.303	0.597	0.754	-0.303
	(0.383)	(0.412)	(0.685)	(0.383)	(0.563)	(0.685)
Method of rice Harvesting	-2.993	-4.750	-24.695	-2.993	0.254	-24.695
	(3.096)	(6.570)	(1423.203)	(3.096)	(1.607)	1423.203)
Pesticide use	-0.012	-0.012	-0.105	-0.012	0.025	-0.105
	(0.254)	(0.375)	(0.478)	(0.254)	(0.334)	(0.478)
No. of observations	496	333	163	330	167	163

***, **, * indicate values statistically significant at 1%, 5% and 10% respectively. Figures in brackets are the standard errors.

The coefficient of sex of household head was positive and statistically significant at 10%. This means male headed households amongst the adopters were less technically inefficient than their female colleagues. It also implies male household heads were more technically efficient than their female counterparts. In Ghanaian households, the male is the household head and the decision maker regrading agricultural production decisions. Males usually have better access to resources than women and the benefits of adoption will not be even. Therefore, gender plays a significant role in determining technical efficiency of rice production in the study area. The socio-cultural setting of an area therefore, plays an important role in determining the productivity of each sex. The finding in this study is in line with that of Solís, Bravo-Ureta and Quiroga (2006) on technical efficiency and soil conservation in El Salvador and Honduras where female-headed households had lower technical efficiency than male-headed households. Nonetheless, Abatania, Hailu and Mugera (2012) found female household heads to be more technically efficient compared with their male counterparts in a study of farm household technical efficiency in Northern Ghana.

Additionally, adopter households that had access to agricultural extension services were more technically efficient than those who did not have access to agricultural advisory services. Out of 216 rice plots that sought the technical advice of agricultural extension agents, 207 (95.8%) acted on the advice given them by the agricultural extension agents. Agricultural extension service is widely known in literature as an important determinant of the adoption of improved production technologies (Gautam, 2000; Evenson, 2001; World Bank, 2008). A well-functioning agricultural extension system is the means by which information on better and new farm technologies are disseminated to farmers and thus plays a pivotal role to increasing the farm productivity.

The practice of lowland rice plot water management strategies such as levelling and bunding collectively known as sawah system (Buri *et al.*, 2012; Ragasa *et al.*, 2013; Abdulai *et al*., 2018) by adopters of improved rice varieties further increased their technical efficiency. Thus, adopters of improved rice varieties who did not practice sawah were more technically inefficient than households that practised the sawah system. About 65.2% of adopter plots in this study practised the sawah system. Studies such as Bam *et al*. (2010) in Ghana have reported improved yield by rice farmers that practised the sawah system.

Weeding with herbicide as opposed to manual hoe weeding reduced the technical inefficiency of adopters of improved rice varieties. It also implies adopters who applied herbicide on their rice plots were more technically efficient than those households that practised manual weed control using hand hoes. The application of herbicide was the first choice of weed control for nearly half (49.6%) of all rice plots in this study, followed by hand pulling of weeds (20.1%) and weeding using hand hoes (17.3%). For the second weeding, about 36%, 20% and 14% of rice plots practised hand pulling of weeds, herbicide application and hand hoe weeding respectively.

Similarly, the frequency of weeding had a negative coefficient which was statistically significant at 5%. This means adopters of improved rice varieties who weeded their rice plots more than once within the same cultivation period were more technically efficient than households that did weeding only once. In this study, 22.5%, 48.1% and 24.3% of adopter plots were weeded once, twice and thrice respectively. Herbicide are increasingly being applied to suppress weed growth in Ghanaian agriculture (Abdulai, 2015). For instance, pre-emergence herbicide application is recommended 2–3 days after sowing, whilst post-emergence herbicide is applied about 3 weeks after sowing (Ragasa *et al.,* 2013). Nonetheless, studies such as Abdulai (2015) have emphasized public education of farmers on the correction application and safe use of the herbicide. Specifically, Abdulai (2015) recommended government regulatory agencies such as the Plant Protection and Regulatory Division of the Ministry of Food and Agriculture, the Food and Drugs Authority and the Environmental Protection Agency in Ghana to play lead roles in regulating herbicide use and educating farmers on their safe use taking into consideration public and environmental safety.

On the other hand, the determinants of technical inefficiency for the non-adopters included the application of sulphate of ammonia fertilizer and weeding frequency. The coefficient of application of ammonia was negative and statistically significant at 1%. This means the application of ammonia fertilizer reduced the technical inefficiency in rice production amongst the non-adopters of improved rice varieties. Therefore, within the non-adopters of improved rice varieties, the application of sulphate of ammonia fertilizer on their rice plots increased their technical efficiency and helped them to produce closer to the frontier output than those who did not apply ammonia fertilizer on their rice plots. In this study, 63 out of 101 non-adopter plots applied sulphate of ammonia fertilizer. Moreover, about 46% of rice plots applied the sulphate of ammonia fertilizer at the recommended time of 7-8 weeks after planting. Nonetheless, 28.6% of rice plots applied sulphate of ammonia 6 weeks after planting.

Amongst the 163 non-adopter rice plots, 101 had been applied chemical fertilizer mostly NPK (nitrogen phosphorus and potassium) compound fertilizer. Similarly, from the 101 non-adopter plots that applied fertilizer, 45 plots (44.6%) applied it within the recommended period of 2-3 weeks after planting (Ragasa *et al.,* 2013; Abdulai *et al*., 2018), although, a third (31%) also applied in the 4th week after planting. The recommended application rate for sulphate of ammonia fertilizer in Ghana is 150kg/ha (Ragasa *et al.,* 2013; Abdulai *et al*., 2018). The coefficient of weeding frequency was positive and statistically significant at 10%. This implies technical inefficiency was associated with increasing number of weeding times on the rice plots of non-adopters of improved rice varieties. Thus, for the households that cultivated traditional rice varieties (non-adopters of improved rice varieties), weeding the rice plot once or twice within the cultivation season led to increased technical efficiency. About 26.7% and 49.7% of non-adopter plots were weeded once and twice within the cultivation season. The recommended practice is weeding two times during the growing season (Ragasa *et al.,* 2013). Nonetheless, 19.6% of rice plots were weeded thrice within the same season.

10.6 Distribution of technical efficiency estimates

Technical efficiency in this study is explained as the ability of a rice farming household to obtain maximum output from a given set of inputs under a given production technology, which is rice cultivation. Thus, technical inefficiency occurs when a given set of rice inputs produces less rice output than what is attainable given the available production technology. Therefore, the existence of technical inefficiency in rice production means there is room to increase rice output without increasing input amounts at the present level of technology. The sub-sections discuss the distribution of technical efficiency estimates for the group frontiers of adopters and non-adopters as well as for the stochastic metafrontier.

10.6.1 Distribution of technical efficiency estimates for the group frontiers

The technical efficiency estimates reported in the unmatched sample in Table 10.10 are biased because they have not been corrected for selectivity bias resulting from both observable and unobservable factors relative to the conventional stochastic production frontier and the presence of observable bias in the case of sample selection stochastic production frontier. Nonetheless, the mean technical efficiency estimates of about 58% in columns 3 and 4 of Table 10.10for the conventional stochastic frontier were statistically not different between adopters and non-adopters of improved rice varieties for the matched sample. The technical efficiency estimates for the conventional stochastic production frontier in the matched sample in Table 10.10 have only been corrected for selectivity bias due to observable factors and not unobservable factors, hence these estimates are still biased.

However, the sample selection stochastic frontier results in columns 6 and 7 of the matched sample in Table 10.10 have been corrected for selectivity bias due to both observable and unobservable factors. Therefore, the mean technical efficiency estimates in these two columns are discussed because they are unbiased.

Table 10.10: Mean TE for the unmatched and matched samples

	Conventional stochastic production frontier				Sample selection stochastic production frontier		
Mean Estimate	Pooled	Adopters	Non-adopters	Test of mean diff	Adopters	Non-adopters	Test of mean diff [a]
Unmatched sample							
TE	0.646 (0.186)	0.702 (0.189)	0.582 (0.218)	0.112***	0.552 (0.146)	0.523 (0.211)	0.059***
Matched sample							
TE	0.551 (0.225)	0.579 (0.243)	0.582 (0.218)	-0.003	0.467 (0.253)	0.515 (0.234)	-0.048**

***, **, *, indicate values statistically significant at 1%, 5% and 10% respectively. Figures in brackets are the standard deviations. [a] Test of mean diff is the t test of difference in mean TE between adopters and non-adopters.

The mean technical efficiency estimates in columns 6 and 7 of the matched sample in Table 10.10 for adopters and non-adopters of improved rice varieties respectively were about 47% and 52%. Although, the technical efficiency estimates of adopters and non-adopters of improved rice varieties cannot be directly compared with each other (Villano *et al*., 2015) because of the estimation of separate production frontiers for each group, they clearly demonstrate the effect of selectivity bias (due to observable and unobservable factors) which when ignored in the estimation process, gives biased and incorrect efficiency estimates.

Regarding the adopters of improved rice varieties, the mean technical efficiency estimate of 47%, implies rice farmers that cultivated improved rice varieties attained 47% of potential rice output. Therefore, adopters of improved rice varieties in the study area could produce an additional 53% of output without changing the quantities of inputs used if it were to improve its farm management performance and operate on the production frontier. On the other hand, the mean technical efficiency estimate of 52% for the non-adopters of improved rice varieties means that, they were producing at 52% of potential output. Thus, the non-adopters could produce an additional 48% of output under the given production technology and input set by improving their farm managerial skills and operating on the production frontier.

Meanwhile, the mean technical efficiency estimates of 47% amongst the adopters and 52% within the non-adopters revealed that for the individual group production frontiers, non-adopters of improved rice varieties performed well by producing closer to the frontier output within their own cohort than the adopters of improved rice varieties. Nonetheless, adopters obtained a higher yield (2.8tonnes/ha) than the non-adopters (1.3tonnes/ha). Moreover, adoption of improved rice varieties led to an upward shift of the production frontier and pushing further the gap between the actual and frontier output for the adopters.

The results of the distribution of technical efficiency scores in column 7 of the matched sample in Table 10.11 revealed about 56% of adopters of improved rice varieties had efficiency estimates below 50%.

Table 10.11: TE Distribution for the unmatched and matched samples

Technical efficiency range	Conventional SPF				Sample selection SPF			
	Adopters		Non-adopters		Adopters		Non-adopters	
	Freq	%	Freq	%	Freq	%	Freq	%
Unmatched sample								
≤ 0.50	54	16.2	57	**35.0**	120	**36.0**	74	**45.4**
0.51-0.60	31	9.3	15	9.2	67	**20.1**	24	**14.7**
0.61-0.70	42	12.6	32	**19.6**	72	**21.6**	22	**13.5**
0.71-0.80	106	**31.8**	31	**19.0**	58	17.4	24	**14.7**
0.81-0.90	76	**22.8**	26	**16.0**	15	4.5	18	11.0
0.91-1.00	24	7.2	2	1.2	1	0.3	1	0.6
Total	333	100.0	163	100.0	333	100.0	163	100.0
Matched sample								
	Freq	%	Freq	%	Freq	%	Freq	%
≤ 0.50	63	**37.7**	57	**35.0**	93	**55.7**	76	**46.6**
0.51-0.60	14	8.4	15	9.2	27	**16.2**	21	12.9
0.61-0.70	24	**14.4**	32	**19.6**	11	6.6	20	12.3
0.71-0.80	28	**16.8**	31	**19.0**	17	**10.2**	23	**14.1**
0.81-0.90	34	**20.4**	26	**16.0**	10	6.0	22	13.5
0.91-1.00	4	2.4	2	1.2	9	5.4	1	0.6
Total	167	100.0	163	100.0	167	100.0	163	100.0

Source: Author’s computation based on survey data.

About 16% recorded efficiency scores in the range of 51-60%, whilst 10% of adopters also had efficiency estimates of 71-80%. Regarding the non-adopters of improved rice varieties, the technical efficiency distribution in column 9 of the matched sample indicated that nearly 47% of non-adopters had efficiency scores below 50%. The results in Table 10.11 clearly demonstrates the existence of technical inefficiency in both the adopters and non-adopters of improved rice varieties.

10.6.2 Distribution of technical efficiency estimates for the stochastic metafrontier

The estimation of the stochastic metafrontier allows for direct comparison of the technical efficiency estimates of adopters with non-adopters of improved rice varieties after controlling sample selection bias. This makes it possible to assess the extent by which the productivity of a farm or group of farms could be increased if it adopted the best technology available in the wider industry.

The results in Table 10.12 indicate the technical efficiency of adopters relative to the stochastic metafrontier was 0.427 (42.7%). Consistent with *a priori* expectation, the metafrontier TE was lower than the group TE of 0.467 (46.7%) for the sample selection SPF. Similarly, the metatechnology ratio, MTR (also known as technology gap ratio, TGR) for the adopters of improved rice varieties was 0.909 (90.9%). The higher MTR value of 0.909 for the adopters implies a narrow gap between the adopters' group frontier and the stochastic metafrontier.

Table 10.12: Estimates of group and metafrontier TEs and metatechnology ratios

Category	Mean	Standard deviation	Maximum	Minimum
Adopters matched sample				
Group TE-Conventional SPF	0.555	0.244	0.923	0.047
Group TE-Sample selection SPF	0.467	0.253	0.969	0.032
Metatechnology ratio (MTR)	0.909	0.106	1.000	0.236
TE relative to stochastic metafrontier	0.427	0.224	0.929	0.031
Non-adopters matched sample				
Group TE-Conventional SPF	0.581	0.218	0.992	0.079
Group TE-Sample selection SPF	0.518	0.232	0.927	0.063
Metatechnology ratio (MTR)	0.785	0.166	1.000	0.150

TE relative to stochastic metafrontier	0.445	0.217	0.919	0.038
Paired t-test of the mean stochastic metafrontier estimates				
	T statistic		*Decision*	
Metafrontier TE diff = mean (Adopters-Non-adopters) = 0.018	0.741 (1.96)		Do not reject H_0	
Metafrontier MTR diff = mean (Adopters-Non-adopters) = 0.124	8.107 (1.96)		Reject H_0: mean (diff) ≠ 0	

Ho: mean (diff) = 0, Ha: mean (diff) ≠ 0. Critical value in brackets is at 5% significance level and obtained from the T distribution table. Source: Author's computation based on survey data.

The estimated metafrontier distance of 0.091 (1 - 0.909) between the adopters' group and the stochastic metafrontier means that the adopters of improved rice varieties need to close a production technology gap of 9.1% with respect to the common metafrontier technology. A maximum MTR value of 1 means that there is no gap between a rice farm in a group and the metafrontier and thus, the farm's group frontier is tangent to the metafrontier. From the results, 5 adopters and 6 non-adopters had an MTR value of exactly 1.

Regarding the non-adopters of improved rice varieties, the stochastic metafrontier TE was 0.445 (44.5%). The metafrontier TE value of 44.5% was less than the group TE of 51.8% obtained from the sample selection SPF for the non-adopters. The technology gap ratio of 0.785 (78.5%) implies that for the non-adopters to be fully technically efficient, they need to close a gap of 21.5% in their production technology. Thus, there is a potential to increase productivity by using the best rice cultivation practices available within the common production technology.

Meanwhile, the results in Table 10.13 indicate that over 60% of both adopters and non-adopters had TE scores of less than or equal to 50% with respect to the metafrontier. The mean difference in metafrontier technical efficiency of adopters (42.7%) and non-adopters (44.5%) were statistically not significant.

Table 10.13: TE Distribution for the stochastic metafrontier

Stochastic Metafrontier TE range	Sample Selection SPF			
	Matched Adopters		Matched Non-adopters	
	Freq	%	Freq	%
≤ 0.50	103	**61.7**	105	**64.4**
0.51-0.60	25	15.0	18	11.0
0.61-0.70	16	**9.6**	14	**8.6**
0.71-0.80	9	5.4	13	8.0
0.81-0.90	7	4.2	12	7.4
0.91-1.00	7	4.2	1	0.6
Total	167	100.0	163	100.0

Source: Author's computation based on survey data.

Notwithstanding, adopters had a higher metatechnology ratio of 0.909 compared with 0.785 for non-adopters. The higher MTR for the adopters' group is much closer to one and implies that they are producing nearer to the maximum potential output using the more advanced production technology available for the whole industry. Generally, the adopters of improved rice varieties had higher MTR values, given that 118 out of 167 had MTR values between 1 and 0.91 compared with only 43 for the non-adopters. Essentially, the non-adopter group fell behind the best available production technology for all rice farmers represented by the stochastic metafrontier production function.

However, the lower metafrontier TE estimates for both adopters and non-adopters could be attributed to differences in farmers' managerial practices, socioeconomic characteristics as well as existing environmental conditions. At the same time, there is a potential to attain higher technical efficiency under the common technology of the stochastic metafrontier by learning from the best practice farmers. For instance, in Table 10.13, 7 out of the 167 adopters had TE scores between 91-100% whereas 1 out of the 163 non-adopters had a TE score between 91-100%.

10.7 Key findings and policy implications

This chapter analysed the effect of adoption of improved rice varieties on farmers' output and technical efficiency using the stochastic frontier model with correction for selectivity bias due to unobservable and observable characteristics. Secondly, a metafrontier was estimated to separate technology gaps (the distance between group frontiers and the metafrontier) from managerial gaps resulting from differences in farmers' technical efficiencies. Selection bias due to observable characteristics was controlled using nearest neighbour matching with replacement. The matched sample was used to estimate the stochastic production frontier with correction for unobservable bias for both adopters and non-adopters conditional on a probit adoption selection equation. The statistical significance (at 1%) of the correlation coefficient between the error term of the adoption of improved rice varieties selection model and the stochastic production frontier for both adopters and non-adopters of improved rice varieties indicated the presence of selection bias due to unobservable characteristics. This validated the application of a stochastic frontier with sample selection to estimate separate stochastic production frontiers for the adopters and non-adopters of improved rice varieties in this study.

From the results, farm size, quantity of rice seed planted, quantity of fertilizer applied, farm labour, and herbicide application had positive effect on the rice output of adopters of improved rice varieties. In addition, inputs such as farm size and seed; farm size and fertilizer; seed and herbicide; fertilizer and labour; as well as labour and herbicide complemented each other in rice production for adopters of improved rice varieties in the study area. Nonetheless, farm size and herbicide; seed and fertilizer; seed and labour; fertilizer and herbicide were substitutes to each other in rice cultivation for the adopters.

On the other hand, farm size and quantity of fertilizer applied had positive effect on the rice output for the non-adopters of improved rice varieties. There was increasing returns to scale in rice production for both adopters and non-adopters of improved rice varieties in the study area. Therefore, an increase in the use of variable inputs such as seed, fertilizer, labour, herbicide and farm size in the production process would in the short run lead to a more than proportionate increase in the rice output of adopters of improved rice varieties. On the other hand, increasing the use of fertilizer and expanding farm size in the short run led to a more than proportionate increase in the rice output of non-adopters of improved rice varieties. Generally, adopters of improved rice varieties performed well by producing closer to the metafrontier output given their higher MTR value of 0.909 than the non-adopters with an MTR of 0.785. Therefore, the non-adopter group fell behind the best available technology for all rice farmers represented by the stochastic metafrontier production function.

The mean technical efficiency estimates of 47% amongst the adopters and 52% within the non-adopters revealed that for the individual group production frontiers, non-adopters of improved rice varieties performed well by producing closer to the frontier output within their own cohort than the adopters of improved rice varieties. Although, adopters had a higher yield (2.8mt/ha) than the non-adopters (1.3mt/ha), adoption resulted in an upward shift of the production frontier, thus pushing the gap between the actual and frontier output. However, the mean difference in metafrontier technical efficiency of adopters (42.7%) and non-adopters (44.5%) were statistically not significant. The lower metafrontier TE estimates are attributable to differences in farmers' managerial practices, socioeconomic characteristics as well as existing environmental conditions. This means that farmers can attain higher technical efficiency under the common technology of the stochastic metafrontier by learning from their best practice colleagues. For this reason, this study estimated the determinants of technical inefficiency to offer explanation for the inability of rice farmers to produce very close to the frontier output.

Regarding the adopters of improved rice varieties, the sex of household head, access to agricultural extension services, practice of sawah system, weeding using herbicide, and weeding frequency statistically influenced technical inefficiency in rice production. Male headed households amongst the adopters were less technically inefficient than their female colleagues. Adopter households that had access to agricultural extension services were less technically inefficient than those who did not have access to agricultural advisory services. Adopters of improved rice varieties who practised rice plot water management strategies such as levelling and bunding (sawah system) were less technically inefficient than households that did not practice the sawah system. Adopters who applied herbicide on their rice plots were less technically inefficient than those households that practised manual weed control using hand hoes. Adopters of improved rice varieties who weeded their rice plots more than once within the same cultivation period were less technically inefficient than households that did weeding only once.

On the other hand, the determinants of technical inefficiency for the non-adopters included the application of sulphate of ammonia fertilizer and weeding frequency. The application of ammonia fertilizer reduced the technical inefficiency in rice production amongst the non-adopters of improved rice varieties than those who did not apply ammonia fertilizer on their rice plots. Technical inefficiency was associated with increasing number of weeding times on the rice plots of non-adopters of improved rice varieties. Thus, weeding of a rice plot once within the cultivation season reduced the technical inefficiency of non-adopters of improved rice varieties.

Based on the empirical findings in this study, the following recommendations are proposed.

First and foremost, farm size had a positive effect on rice output for both adopters and non-adopters of improved rice varieties. Government policy through land tenure legislation should be geared towards facilitating access to land to expand production.

Secondly, fertilizer application had a positive effect on rice output for both adopters and non-adopters of improved rice varieties in the study area. Furthermore, the application of ammonia fertilizer also reduced the technical inefficiency of farmers who cultivated traditional rice varieties. The aim of the fertilizer subsidy being implemented by the government of Ghana is to make fertilizer more affordable to increase application rate and boost output (Banful, 2008; Benin *et al*., 2011). Ghana has a very good fertilizer distribution system with the active participation of the private sector engaged in both the wholesale and retail chain (Banful, 2008). However, there is still a need to expand access and ensure timeliness as delays in fertilizer application by farmers have negative effect on rice output.

Thirdly, the cultivation of improved varieties increased rice output of adopters. In this regard, timely access to improved rice varieties should be encouraged by the Ministry of Food and Agriculture (MoFA) in partnership with the national agricultural research institutes and the private sector. Particularly, there should be a seed policy to ensure seed certification and quality of varietal releases. A vibrant private sector seed development and distribution system would also go a long way to improve access to high yielding seed varieties by farmers.

Fourthly, the application of herbicide resulted in an increase in rice output for adopters of improved rice varieties. In addition, adopters who applied herbicide were less technically inefficient as opposed to adopters who practised manual hand hoe weeding. This brings to the fore, the need to educate farmers on the correct use of herbicide on their rice fields by the relevant state agencies. Especially, the Plant Protection and Regulatory Division of MoFA, the Food and Drugs Authority and the Environmental Protection Agency should play lead roles in regulating and educating farmers on the safe use of these chemicals taking into consideration public and environmental safety.

Access to agricultural extension services reduced the technical inefficiency of adopters of improved rice varieties. A well-resourced agricultural extension service plays the dual role of promoting the adoption of improved rice varieties as well as accompanying cultural practices to reduce technical inefficiency in rice production. For instance, the practice of rice plot water management strategies such as bunding and levelling reduced the technical inefficiency of adopters of improved rice varieties.

Lastly, male headed households amongst the adopters of improved rice varieties were less technically inefficient than their female colleagues and efforts should be made to narrow this gap. For example, providing support in the form of access to economic resources, farmer education, information and decision-making for female adopters of improved rice varieties will help to reduce their technical inefficiency in rice production.

10.8 Conclusions

This chapter addressed the second objective by analysing the effect of adoption of improved rice varieties on farmers' output and technical inefficiency using the stochastic production frontier with correction for selectivity bias and a metafrontier. Farm size, seed, fertilizer, farm labour, and herbicides application increased rice output of adopters of improved rice varieties. Farm size and seed; farm size and fertilizer; seed and herbicide; fertilizer and labour; labour and herbicide were complementary inputs that increased the rice output of adopters. Meanwhile, farm size and fertilizer had positive effect on output of non-adopters of improved rice varieties. The mean group technical efficiency estimates were 47% and 52% respectively for adopters and non-adopters of improved rice varieties. The mean difference in metafrontier technical efficiency of adopters (42.7%) and non-adopters (44.5%) were statistically not significant, although adopters had a higher metatechnology ratio of 0.909 compared with 0.785 for non-adopters. Thus, the non-adopter group was behind in applying the best available technology for all rice farmers depicted by the stochastic metafrontier.

Farm size had positive effect on rice output for both adopters and non-adopters of improved rice varieties. Government land tenure legislation should be geared towards facilitating access to land to expand production. A vibrant certified seed production and distribution system would ensure timely access to improved rice varieties given that cultivation of improved varieties increased rice output of adopters. Meanwhile, the Ministry of Food and Agriculture (MoFA) can regulate seed certification to ensure quality of varietal releases. Fertilizer application had positive effect on the rice output of both adopters and non-adopters of improved rice varieties. Ammonia fertilizer application also reduced the technical inefficiency of non-adopters. Although, a fertilizer subsidy exists, there is need to ensure timely access as delays in application can negatively affect yield. Herbicide application led to increased output and technical efficiency for adopters of improved rice varieties as opposed to manual hand hoe weeding. The Plant Protection and Regulatory Division of MoFA, the Food and Drugs Authority and the Environmental Protection Agency should play lead roles in regulating and educating farmers on the safe use of herbicides taking into consideration public and environmental safety.

Access to agricultural extension services reduced the technical inefficiency of adopters of improved rice varieties. A well-resourced agricultural extension service plays the dual role of promoting the adoption of improved rice varieties and accompanying cultural practices to reduce technical inefficiency in rice production. For instance, the practice of managing rice plot water levels through bunding reduced the technical inefficiency of adopters. Lastly, male headed households amongst the adopters of improved rice varieties were less technically inefficient than females. Support in the form of access to economic resources and farmer education will help reduce female technical inefficiency in rice production.

CHAPTER ELEVEN

ANALYSIS OF ADOPTION OF IMPROVED RICE VARIETIES ON HOUSEHOLD NET RICE INCOME

11.1 Introduction

This chapter addresses the third objective of this research which "examines the effect of adoption of improved rice varieties on household net rice income". A one-step, full information maximum likelihood (FIML) endogenous switching regression (ESR) model is used to estimate household net rice income per hectare (ha), conditional on the adoption of an improved rice variety. For a detailed discussion of the methodology, refer to section 6.2 in Chapter 6.

The FIML ESR was estimated using only the 480 households who knew of the existence of improved rice varieties. This chapter assesses whether households that are aware of, and adopt, improved rice varieties are more likely to benefit from increased output for home consumption and or, for sale to obtain cash income to support household expenditure compared with the non-adopters. Table 11.1 presents a summary definition of variables used in the estimation of the effect of adoption of improved rice varieties on household net rice income per ha in the study area.

Table 11.1: Summary definition of variables used in net rice income analysis

Variable	Description
Adoption	Dummy; 1 if a household head cultivated at least one improved rice variety, 0, otherwise
Community participation in rice projects	Dummy; 1 if community ever participated in a rice project, 0, otherwise
Being a model farmer	Dummy; 1 if household head has ever been a model farmer, 0, otherwise
Participation in block farming	Dummy; 1 if household head has ever participated in block farming, 0, otherwise. Block farming was a government intervention that provided farmers with production inputs on credit and extension service to boost arable crops production.
Agricultural extension	Dummy; 1 if household head has access to agricultural extension services, 0, otherwise
Forest zone	Dummy; 1 if agro-ecological area of rice farm is forest, 0, coastal zone
Guinea savannah zone	Dummy; 1 if agro-ecological area of rice farm is guinea savannah, 0, coastal zone
Lowland rain fed	Dummy; 1 if rice cultivation system is lowland rain fed, 0, upland rain fed
Irrigated production	Dummy; 1 if rice cultivation system is irrigation, 0, upland rain fed
Higher yield	Dummy; 1 is whether farmer seeks higher rice yield, 0, otherwise
Market demand	Dummy; 1 is whether farmer produces rice for sale in the market, 0, otherwise. Rice characteristics such as good taste and aroma, ease of milling, long grain, parboiling and swelling properties have high market demand.
Own consumption	Dummy; 1 if household consumption is reason for cultivating improved rice variety, 0, otherwise
Growing farm saved seed	Number of years farm saved seed of current rice variety was continuously cultivated by household
Farm size (ha)	Number of hectares of cultivated rice per year
Presence of agro-input shop in community	Dummy; 1 if community has agro-input shop, 0, otherwise
Sex of household head	Dummy; 1 if household head is female, 0, male

Educational level	Number of years of formal education of household head
Last season's crop income	Last season's crop income as proportion of household income (in %)
Rice output	Total tonnes of rice harvested from farm per year
Rice sold (tonnes) per household per year	Total tonnes of rice from harvest sold for income by household per year
Motorcycle ownership	Dummy; 1 if household owns a motorcycle, 0, otherwise
Bicycle ownership	Dummy; 1 if household owns a bicycle, 0, otherwise
Electricity	Dummy; 1 if household has access to electricity, 0, otherwise
Household size	Number of members in household
Net rice income per ha	Net rice income of a household (in GH¢) divided by the rice farm area in hectares of that given household

Source: Author's construction based on survey data set. Currency GH¢ = Ghana cedi. Bank of Ghana exchange rate was £1 = GH¢ 6.27 as at January 16, 2019.

11.2 Determinants of adoption of improved rice varieties of the FIML ESR

The FIML ESR was used to estimate household net rice income per ha conditional on an adoption decision, also known as the selection equation (a detailed discussion is in section 6.2 of Chapter 6). The first stage of the FIML ESR estimates the determinants of adoption of improved rice varieties, using the exposed subsample of which the results are presented in Table 11.2. The selection variables and findings in this section are similar to those in section 9.3 of Chapter 9, which discussed the adoption rate and the factors that determined the adoption of improved rice varieties by the method of treatment effect. However, unlike the estimation of the adoption rate and the determinants of adoption in Chapter 9, the adoption selection model estimated here also includes all the explanatory variables in the household net rice income per ha outcome variables.

First, community participation in a rice project and the selection of a household head as a model farmer respectively had a positive and statistically significant influence on the decision to adopt improved rice varieties. Likewise, from the results in Table 11.2, the cultivation of rice through irrigation and household own rice consumption need positively influenced household improved rice adoption decisions.

Table 11.2: Results of the adoption selection equation for the switching regression

Variable	Coefficient	Standard error
Constant	0.498	0.461
Community participation in rice projects	0.447**	0.222
Being a model farmer	0.807***	0.232
Participation in block farming	0.106	0.288
Agricultural extension	0.221	0.169
Forest zone	-0.430*	0.237
Guinea savannah zone	-0.891***	0.258
Lowland rain-fed production	0.285	0.271
Irrigated production	1.682***	0.324
Higher rice yield	0.122	0.142
Rice market demand	0.039	0.141
Own consumption of rice	0.260*	0.153
Rice quantity sold	0.001	0.002
Growing farm saved seed	-0.025*	0.015
Farm size	-0.047*	0.025
Presence of agro-input shop in community	-0.102	0.148

Sex of household head	0.108	0.144
Last season's crop income (as % of household income)	-0.003	0.003
Motorcycle ownership	-0.026	0.159
Electricity access	0.028	0.166
Household size	0.003	0.009

***, **, *, indicate values statistically significant at 1%, 5% and 10% respectively.

Nonetheless, farm households located in the forest and guinea savannah agro-ecological zones of Ghana, respectively were less likely to adopt improved rice varieties compared with their counterparts located in the coastal zone. As noted by Ragasa *et al* (2014), traditional varieties are still widely planted by farmers in the guinea savannah zone of Ghana.

Lastly, growing farm saved seed by a household as well as larger rice farm sizes had a negative, but statistically significant effect on improved rice cultivation decision. The adopter households in this study generally had smaller rice farm sizes (3.85 ha) compared with the non-adopters (5.75 ha). The repeated cultivation of rice seed taken from the household's own harvested rice was common for both improved and traditional varieties with an average of over four consecutive years or planting seasons.

11.3 Effect of adoption of improved rice varieties on household net rice income

The FIML estimates of the parameters of the endogenous switching regression were obtained using the *movestay* command in STATA (Lokshin and Sajaia, 2004). The differences in the coefficients (presented in Table 11.3) of the net rice income per ha between the farm households that adopted improved rice varieties and those that did not adopt, indicate the presence of heterogeneity in the sample. This means that the characteristics of adopter households are markedly different from the non-adopting households.

Furthermore, the statistical significance of the correlation coefficients (ρ_1, ρ_0) between the error terms of the adoption selection and outcome equation of household net rice income per ha in Table 11.3, provide an indication of selection bias. For instance, in Table 11.3, the correlation coefficient (ρ_1) was positive and statistically significant at 1% for adopters of improved rice varieties. This implies the existence of self-selection, hence the net rice income per ha of adopters of improved rice varieties was significantly different from their non-adopter counterparts. It also means that both observed and unobserved factors influenced the household improved rice varieties adoption decision of adopters and their net rice income per ha. Therefore, the adoption of improved rice varieties would not have the same effect on the non-adopters should they choose to adopt, as it would on the adopters.

On the other hand, the correlation coefficient, ρ_0 between the adoption selection and the household net rice income per ha outcome was not statistically significant for the non-adopters. This implies the absence of selection bias and no statistically significant influence of observed and unobserved factors on their non-adoption decisions. The statistical significance (at 1%) of the likelihood ratio tests for independence of equations (H_0: ρ_1= $\rho_0 = 0$ is rejected) at the bottom of Table 11.3 indicates joint dependence between the adoption selection and the household net rice income per ha respectively for adopters and non-adopters of improved rice varieties.

In order to better[50] satisfy the identification condition for the FIML switching regression model (Lokshin and Sajaia, 2004 and 2011; Di Falco *et al*., 2011), an exclusion restriction through an instrumental variable (Asfaw *et al*., 2012; Tambo and Wünscher, 2014) was used. The exclusion restriction through instrumental variable requires at least one variable that affects adoption decision but has no direct statistically significant effect on the net rice income of the household. The instrumental variable was selection as a model farmer for the household net rice income per ha outcome. The validity of this instrumental variable for the net rice income per ha outcome was tested using a falsification test (Di Falco *et al*., 2011) and when appropriate, it only affects adoption decision and not affect the net rice income per ha outcome of non-adopters. The instrument was valid in this study (please refer to results in Tables 11.2 and 11.3) with selection as model farmer having a positive and statistically significant (at 1%) effect on adoption of improved rice varieties, but no statistically significant influence on the net rice income per ha outcome of the non-adopter households.

Next, the results of the determinants of household net rice income per ha conditional on the household improved rice adoption decision presented in Table 11.3 are discussed. From Table 11.3, the proportion of last season's crop income relative to total household income had a positive and statistically significant effect on the net rice income per ha of only non-adopters of improved rice varieties. The coefficient of guinea savannah, a dummy variable, was negative and statistically significant relative to household net rice income per ha for both adopters and non-adopters of improved rice varieties. This means that net rice income

[50] The FIML is identified through the non-linearities of the inverse mills ratios, λ_0 and λ_1(Lokshin and Sajaia 2004), however identification is enhanced by the introduction of an instrumental variable.

per ha was lower for rice farming households located in the guinea savannah zone in comparison with those in the coastal zone.

Table 11.3: FIML ESR results on effect of adoption on net rice income

Variable	Net rice income per ha	
	Adopters	Non-adopters
Constant	330.302	-156.452
	(375.627)	(190.534)
Last season's crop income (as % of household income)	0.552	3.154**
	(2.414)	(1.358)
Guinea savannah	-636.42***	-201.881**
	(151.326)	(95.930)
Farm size	-73.071***	- 45.227***
	(15.380)	(5.981)
Being a model farmer	978.052***	11.967
	(143.621)	(147.744)
Electricity access	151.005	157.141**
	(127.789)	(62.481)
Motorcycle ownership	93.551	143.289**
	(128.049)	(60.650)
Household size	- 12.274	-6.584**
	(8.231)	(3.308)
Lowland rain-fed production	9.484	300.259***
	(298.606)	(99.002)
Irrigated production	1195.789***	471.658**
	(297.027)	(205.318)

Growing farm saved seed	-40.447**	-2.190
	(16.212)	(5.855)
Rice quantity sold	4.549***	7.054***
	(0.465)	(0.620)
$ln\sigma_1$, $ln\sigma_0$	6.956***	5.784***
	(0.045)	(0.075)
ρ_1, ρ_0	0.923***	-0.294
	(0.026)	(0.276)
LR test of indep. eqns	49.42***	
Log likelihood	-3963.183	
Chi-squared test statistic	430.29***	
No. of observations	480	

***, ** indicate values statistically significant at 1% and 5% respectively. Figures in brackets are the standard errors. $ln\sigma_1$ and $ln\sigma_0$ are the natural logs of the square roots of the variances of the residuals of the net rice income per ha of adopters and non-adopters of improved rice varieties. ρ_1 and ρ_0 are the correlation coefficients of the error terms between the adoption decision and net rice income per ha of adopters and non-adopters respectively. LR test of indep. Eqns (H_0: $\rho_1 = \rho_0 = 0$) value is 49.42 at 1% and H_0 is rejected.

The size of rice farm in Table 11.3, indicate that households (both adopters and non-adopters) with smaller rice farms had a higher net rice income per ha than larger in area rice farm households. This means that households with smaller rice farm sizes produced a higher yield, which translated into a higher net rice income per ha. The smaller rice farm sizes were mainly into irrigated production, which requires intensive input use, but gives the highest yield in Ghana (MoFA, 2009). Selection as a model farmer had a positive influence on the net rice income per ha only for adopters of improved rice varieties. This implies that model farming households who were also adopters of improved rice varieties obtained a higher net rice income per ha.

Regarding the ownership of household assets, motorcycle ownership had a positive effect on household net rice income per ha of non-adopters at the 5% level of statistical significance. Thus, the net rice income per ha was higher for non-adopter households who owned motorcycles than those who did not possess motorcycles. Similarly, access to electricity had a positive and statistically significant effect on the net rice income per ha of only non-adopters of improved rice varieties. Meanwhile, large households had a lower net rice income per ha than those with smaller households amongst the non-adopters.

Relative to the rice cultivation system, irrigated production had a positive and statistically significant effect on the net rice income per ha for both adopters and non-adopters. This implies that irrigated rice production offered a higher net rice income per ha for both adopters and non-adopters of improved rice varieties. Nonetheless, lowland rice production also had a positive and statistically significant influence on the net rice income per ha amongst non-adopters of improved rice varieties.

Growing farm saved rice seed had a negative impact on net rice income per ha only for adopters of improved rice varieties. This means that cultivating farm saved seed amongst the adopter households reduced their net rice income per ha.

Lastly, the quantity of rice sold by a household had a positive and statistically significant effect (at 1%) on its net rice income per ha respectively for both adopters and non-adopters of improved rice varieties. This means that a higher quantity of rice sold led to an increase in the net rice income per ha for both adopters and non-adopters of improved rice varieties.

11.4 Conditional expectations, treatment, and heterogeneity effects

The predicted values of household net rice income per ha are obtained from the FIML ESR results in Table 11.3. The predicted values are used to estimate both the average treatment effect on the treated (ATT) and average treatment effect on the untreated (ATU). The ATT estimates the difference in household net rice income per ha of adopters (in cell (a) of Table 11.4) and what their wellbeing would have been if they had not adopted (in cell (c) of Table 11.4) improved rice varieties. On the other hand, the ATU indicates the difference in net rice income per ha for non-adopters (in cell (b) of Table 11.4) and the counterfactual (in cell (d) of Table 11.4) had they adopted (Heckman *et al*., 2001; Di Falco *et al*., 2011). Please, refer to section 6.2 in Chapter 6 for a detailed discussion of the methodology of this section.

From Table 11.4, the observed net rice income per ha of the adopters of improved rice varieties (in cell (a)) was GH¢ 1032.641. On the other hand, the observed net rice income per ha of non-adopters of improved rice varieties (in cell (b)) was GH¢ 349.870. The observed difference in net rice income per ha between the adopters and non-adopters reveal that adopting households on average, obtained an additional net rice income per ha of GH¢ 682.771. However, Carter and Milon (2005) note that this comparison is inappropriate becuase it does not take into account unobserved factors that might have influenced net rice income per ha.

The treatment effect of adoption for the adopters, also known as the ATT (cell (a) minus cell (c) of Table 11.4) of improved rice varieties on household net rice income per ha was GH¢ 374.633. This means adopter households increased their net rice income per ha by 56.934%. Meanwhile, the treatment effect of the non-adopter households had they chosen to adopt (cell (d) minus cell (b) of Table 11.4) would have been GH¢ 867.458 per ha. This would have translated into a potential increase in net rice income per ha by 247.937% for the non-adopter households, had they decided to adopt improved rice varieties. This implies that both groups (adopters and non-adopters) stand to increase their net rice income per ha as adopters of improved rice varieties. A comparison of mean yield revealed that non-adopters had a lower yield of 1.31 tonnes/ha whereas adopters of improved rice varieties obtained a higher yield of 2.81tonnes/ha. Similarly, non-adopters had a lower cost of rice production per ha of GH¢ 472.15 in comparison with GH¢ 737.31 for the adopting households. The quantity of tradable input use partly reflects in the input cost. For instance, there was a marked difference in fertilizer application between adopters (289.86kg/ha) and non-adopters (82.33kg/ha).

Table 11.4: Average expected household net rice income per ha

Net rice income per ha (in GH¢)	Decision stage: To adopt	Decision stage: Not to adopt	Treatment effect	Treatment effect[51] in %
Adopter households	(a) 1032.641 (52.791)	(c) 658.008 (60.479)	374.633*** (25.465)	56.934
Non-adopter households	(d) 1217.328 (29.841)	(b) 349.870 (31.269)	867.458*** (43.440)	247.937
Heterogeneity effects	BH_1 = -184.687 (4.518)	BH_2 = 308.138 (5.120)	TH = -492.825 (0.479)	

***, **, indicate values statistically significant at 1%, and 5% respectively. Figures in brackets are the standard errors. BH and TH are base and transitional heterogeneity respectively. BH_1 is the difference in net rice income per ha in cells (a) and (d). BH_2 is the difference in net rice income per ha in cells (c) and (b). TH is the mean difference in treatment effect between the adopter and non-adopting households.

[51] This is calculated with respect to the “not to adopt” decision in each case.

Additionally, herbicide application by adopters (3.3 litres/ha) was almost double that of the non-adopters (1.82 litres/ha). Nonetheless, non-adopters had a higher seed planting rate (102.12kg/ha) whereas adopters had a lower rate (92.52kg/ha). In terms of growing farm saved seed, both adopters and non-adopters continuously planted the same rice varieties for more than four years. The average years of formal education attained by adopters (5.56) was slightly higher than that of the non-adopters (3.23) of improved rice varieties.

The heterogeneity effects accounts for unobserved factors in the net rice income per ha of adopters and non-adopters given their different structural characteristics (Carter and Milon, 2005; Di Falco *et al*., 2011; Asfaw *et al*., 2012). The heterogeneity effects also make it possible to assess the potential effects of adoption of improved rice varieties on net rice income from the counterfactual values in cells (c) and (d) of Table 11.4. The base heterogeneity of adoption (BH_1) in Table 11.4, defined as the mean difference in net rice income per ha between actual adopter households (in cell (a) of Table 11.4) and the counterfactual hypothetical adopters (in cell (d) of Table 11.4) was negative (-184.687). Therefore, by taking unobserved factors into consideration, the net rice income per ha of the actual adopters in the sample was likely to reduce by GH¢ 184.687.

Similarly, the base heterogeneity of non-adoption (BH_2) in Table 11.4, defined as the mean difference in household net rice income per ha between the actual non-adopters (in cell (b) of Table 11.4) and the counterfactual non-adopters (in cell (c) of Table 11.4) was 308.138. This means that even after accounting for unobserved factors, the adopters had they not cultivated improved rice varieties would have obtained GH¢ 308.138 more in net rice income per ha than the actual non-adopters in the sample. This implies the existence of systematic differences between the adopters and non-adopters of improved rice varieties for which the observed determinants of net rice income per ha could not fully account for.

The transitional heterogeneity (TH) effect in Table 11.4 of household net rice income per ha was negative (-492.825). This implies the effect of treatment (adoption of improved rice varieties) on net rice income per ha in Table 11.4 was larger for the non-adopting households resulting in a negative value for the transitional heterogeneity. The estimated treatment effects imply that both groups (adopters and non-adopters) as non-adopters would over-estimate the net rice income per ha.

11.5 Key findings and policy implications

The FIML ESR was applied to estimate the causal impact of adoption of improved rice varieties on household net rice income per ha. The *a priori* expectation of this study is that households that are aware of, and adopt, improved rice varieties are more likely to benefit from increased yield for own consumption as well as for sale to obtain cash income. Thus, this study assessed whether adoption translated into improved household welfare, after controlling for both observed and unobserved factors likely to influence adoption decision and its effect on household net rice income per ha.

The predicted values of household net rice income per ha from FIML ESR results in Table 11.4 were used to estimate the effect of treatment on the adopters and non-adopters as well as the counterfactual in each case. From the results in this chapter, adopters of improved rice varieties, increased their net rice income per ha by GH¢ 374.633 (a 56.934% rise in net rice income per ha).

However, the potential[52] gain in net rice income per ha to the non-adopters, had they decided to adopt improved rice varieties would have been GH¢ 867.458 (a 247.937% rise in net rice income per ha). This means that both groups (adopters and non-adopters) stand to increase their net rice income per ha as adopters of improved rice varieties. Thus, the cultivation of improved rice varieties led to an increase in household net rice income per ha, and for that matter, households are better off as adopters than as non-adopters of improved rice varieties in the study area.

From the empirical results in this chapter, adoption of improved rice varieties led to a higher household net rice income per ha. Adopters obtained a higher mean net rice income per ha compared with non-adopters, although the income effect would have been greater for the non-adopters had they adopted.

The positive outcome of adoption of improved rice varieties through a higher net rice income per ha implies an improvement in welfare for the adopter households in the study area. This study thus provides evidence to support the adoption of improved rice varieties as an effective strategy to raising household net rice income through increased rice yield and output. Results of the first objective of this study (in Chapter 9), indicate an above average adoption rate of 67.2% within the population of rice farmers who knew of the existence of improved rice varieties. This calls for the intensifying of dissemination efforts by agricultural extension officers, to encourage more rice farmers to adopt improved rice varieties, given its potential to improve household welfare in the study area. This is in line with government's goal of poverty alleviation through agriculture as outlined in the Food and Agriculture Sector Development Policy of the Ministry of Food and Agriculture in Ghana.

[52] The observed net rice income per ha for the non-adopters was GH¢ 349.870.

11.6 Conclusion

This chapter addressed the third objective of this study by analysing the effect of adoption of improved rice varieties on household net rice income per hectare using endogenous switching regression. Households were better off adopting than not adopting improved rice varieties. Generally, adopters increased their net rice income per ha by GH¢ 374.6 (a 56.9% rise). The potential gain in net rice income per ha to the non-adopters, if they had adopted would have been GH¢ 867.5 (a 247.9% rise). Therefore, the study has provided evidence that the adoption of improved rice varieties is an effective strategy to raising household net rice income and reducing poverty through increased rice yield.

CHAPTER TWELVE

DISCUSSION OF RESULTS FROM QUALITATIVE DATA

12.1 Introduction

This chapter addresses the fourth objective of this study, which identifies specific constraints to rice cultivation in the study area. In-depth interviews and focus group discussions are applied in assessing the importance of rice cultivation to farmers, rice varietal diffusion, access and adoption, farmers' perceptions of varietal traits, constraints to rice cultivation and how to ease these constraints. Nonetheless, due to time and resource constraints, the qualitative data collection was limited to two regions out of the eight regions that the secondary data covered.

The secondary data, mainly a quantitative survey collected in 2013, provided a broader picture of rice cultivation in Ghana. However, the qualitative data collected between January and February 2020 in the Upper East Region for the northern sector as well as the Volta Region representing southern Ghana is a recent follow-up and covers in more depth aspects of this research that are not contained in the quantitative analysis. For instance, the results will provide in detail the constraints to rice cultivation, farmers' perceptions of varietal traits and how to facilitate adoption. Secondly, the results of personal interviews with agricultural extension agents and improved seed suppliers will reveal any constraints regarding dissemination, and access to improved varieties from their perspective as stakeholders, and what measures need to be put in place to improve adoption rates as service providers to rice farmers.

12.2 Analysis of results from in-depth interviews and focus group discussions

Two focus group discussions involving both men and women were organized with rice farmers, each in the Volta Region and the Upper East Region (see map of study area in Figure 7.1). The Volta Region which produces about 34% of national output recently overtook the Northern Region as the largest rice producer in Ghana (Ragasa *et al.,* 2013). Nonetheless, northern Ghana comprising the Northern and Upper East Regions produce about 53% of the national output (MoFA, 2016).

Four in-depth personal interviews with rice farmers were conducted in each region, giving a total of eight for the two regions. Rice farmers who had been cultivating rice since 2012 up to the 2019 cropping year was the inclusion criterion for both the personal interviews and focus group discussions. Through the assistance of a community focal person, invitations were sent out to rice farming households who met this criterion, and those willing to participate in the focus group discussions were identified. Regarding the personal interviews, where farmers who met the inclusion criteria were more than the required number, simple random sampling through balloting[53] was employed to pick those to participate in the interviews.

[53] Balloting is where numbers are written on pieces of identical paper representing potential respondents and picked at random to select final respondents.

Based on time and resource constraints, four in-depth personal interviews were held with agricultural extension agents, two in each region. Where there were many agricultural extension agents in the district, random sampling through balloting was employed in choosing the respondents to be interviewed. Similarly, two improved seed suppliers/sellers, one in each region, respectively were interviewed. The Upper East Region and Volta Region are part of the eight sampled regions where the secondary data were collected. The interview guides for the farmers, agricultural extension agents and improved seed suppliers are contained in appendices A1 to A5.

Following Riessman (1993), the first step in the qualitative data processing involved a broad and an unfocused verbatim typing down of the recorded conversations without any analytic focus. Whilst listening to the recording, the transcript was checked for consistency, accuracy, and to get a good sense of what the text is about (Darlington and Scott, 2002). This was followed by a focused transcription that goes beyond just writing down what has been said (Gibson and Brown, 2009), to choosing and emphasizing what aspects are relevant to present and how to present them.

12.3 The importance of rice cultivation to farmers

The main reasons farmers cultivated rice were for household consumption and for sale to supplement household income. The following responses are excerpts from interviews with rice farmers on why they cultivated rice.

> Farmer 1: *In this part of the country [northern Ghana], we grow rice both to eat and sell. Rice is a major part of household's lunch. In comparison with other cereals, rice*

gives us a better and higher yield. For instance, the average yield of maize is 4-5bags per acre[54]*, whereas rice [paddy] is about 15 bags per acre. If you harvest the rice and sell, you would buy more maize for home consumption because rice also attracts a higher market price than maize.*

Farmer 2: *We cultivate rice to feed our families and also to sell to supplement family income.*

Farmer 4: *We grow for home consumption and also for sale to support family expenditure.*

The responses above reinforce the role of rice cultivation as a principal source of household income for semi-commercialised farmers who produce partly for sale to support family expenditure and partly for their own consumption. Nonetheless, rice is mainly a cash crop as much of the rice produced by the smallholder farmers in Ghana is sold. Descriptive statistics of the secondary data in Chapter 8 (in Table 8.2) revealed rice farmers in the study area sold an average of 6.55 tonnes whereas a tonne was reserved for household consumption. Rice is second to maize in Ghana as the most important staple crop with a growing domestic demand (MoFA, 2012, MiDA, 2010). Rice per capita consumption in Ghana increased from 24kg per annum to 32kg per annum between 2010 and 2015 (MoFA, 2011 and 2016). This underscores the importance of rice not only as a food security crop, but also as an economic crop given that Ghana spent in excess of USD 285 million in 2015 on rice importation with its effect on the country's foreign exchange (MoFA, 2016, Nutsugah *et al*., 2011).

[54] Although, plot sizes have been reported in hectares in the quantitative analysis, in Ghana, farmers usually state in acres which are then converted into hectares for analysis.

12.4 Rice varietal diffusion, varietal access, and varietal adoption

The sources of knowledge about improved rice varieties for farmers gained from the in-depth interviews were through the Government agricultural extension service and colleague farmers. This means farmers learn from each other and underscores the role of farmer colleagues in spreading improved rice varietal awareness. Although agricultural input suppliers are involved in the sale of improved rice varieties, they were not the most popular source of information or knowledge about the existence of improved rice varieties. Similarly, the national agricultural research institutes were not a very common source of exposure to improved rice varieties for farmers, despite their involvement in the breeding and release of new varieties. Meanwhile, community participation in rice projects implemented in partnership with agricultural extension agents and community agricultural input dealers positively influenced improved varietal exposure in the quantitative analysis in section 9.3.

Nonetheless, the efforts of the agricultural research institutes in breeding and releasing rice varieties were recognised during personal interviews with agricultural extension agents. In Ghana, the agricultural extension service and the national agricultural research institutes interface through the research extension liaison committees, RELCs (FASDEP, 2007; METASSIP, 2010). The RELCs is an intermediary between agricultural researchers and farmers through the agricultural extension service. The agricultural extension agents convey farmers' feedback of agricultural technologies to agricultural researchers and also disseminate information on new agricultural technologies from researchers to farmers.

As noted by Campbell (1966), the adoption of an agricultural technology is not instant, rather it evolves over time and is largely influenced by creating awareness and interest, followed by trial, evaluation and eventual adoption by the farmer. More importantly, Rogers (2003) described adoption as an individual farmer or household decision whereas diffusion is a collective occurrence or phenomenon within a given social system or community. Awareness creation can lead to greater exposure to improved rice varieties within rice farming communities and, subsequently, influence their adoption by rice farming households. Traditional training and the visit method of agricultural extension delivery can be augmented with other forms including the use of electronic media such as radio and television to increase coverage and effectiveness.

Personal interviews with agricultural extension agents (AEA) revealed the following about varietal diffusion, access and adoption over the years:

AEA 2: *I have worked over the years [with over 20yrs working experience] in the dissemination of earlier improved varieties such as GR18. However, with the introduction of higher yielding varieties in recent years, many farmers now cultivate these new varieties. For instance, jasmine 85 was introduced to farmers under JICA [with support from Japanese gov't] project.*

AEA 2: *For now, access to the improved rice varieties is not much of a problem. For instance, you can get AGRA rice seed to buy at the district agricultural office at 1kg for GH¢1. The improved rice variety is subsidised by the government under the planting for food and jobs programme.*

AEA 1: *Of late, the prominent rice varieties known by farmers are jasmine 85 and AGRA. These new varieties have been released to farmers by the Crops Research Institute (CRI) and Savannah Agricultural Research Institute (SARI). Access to improved rice varieties such as AGRA is easy, thanks to the planting for food and jobs* *programme. Improved rice varieties can easily be purchased from an agricultural input shop.*

The interviews with the agricultural extension agents revealed widespread access and availability of the improved rice varieties. For instance, improved varieties can easily be purchased from the district agricultural office or from an agricultural input shop. Indeed, a personal interview with an agricultural input supplier re-emphasised the widespread availability of subsidised improved rice varieties to support the government's planting for food and jobs programme. The following is what an input seller in Navrongo had to say about the access and sale of improved rice varieties in the Upper East Region:

Input seller: *Although many varieties have been introduced over the years, AGRA is currently in high demand. I do not face any challenges in obtaining AGRA as an improved seed seller. We have certified out-growers at ICOUR [state-owned irrigation site in the Upper East Region] who mass produce the seeds for us to sell to rice farmers. Input dealers from places such as Tamale also buy from ICOUR seed out-growers. I also get AGRA seeds from Ganorma agro-chemicals (a wholesaler in Tamale) which are subsidised under the planting for food and jobs programme.*

AEA 1: *With the support of Alliance for Green Revolution in Africa (an NGO) through SARI, we were able to organize a lot of field demonstrations for rice farmers on these new varieties. As we speak, a large number of certified seed producers are producing AGRA rice seeds to increase their access and adoption in support of the government backed planting for food and jobs programme.*

The AGRA variety is a lowland, early maturing (120 days) variety, resistant against yellow mottle virus disease, aromatic with good processing and cooking qualities and yield of 5.8-8mt/ha. The planting for food and jobs programme is a Government of Ghana policy intervention launched in April 2017 to increase the country's self-sufficiency in staple food crops to improve the national food security status and create jobs (MoFA, 2019). The programme is implemented by Ghana's Ministry of Food and Agriculture with offices across the regions and districts in the country.

12.5 Farmers' reasons for cultivating traditional rice varieties

Although farmers know the existence of some improved rice varieties released over the years, some farmers, especially in northern Ghana, still cultivate traditional varieties such as mandii, agona and Paul. The in-depth interviews with rice farmers in the Upper East Region [in northern Ghana] revealed the following about their continuous cultivation of local rice varieties:

Farmer 1: *I grow mandii because the rice processors who parboil prefer mandii. There is a high demand for mandii by rice consumers in the local market.*

Farmer 3: *Mandii is quite resistant to insect and pest infestation, particularly bird infestation. Birds infestations pose a serious threat to AGRA [an improved rice variety] leading to heavy yield losses.*

Farmer 4: *Mandii is mostly demanded by the rice processors who parboil and sell in the local market. Unlike AGRA variety [with 90 days' maturity] where they plant around June/July, mandii is planted around May. Between planting and harvesting of mandii, it takes 4-5 months. It is only around May that you can get* *a tractor to plough your rice field. Afterwards, it is difficult to get tractor services, because the distance to the rice field is very far.*

Farmer 1: *Mandii also gives a higher yield compared with other varieties.*

One of the reasons for the continuous cultivation of local rice varieties was to meet the demand of the local market through local aggregators and women who parboil, mill and sell in the local market. However, these localized demand does not attract any market price premiums and paddy prices are fairly the same across varieties in local markets. Farmers also cultivated mandii because of its longer maturity period (160-180 days) which is advantageous for purposes of early access to tractor ploughing services. Farmers also perceived mandii to be resistant to bird infestation unlike improved varieties such as jasmine 85 and AGRA which are prone to insect and bird attack. Another farmer indicated that mandii offered equally higher yield like other varieties. According to Ragasa *et al*. (2013), one of the reasons why farmers in northern Ghana cultivated mandii, as opposed to, improved rice varieties was their perception that, mandii offered them a comparatively higher yield. Indeed, a rice farmer with at least 20 years of experience in rice cultivation reported continuously cultivating mandii for over 5 years. Risk averse rice farmers have relied on these traditional varieties over the years because, yields are modest and certain without external inputs like fertilizer (Gyimah-Brempong *et al*., 2016).

12.6 Farmers' reasons for cultivating improved rice varieties

Notwithstanding, traditional varieties such as mandii had undesirable characteristics/traits that farmers did not like and dis-adopted mandii for an improved variety. The main reasons farmers switched from cultivating a traditional variety such as mandii and Paul to an improved rice variety such as AGRA were mainly because of higher yield and disease resistance. The following are the reasons farmers gave for choosing to cultivate improved rice varieties:

Farmer 3: *Mandii gives lower yield compared with AGRA.*

Farmer 5: *Unlike Paul [a traditional rice variety], the newer variety AGRA offered me a higher yield.*

Farmer 2: *During grain formation a disease infection sets in, which inhibits mandii grain formation leading to yield losses. Normally, I harvest 20 bags per acre, but I got 30 bags from the 4 acres of mandii due to the disease infection.*

The commonly reported diseases that affect rice plants in Ghana include rice smut, blast, brown spot, rust, African rice gall midge, and yellow mottle virus disease (Chipili *et al*.,2003; Kranjac-Berisavljevic' *et al*., 2003; Nutsugah *et al*., 2003 and 2005). Blast is caused by the fungus, *pyricularia gyseria* that infects both upland and lowland rice at different stages of growth and can cause heavy yield losses (Chipili *et al*.,2003). A traditional variety such as agona is very susceptible to blast disease whereas improved varieties such as jasmine 85, sikamo and Nerica 1-6 varieties are blast resistant (Nutsugah *et al*., 2005; Abebrese *et al*., 2019). Rice yellow mottle virus disease can be transmitted mechanically by several species of beetles particularly in lowland rice ecologies (Nutsugah *et al*., 2003). Improved varieties such as WITA and TOX and newly released variety AGRA are resistant against the rice yellow mottle virus disease (Nutsugah *et al*., 2003; AGRA bulletin, 2017). African rice gall midge is spread by larvae which creates a cavity on the leaf sheath and lodge in it, resulting in stunting of the rice plant, inhibiting tillering and panicles production (Nutsugah *et al*., 2003). Digang and NERICA are early maturing, drought-tolerant, high yielding, and non-aromatic varieties. The marshall variety is also resistant to rice blast disease, aromatic long grain, and has superior milling with low broken grains.

To encourage the cultivation of AGRA rice variety, some rice processing companies are resorting to out-growers to feed their factories through contract farming. A farmer revealed the following about contract farming during an interview:

Farmer 4: *AGRA is farmed by contract farmers in Wungu community who sell to Nasia Rice Processing Company. They first pay a registration fee of GH¢70 per acre. The company does not have its own tractors to provide ploughing services to farmers, although they provide the AGRA rice seed.*

Another privately owned rice processing company in northern Ghana aside Nasia rice processing company, is Avnash Company Limited with a main factory in Nyankpala in the Northern Region. Similar to Nasia rice, Avnash Company relies on out-grower farmers and paddy traders to feed its factory which has a milling capacity of 150,000mt per annum. Contract farming provides a ready market and acts as an incentive to boost domestic rice output. Nonetheless, contract farming enforcement can be undermined and lead to side-selling of harvested produce, where there is a high variation in output price between the contracting company and what is being offered in the open market (DFID, 2015).

Although AGRA rice is a high yielding and early maturing variety, manual threshing of it is considered very laborious. A farmer contracted to produce paddy for Nasia Rice Processing Company pointed out the following:

Farmer 4: *The company does not have its own tractors to provide ploughing services to farmers, although they provide the AGRA rice seed.*

This means that even though tractor ploughing for land preparation is the most common form of agricultural mechanization service in Ghana (MoFA, 2010), it does not form part of the contractual arrangement between the rice out-growers and the rice processing companies. Nonetheless, easy access to tractor services can facilitate timely land preparation and harvesting, and reduce the drudgery involved in rice cultivation. Manual harvesting is mostly done by men using sickles. This is what a farmer in the Upper East Region revealed about the cultivation of AGRA:

Farmer 5: *When you employ hired labour to manually thresh AGRA rice after harvesting, they [mostly done by women] complain it is difficult to thresh and requires more effort than jasmine 85. Some women [hired labour] will completely refuse to work if they get to the field and realize it is the AGRA variety.*

Threshing is usually done by hitting the paddy with sticks on bare floors where soil particles and pebbles get mixed up with the paddy (Kranjac-Berisavljevic' *et al*., 2003). This brings to the fore the challenge of employing manual labour as opposed to the mechanization of farm operations. Except for ploughing by tractor, the remaining cultivation practices including harvesting, threshing and winnowing are mostly done manually, using hired and family labour.

12.7 Application of recommended practices to support rice cultivation

After ploughing, the recommended practices promoted by the agricultural extension service are harrowing, seed priming, herbicide application, direct rice seed planting by drilling or dibbling recommended over broadcasting, transplanting, fertilizer application rate of 200–300kg/ha of NPK compound fertilizer and 150kg/ha of sulphate of ammonia or 75kg/ha of urea, bund construction, farrowing, puddling, or levelling. Indeed, a personal interview with an agricultural extension agent (AEA) re-emphasised the recommendations of the national agricultural extension service regarding these cultivation practices as follows:

AEA 1: *Now aside ploughing, we encourage farmers to harrow their rice fields before planting. We also recommend direct planting instead of seed broadcasting. Last two years, we did a field demonstration for rice farmers on direct rice seed planting with seed broadcasting as a control. The yield from both methods were compared after harvest, and the farmers realised that direct seed planting gave a higher yield than broadcasting.*

Following the recommendations of the agricultural extension service, farmers were asked during the in-depth interviews whether they performed other cultivation practices aside tractor ploughing for land preparation. The following are excerpts from the interviews on application of these cultivation practices by rice farmers:

Farmer 1: *After ploughing, I do direct sowing using a hand hoe, and later transplant. I continuously weed and after a few weeks, we uproot the weeds by hand regularly. I do not apply fertilizer. [A farmer who cultivated traditional varieties, agona and mandii]*

Farmer 2: *I practice direct sowing through dibbling and later transplant over-crowded seedlings on portions of the field. I do not apply fertilizer. I obtain my seeds for next season's planting from the harvest. [A farmer who cultivated traditional variety, mandii]*

Farmer 4: I *broadcast just after ploughing and use sticks to spread thin soil on the seeds to enable germination [for AGRA rice variety]. I do not apply fertilizer, but spray* *and uproot weeds from the rice field and sometimes too, we do construct bunds to manage field water levels. [A farmer who cultivated improved variety, AGRA and traditional variety, mandii]*

Farmer 5: *Normally, I transplant the rice seedlings after broadcasting when the seedlings are crowded. When the rice plants are crowded, they do not develop bigger branches which affect yield negatively. However, when you space at the recommended planting density, the panicles stretch out and the yield is good. I also apply a bag of sulphate of ammonia and two bags of NPK compound fertilizer per acre**.** [A farmer who cultivated traditional variety, mandii and improved varieties, AGRA and jasmine 85]*

The interview responses above do not indicate complete adoption of the recommended complementary practices. Rather, rice farmers chose what practices to perform after land preparation. Although, harrowing is the recommended practice after tractor ploughing, none of the interviewed farmers reported harrowing their rice fields. The agricultural extension service encourages rice farmers to harrow their fields as part of the land preparation process as contained in this extract:

AEA 1: *Now, aside ploughing, we encourage farmers to harrow their rice fields before planting. We also recommend direct planting instead of seed broadcasting.*

Another cultivation practice not carried out by farmers is seed priming, although field trials by the Crops Research Institute indicates seed priming could boost yield by 25% to 40% (Ragasa *et al.,* 2013). Seed priming involves soaking rice seeds in water for 12–24 hours and drying them in the open for a day or two before sowing (Abdulai *et al*., 2018). Direct sowing and transplanting which are recommended [by agricultural extension agents] over seed broadcasting for efficient use of seed and optimum plant density (Buah *et al*., 2011; Abdulai *et al*., 2018) are increasingly being practised by farmers. Although not a regular practice, farmers construct bunds to allow the flow of excess water in lowland rice fields as a water management strategy. Studies such as Bam *et al*. (2010) reported improved yield from field trials where water control strategies such as bund construction was carried out. Surprisingly, during the interviews, some farmers did not apply fertilizer on their rice fields despite the existence of a fertilizer subsidy programme over the last decade. For instance, a farmer who cultivated traditional varieties, mandii and agona had this to say about fertilizer application:

Farmer 1: *For my rice field, I do not apply fertilizer because the field is fertile. From experience, once the rice field has adequate water, even without fertilizer, the rice plants will be fine. [A farmer who cultivated traditional varieties, mandii and agona]*

Farmer 4: *If the water level of the rice field is just right, and you weed properly, even without fertilizer, I got 23 bags from just an acre. [A farmer who cultivated improved variety AGRA, and traditional variety, mandii]*

The responses above reveal the importance farmers attached to availability of water in the rice field, beside weeding, particularly for rain-fed lowland ecologies, where drought poses a major challenge. Meanwhile, a farmer who won the district best farmer award on two occasions revealed the following about fertilizer application for rice:

Farmer 5: *For AGRA variety, I apply a bag (50kg) of ammonia and 2 bags of NPK compound fertilizer. For urea, the 50kg bag contains 46% nitrogen, so I apply 50kg on 2 acres. It is important to gauge the moisture level of the rice field when applying urea because it absorbs a lot of water. A 50kg bag of NPK contains 21% nitrogen. Over application of nitrogen leads to vegetation growth of the rice plant and not* *necessarily increased yield. [A farmer who cultivated improved varieties, AGRA and Jasmine 85 and traditional variety, Paul]*

A major reason for the partial application of the complementary cultivation practices is the labour levels involved in carrying out these practices. Recommended practices, such as direct sowing, transplanting, fertilizer application and weeding are very labour-intensive and expensive, especially for hired labour. An interview with an agricultural extension agent highlighted the labour challenges of these cultural practices as follows:

AEA 1: *Farmers who cultivate on a large scale complain that direct seed planting is very labour intensive and expensive to carry out. Currently, we are collaborating with a company to design cheaper planters to reduce the drudgery involved in direct seed planting.*

This reinforces the high labour intensity in rice cultivation in Ghana which averaged at 125 person-days/ha relative to 80 person-days/ha in Senegal (DFID, 2015). Indeed, the quantitative aspect of this study (see Table 8.2) found an even higher mean labour quantity of 149 person-days/ha in rice cultivation. Ragasa *et al* (2013) identified labour constraint as the reason why majority of rice farmers did not practice seed priming, transplanting and row planting, although they are recommending cultural practices in Ghana. Similarly, a study by Nin-Pratt and McBride (2014) identified high labour costs as a constraint to the adoption of labour-intensive cultivation practices in Ghana. Against this backdrop, and in line with the planting for food and jobs programme, the Ministry of Food and Agriculture in Ghana is facilitating the importation and distribution of small hand-held machinery and equipment to small holder farmers (MoFA, 2019).

12.8 Constraints to rice cultivation identified by farmers

The main constraints to rice cultivation identified during the farmer interviews were weed infestation, diseases, incidence of birds eating grains on rice fields, intermittent flash flooding, and drought. Although many rice farmers sprayed herbicide as part of the land preparation process before tractor ploughing, manual weeding using hand hoe and uprooting of weeds by hand were also common practices as indicated below:

Farmer 1: *Our main challenge is weed infestation. We continuously weed and after a few weeks, we uproot the weeds by hand regularly. However, when there is enough water in the field, the weeds are inundated and do not get enough sunlight, hence they die. [A farmer who cultivated traditional varieties, mandii and agona]*

Farmer 4: *I spray herbicide and uproot weeds on my rice field. [A farmer who cultivated improved variety AGRA, and traditional variety, mandii]*

Weeds commonly found in rice fields include *Rottboellia cochinchinensis*, *Oryza barthii, Andropogon gayanus, Ageratum conyzoides, Vetiveria spp., Pennisetum spp*., *Cyperus rotundus, Cynodon dactylon*, *Imperata cylindrica, Chromolaena odorata* and *Panicum spp*. For instance, Akobundu (1987) reported that *Rottboellia cochinchinensis* weed competes heavily against rice plants in lowland ecologies in northern Ghana. Another weed with very close resemblance to rice plants and serves as host for fungal pathogen is *Oryza barthii*. It is also difficult to control by spraying herbicide selective to rice (Akobundu, 1987). Weed infestation is common in both improved and traditional rice varieties. Although not explicitly linked to adoption decisions, the quantitative analysis revealed that 72.4% of adopter plots were weeded more than once whereas 49.7% of non-adopter plots were weeded only once within the cultivation season. Moreover, in section 10.5, adopters who applied herbicide on their rice plots were more technically efficient than those that practised manual weed control using hand hoes.

There is a growing application of herbicide as a substitute and or complement to manual weeding in Ghana (Ragasa *et al.*, 2013). Results of the descriptive analyses in Chapter 8 (Table 8.2) revealed rice farmers applied about 2 litres per hectare of herbicide and weeded their rice plots at least two times within the cultivation season. More so, herbicide application is cheaper relative to hiring labour to undertake manual weeding due to the high daily wage of hired labor (Nin-Pratt and McBride, 2014). The application of herbicide is one of the recommended complementary practices (Ragasa *et al.*, 2013; Abdulai *et al.*, 2018). An agricultural extension agent shared his experience on farmers' application of herbicide in the following extract:

AEA 1: *Mostly farmers who cultivate on a large scale apply herbicide before germination just immediately after planting. They usually apply two classes of selective herbicide, namely broad-leafed herbicide and grass leafed herbicide as strategy to control weeds. However, there are public health concerns regarding herbicide application as many of these farmers do not wear protective gear during spraying.*

However, some farmers were still skeptical about herbicide application. For instance, a farmer who cultivated traditional varieties had this reservation about herbicide application:

Farmer 1: *I do not recommend herbicide application because spraying when the rice is grown may kill the weeds, but then it is also likely to cause wilting and yellowing of the rice plants which in turn affects its growth and yield. [A farmer who cultivated traditional varieties, mandii and agona]*

Closely related to weed infestation is the incidence of disease occurrence especially the traditional rice varieties. For instance, a farmer gave the following reason for cultivating AGRA, an improved variety over mandii, a traditional variety:

> Farmer 2: *During grain formation a disease infection sets in, which inhibits mandii grain formation leading to yield losses.*

AGRA is resistant against rice yellow mottle virus disease, that is transmitted by beetles particularly in lowland rice ecologies (Nutsugah *et al*., 2003; AGRA bulletin, 2017).

Another constraint mentioned by farmers and of particular concern for lowland rice fields is flash flooding which inundated many rice fields in the 2019 cropping season leading to total crop failure for some farmers. Rice should not be submerged for more than 48 hours (Windmeijer and Andriesse, 1993). This is what a lowland rain-fed rice farmer in the northern part of Ghana revealed about flooding of his rice field:

Farmer 3: *The main challenge is intermittent flash flooding of the rice field. My rice field was inundated with flood water for about 2 months (66 days). I got nothing from that field last year. [A farmer who cultivated traditional variety, mandii]*

Nonetheless, improved rice varieties such as WITA 4 Sub1 and NERICA L-19 Sub1 are flood resistant varieties (AfricaRice Centre, 2007; Macauley, 2015). At the other extreme is drought, where the rain ceased in the middle of the unimodal growing season around the Fumbisi valley area [in northern Ghana] which severely affected rice yield. A farmer revealed the following:

Farmer/Input seller: *The main challenge is the unpredictable rainfall pattern which affects yield. For instance, this year the rain halted just in the middle of the season at a time that farmers had applied fertilizer and badly needed rainfall. [This input seller also farmed AGRA rice variety at the Fumbisi valley]*

Drought-tolerant improved rice varieties include NERICA 1 and 2, Digang, and GR 22. The presence of irrigation schemes across rice growing communities can reduce the total reliance on rainfall and mitigate the effects of prolonged drought during the cultivation season. Ghana's irrigation potential is untapped with just 3.4% of cultivable land under irrigation (Osei-Asare, 2010; MoFA, 2016). The main schemes that support rice cultivation are Tono and Vea irrigation schemes in the Upper East Region, Bontanga and Golinga irrigation schemes in Northern Region, Kpong, and Afife irrigation schemes in Greater Accra Region (CARD, 2010).

Bird infestation remains a major constraint to rice cultivation across the country. The birds attack the rice plants during the grain filling, ripening and drying stages. The birds first suck the 'whitish glucose syrup' that forms in the process of grain filling. The second attack by birds which is independent of the grain filling stage, is when the birds eat the rice grains during the ripening and drying stage. The incidence of bird infestation was widely acknowledged by both rice farmers and agricultural extension agents during the interviews as follows:

Farmer 5: *Another challenge this season [2019/20] is the high incidence of birds eating the rice plants during the grain filling, ripening and drying stages. The birds suck the milk [glucose] syrup out of the rice husk. This denies grain formation leading* *to empty rice husks with no grain. [A farmer who cultivated improved varieties, AGRA and jasmine 85 and traditional variety, Paul]*

Farmer 4: *Our main challenge is bird infestation during the ripening and drying stage just before harvesting. AGRA and jasmine 85 are 3-month early maturing varieties. When planted early in the season, they mature early and that predisposes these varieties to bird infestation. [A farmer who cultivated improved variety, AGRA and traditional variety, mandii]*

AEA 1: *A major challenge facing rice farmers is the incidence of bird infestation. The birds eat the rice grains during ripening and drying.*

AEA 2: *Another challenge for rice farmers is the incidence of birds eating the grains during the ripening and drying stage.*

The responses above further articulated the views of 395 (about 68%) rice farming households from the secondary data who mentioned bird infestation posed a serious challenge in rice cultivation (See Figure 8.8 in Chapter 8).

One of the reasons some farmers did not cultivate recommended varieties such as AGRA and jasmine 85 is that they are early maturing varieties which predisposes them to bird infestation. Bird infestation can be minimized by bird scaring and speedy harvesting using combine harvesters. In addition, these improved varieties are yet to command an appreciable level of local market share unlike a traditional variety such as mandii. Indeed, a farmer cited the reason for cultivating mandii as:

Farmer 1: *Mandii is mostly demanded by the rice processors [mostly women] who parboil and sell in the local market*.

Nonetheless, urban consumption of locally produced rice is about 20% of total national production as it is unable to substitute and compete with imported rice (Angelucci *et al*., 2013). Meanwhile, an interview with an agricultural extension agent [AEA 2] revealed improper parboiling of jasmine 85 by rice processors who sell at the local market is to blame for the low market share of jasmine 85.

AEA 2: *Jasmine 85 is yet to receive the needed market share in the local market due to improper parboiling by local rice processors. Mostly, they add plenty of water when parboiling and leave it unattended, thereby over-boiling and soaking the rice in water. The rice gets sticky when cooked by the final consumer and they complain to the rice processors.*

Given that the bulk of domestic rice is parboiled, milled and sold by women in local markets and rarely in supermarket shops, there is the need to train local processors on the correct parboiling of jasmine 85 to increase its consumption in the local market. The parboiling process begins with soaking paddy in water for a day and followed by steaming in a cauldron (Dandedjrohoun *et al*., 2012). made of a single piece of equipment. For instance, an improved parboiling method is being promoted in Benin where paddy is placed in a holding vat with perforated holes at its base and above the cauldron (Houssou and Amonsou, 2004). This prevents over-boiling and soaking of the paddy because only the steam generated from the boiling water in the cauldron passes through the perforated vat to parboil the paddy.

Unlike other improved rice varieties, jasmine 85 is aromatic, long grain, and tastes good. These attributes of jasmine 85 are the same as imported rice which has a high demand amongst urban rice consumers for its aroma, long grain and good taste when cooked (Tomlins *et al*., 2005; Diako *et al*., 2010). Nonetheless, post-harvest processing of jasmine 85 by community micro-processors does not meet the marketable standard (brownish, unpolished with pebbles found in it) to compete with imported polished rice. Large scale rice processing companies can take up the task of processing jasmine to imported rice standard and make it a good substitute for imported rice amongst urban consumers.

12.9 How to ease the constraints to dissemination and adoption of improved rice varieties

The in-depth interviews revealed about 70% of rice farmers had knowledge about the existence of improved rice varieties. However, having knowledge about improved rice varieties does not imply automatic cultivation of these varieties by farmers. Admittedly this challenge was mentioned by an agricultural extension agent during a personal interview as follows:

AEA 2: *The challenge is more education to convince rice farmers to adopt them [improved varieties] over the old traditional varieties.*

The main form of agricultural extension delivery has been training and visit. Nonetheless, training and visit alone may not be able to produce the desired impact of reaching many farmers at the same time and stimulate adoption of improved rice varieties. Therefore, combining training and visit with targeted extension messages highlighting the superiority of the improved varieties over the traditional varieties via mass communication tools such as radio, television, information vans and posters can speed up and increase the adoption of improve rice varieties.

Moreover, under the government of Ghana planting for food and jobs programme that begun in 2017, there have been conscious governmental efforts to increase the available quantity of improved rice varieties through the involvement of certified seed growers (MoFA, 2019).

Indeed, in-depth interviews with two government agricultural extension agents corroborated the production of certified AGRA rice seeds by locally trained farmers as follows:

AEA 1: *We have trained local farmers in selected villages to produce certified AGRA seeds to serve the needs of their colleague farmers in their localities.*

AEA 2: *The improved rice variety [AGRA] is subsidised by the planting for food and jobs programme and you can get it to buy at the district agricultural office at 1kg for GH¢1.*

Furthermore, the government has extended the subsidy on fertilizer to cover the planting seed of improved rice varieties. Although the subsidized price of 1kg for GH¢1[55] is a giveaway price, another agricultural extension agent proposed the distribution of the improved rice varieties free of charge to farmers [including laggards] to try out and make an adoption decision afterwards.

AEA 1: *I will recommend that the improved rice varieties are supplied free of charge to all rice farmers to cultivate them. In this way, all farmers have the opportunity to try them and can subsequently adopt them. Laggards who select planting seeds from harvest and will be unwilling to buy improved varieties can then have access to the seeds to cultivate.*

Growing farm saved seed [a practice whereby farmers select planting seeds for the next season from their own harvest] was carried out by both adopters and non-adopters of improved rice varieties as revealed in the following excerpt:

Farmer 5: *For about 4 years now, I have been cultivating AGRA. [an improved variety]*

Farmer 2: *I have been growing Mandii for about 5 years. [a traditional variety]*

[55] GH¢1= £ 0.14 as at February 2020.

The responses regarding the planting of farm saved seed from the in-depth interviews confirms the descriptive results from the secondary data (in Table 8.2) where adopters and non-adopters of improved rice varieties continuously cultivated farmer saved seed for about 4 years and 5 years respectively. Notwithstanding, the recommended practice is for farmers to obtain new and pure certified seeds for planting every season. This recommendation was reiterated in an interview with an agricultural extension agent as follows:

AEA 1: *Although farmers can select planting seeds from own harvest, we urge farmers to buy new AGRA seeds for planting every season to maintain the genetic purity and vigour of the seeds for improved yield.*

In order to control the incidence of birds eating the rice grains during the ripening and drying stage, farmers employed various measures including bird scaring, chemical application and hiring of combine harvesters to speed up harvesting. This is how a farmer described the application of chemicals to control birds on his rice field:

Farmer 5: *To control the birds, I applied paradoxone and the birds died. The chemical drags the birds to the ground and they die. [A farmer who cultivated improved varieties, AGRA and Jasmine 85 and traditional variety, Paul]*

Unlike the application of chemicals to kill the birds, bird scaring and use of combine harvesters were common practices. Hiring of a combine harvester comes at a cost [GH¢ 250 or 3 bags of harvested paddy per acre] that smallholder rice farmers have to consider as intimated by an agricultural extension agent in the following excerpt:

AEA 1: *The incidence of bird infestation can be mitigated with easy access to combine harvesters to speed up harvesting. The combine harvester charges GH¢ 250 or 3 bags of harvest per acre.*

The combine harvester is able to perform harvesting, threshing and winnowing all at the same time, unlike manual harvesting where these are separate activities done at different periods. In the case of manual threshing following manual harvesting, the recommendation is to cover the floor before threshing the paddy to avoid mixing with soil particles and pebbles and to increase its marketing appeal. An agricultural extension agent recommended the following:

AEA 2: *We also urge farmers to place the harvested rice on a covered floor before threshing to eliminate the incidence of stone particles in the threshed rice.*

Threshing on bare floors produces low-grade rice mixed up with soil particles and pebbles (Kranjac-Berisavljevic' *et al*., 2003).

Employing tractors in land preparation reduces production inefficiency through timely land preparation and planting (Abdulai, Donkoh and Nkegbe, 2018). Accessing tractor services is a major challenge in the Northern Region of Ghana, where farmers experience up to three weeks' delay in accessing ploughing services at the beginning of the cultivation season because tractor owners could not attend to all farmers at the same time (Nakamura, 2013). To mitigate the challenges in accessing tractor services, an agricultural extension agent suggested the following during an interview:

AEA 2: *In order to reduce delays in access to tractor services, efforts should be geared towards the availability of cheaper medium horse-power power tillers to mitigate the effect of late ploughing and planting due to the inability of few tractors trying to serve all farmers almost at the same time.*

Similarly, Ghana's Ministry of Food and Agriculture has acknowledged the difficulty of farmers in accessing tractor services and is facilitating the importation and distribution of agricultural machinery and equipment such as power tillers and rotovators to smallholder farmers (MoFA, 2019).

12.10 Key findings and policy implications

This chapter discussed the application of in-depth interviews and focus group discussions to assess the importance of rice cultivation to farmers, rice varietal diffusion, access and adoption, farmers' perceptions of varietal traits, constraints to rice cultivation and how to ease these constraints. They together address the fourth objective of this study that seeks to identify the specific constraints to rice cultivation in the study area.

Rice farmers are semi-commercialised producing for sale and own consumption. This finding supports the quantitative analysis where households sold 6.55mt and reserved a tonne for own consumption. The sources of knowledge about improved rice varieties and varietal diffusion for farmers from the in-depth interviews were through the government agricultural extension service and colleague farmers. Interviews with agricultural extension agents and agricultural input dealers revealed widespread access and availability of subsidised improved rice varieties in support of the government's planting for food and jobs programme. Improved rice varieties such as jasmine 85 and AGRA could easily be purchased from the district agricultural office or from an agricultural input shop.

Farmers cultivated improved rice varieties because of higher yield and disease resistance, although manual threshing of AGRA is considered difficult. A traditional variety such as agona is prone to blast disease whereas improved varieties such as jasmine 85, sikamo and Nerica 1-6 varieties are blast resistant. Jasmine 85 is yet to gain ground in the local market due to improper parboiling by local rice processors. There is the need to train local processors on the correct parboiling of jasmine 85 to increase its consumption in the local market. Other improved varieties such as WITA, TOX and AGRA are resistant against rice yellow mottle virus disease. Nonetheless, some farmers continued to cultivate mandii, a traditional rice variety because of its high demand by local rice processors who parboil and sell in the local market, perceived resistance to bird infestation due to longer maturity period and higher yield.

Although many farmers were aware about the existence of improved rice varieties, some farmers still cultivated improved rice varieties. Awareness creation can lead to greater exposure to improved rice varieties within rice farming communities and subsequently influence their adoption by rice farming households. Traditional training and visit method of agricultural extension delivery can be augmented with other forms including the use of electronic media such as radio and television to increase coverage and effectiveness.

Labour constraints was a major reason why rice farmers could not carry out all the recommended complementary cultivation practices. Easy access to tractors and combine harvesters can facilitate timely land preparation, harrowing, direct seed planting, fertilizer application, weeding, harvesting, etc and reduce the drudgery involved in rice cultivation. To mitigate the challenges in accessing tractor services, Ghana's Ministry of Food and Agriculture is facilitating the importation and distribution of agricultural machinery and equipment such as power tillers and rotovators to smallholder farmers (MoFA, 2019). Other government interventions such as the Agricultural Mechanization Services Enterprise Centres (AMSECs) designed to expand access to agricultural mechanization services is in the right direction. Although the number of AMSECs across the country increased to from 92 to 168 between 2011 and 2019, more still needs to be done to expand access to cover many locations (Benin, *et al.*, 2011; MoFA, 2019). The government under the national agriculture investment plan intends to expand the number of centres to 290 by 2022.

The other constraints to rice cultivation identified were weed infestation, incidence of birds eating grains on rice fields, intermittent flash flooding, and drought. Herbicides are increasingly being applied to control weeds in Ghana. Nonetheless, there are safety concerns regarding herbicide application as many farmers do not wear protective gear during spraying. Improved rice varieties such as WITA 4 Sub1 and NERICA L-19 Sub1 are flood resistant varieties.

Ghana has comparative advantage in rice production (Asuming-Brempong, 1998) and together with good post-harvest processing and milling quality, domestic rice can compete favourably with imported rice in terms of appearance and taste (Diakité *et al*., 2012; DFID, 2015). The per capita consumption of rice in Ghana continues to increase annually (MoFA, 2011 & 2016) and in order to boost domestic production, some studies (Winter-Nelson and Aggrey-Fynn, 2008; Akramov and Malek, 2012) have favoured the imposition of tariffs on imported rice. The National Rice Development Strategy (MoFA, 2009) aims to double domestic rice output by working closely with farmers to tackle constraints regarding to access to improved rice seed varieties, fertilizer, agricultural mechanization services as well as promoting agricultural research and technology dissemination. Under the Government of Ghana planting for food and jobs programme that begun in 2017, there have been conscious governmental efforts to increase the available quantity of improved rice varieties through the involvement of certified seed growers. The government has extended the subsidy on fertilizer[56] to cover the planting seed of improved rice varieties to eliminate the planting of

[56] The fertilizer subsidy covers 20-22.6% of the total cost per bag of 50kg (MoFA, 2016).

farmer saved seed because the recommended practice is for farmers to obtain new and pure certified seeds for planting every season.

12.11 Conclusions

This chapter applied in-depth interviews and focus group discussions to assess the importance of rice cultivation to farmers, rice varietal diffusion, access and adoption, farmers' perceptions of varietal traits, constraints to rice cultivation and how to ease these constraints. The main sources of knowledge about improved rice varieties were through the agricultural extension service and colleague farmers. Interviews with agricultural extension agents and agricultural input dealers indicated the availability of government subsidised improved rice varieties such as jasmine 85 and AGRA for farmers to purchase.

The government is also encouraging trained seed growers to expand production of certified improved rice varieties. Farmers mainly cultivated improved rice varieties because of higher yield and disease resistance. Nonetheless, traditional rice varieties were still cultivated because of their demand in the local market, longer maturity period, perceived resistance to bird infestation and higher yield. Local market demand for jasmine 85 is low because of improper parboiling by local rice processors. Training local processors on the correct parboiling of jasmine 85 can increase its consumption in local markets. Relative to rice cultivation activities, labour constraint was a reason why rice farmers could not carry out all of the recommended complementary practices such as direct seed planting, transplanting, fertilizer application, weeding, and bund construction to manage water levels in lowland rice fields. Nonetheless, in order to mitigate the labour-intensity of rice cultivation, the government of Ghana is facilitating the importation and access to agricultural machinery and equipment such as tractors, power tillers, rotovators and combined harvesters to small holder farmers. Other constraints to rice cultivation were weed infestation, incidence of birds eating grains during the ripening and drying stage on rice fields, intermittent flash flooding and drought.

CHAPTER THIRTEEN

GENERAL CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE STUDY

13.1 Introduction

This final chapter gives a summary of the study findings from the results and discussion chapters. It also presents the conclusions and recommendations emerging from the chapters as well as recommendations for future research.

13.2 Comparison of quantitative and qualitative results

Rice cultivation is a source of household income for farmers. Results of the interviews with farmers revealed that rice was cultivated mainly for sale and for household consumption. This supports the descriptive results [in section 8.3] from the quantitative data where the mean proportion of rice sold was 1.98 tonnes/ha for adopter households and 0.90 tonnes/ha for non-adopters of improved rice varieties. Translating into net rice income, it means households were better off as adopters than as non-adopters of improved rice varieties. Similarly, the mean proportion of rice consumed was slightly higher amongst adopters (0.41 tonnes/ha) than the non-adopter households (0.21 tonnes/ha).

Farmer awareness about improved rice varieties were enhanced by community participation in rice projects [involving agricultural extension agents] and agricultural input dealers in communities. However, the personal interviews identified agricultural extension agents and colleague farmers as sources of knowledge about improved rice varieties. Meanwhile, the results in section 9.3 revealed adoption under incomplete exposure under-estimated the adoption rate as 55.9%, producing a non-exposure bias of 11.3%. The exposure rate and adoption rate of improved rice varieties were 82.5% and 67.2%.

Regarding the application of recommended cultivation practices, farmers were selective in what they applied on their rice fields after ploughing. During the interviews, farmers attributed the partial application of the recommended cultivation practices to labour constraint and cost. Rice cultivation is labour intensive because most of the cultivation practices, harvesting and post-harvest activities are performed manually using both hired and family labour. The high labour intensity was reinforced by the findings from the quantitative data, where the average labour used in rice cultivation were 167 person-days/ha and 160 person-days/ha respectively for non-adopters and adopters of improved rice varieties. The in-depth interviews revealed herbicide application was one of the strategies rice farmers adopted in mitigating labour constraints. Manual weeding using hand-held hoes was increasingly being substituted with herbicide application including land clearing before ploughing. Adopters of improved rice varieties had a higher herbicide application rate of 3.3litres/ha compared with 1.8 litres/ha for non-adopters.

Although discouraged, planting farmer saved seed was widely practised by both adopters and non-adopters of improved rice varieties. Responses from the in-depth interviews confirmed rice farmers continuously cultivated the same variety for at least 4 years. Likewise, descriptive results (in Table 8.2) from the quantitative data indicated adopters and non-adopters of improved rice varieties grew farmer saved seed for 4 and 5 years respectively. Direct sowing was mostly by broadcasting, albeit few rice farmers practiced the recommended row dibbling from both the quantitative and qualitative results. Broadcasting is inefficient in rice seed use and does not produce optimum plant density. Fertilizer application rate was lower amongst non-adopters (82.3kg/ha) compared with the adopters (218.3kg/ha) of improved rice varieties. The in-depth interviews also revealed low fertilizer application rates contrary to the recommended rate of at least 350kg/ha.

Lastly, bird infestation was widely acknowledged by rice farmers and agricultural extension agents during the qualitative interviews, as a major challenge to rice cultivation during grain filling, ripening and drying stages before harvesting. Moreover, Figure 8.8 revealed that over 68% of households reported bird infestation on their rice fields.

13.3 Brief discussion and summary of research findings

This study assessed smallholder farmers' exposure to improved rice varieties and the effect of adoption of improved rice varieties on output, technical efficiency, and household net rice income as well as the constraints to rice cultivation.

Chapter 9 addressed the first objective of this study by the identifying the factors that influenced adoption of improved rice varieties. First, exposure to improved rice varieties was estimated using a probit model, followed by determinants of adoption of improved rice varieties using the method of treatment effect. Adoption under incomplete exposure under-estimated the adoption rate as 55.9%, giving a non-exposure bias of 11.3%. The exposure rate and adoption rate of improved rice varieties were 83.3% and 67.2% respectively. This adoption rate is higher than the 37% adoption rate for Nerica rice varieties in neighbouring Ivory Coast (Diagne and Dermont, 2007). Awareness about the improved rice varieties were enhanced by community participation in rice projects implemented by government and non-government organizations and the presence of agricultural input shops in communities.

Adoption was positively influenced by community participation in rice projects, household participating as a model farming unit for improved rice varieties, participation in block farming, agricultural extension, seeking higher rice yield, and cultivating irrigated rice. Farm size and growing farmer saved seed had negative effect on adoption.

The second objective analysed the effect of adoption of improved rice varieties on farmers' output and technical inefficiency using the stochastic production frontier with correction for selectivity bias and a metafrontier. Regarding the adopters of improved rice varieties; farm size, quantity of rice seed planted, quantity of fertilizer applied, farm labour, and herbicide application increased rice output. Farm size and seed; farm size and fertilizer; seed and herbicide; fertilizer and labour; labour and herbicide were complementary inputs that increased the rice output of adopters. Relative to the non-adopters, farm size and fertilizer had positive effect on rice output. These findings are consistent with Mabe, Donkoh, and Al-Hassan (2018) who found farm size, seed, fertilizer, and labour had positive effect on the rice output of farmers across the guinea savannah, forest and coastal zones of Ghana.

The mean group technical efficiency estimates were 47% and 52% respectively for adopters and non-adopters of improved rice varieties. The mean difference in metafrontier technical efficiency of adopters (42.7%) and non-adopters (44.5%) were statistically not significant, although adopters had a higher metatechnology ratio of 0.909 compared with 0.785 for non-adopters. This implies adopters operated closer to the metafrontier output whereas non-adopters were behind in applying the best available technology for all rice farmers. Villano *et al*. (2015) found adopters had a higher metafrontier technical efficiency of 61% and metatechnology ratio of 0.90 than non-adopters of certified rice seeds with 37% and 0.54 respectively. Mabe, Donkoh, and Al-Hassan (2018) reported mean metatechnology ratios of 0.926, 0.911 and 0.844 for farmers in the guinea savannah, forest and coastal zones in Ghana respectively. The corresponding mean technical efficiency scores were 82.2%, 83.6%, 89.1% in the in the guinea savannah, forest and coastal zones. However, Asravor *et al*. (2020) found a sharp difference in mean metatechnology ratio between Ghanaian rice farmers in the forest zone (0.95) and those in the guinea savannah zone (0.50) whereas the mean metafrontier technical efficiency estimates were 50% and 42% respectively in the forest and guinea savannah zones.

Agricultural extension access, controlling plot water levels and weeding twice using herbicides increased the technical efficiency of adopters. Amongst the adopters, males were more technically efficient than their female colleagues. Applying ammonia fertilizer and weeding increased the technical efficiency of non-adopters. Owusu (2020) found males were technically efficient than females in Northern Ghana under both rain-fed and irrigated rice cultivation systems. Mabe *et al*. (2018) found rice farmers in the forest zone of Ghana who had access to agricultural extension services to be technically efficient than those without access.

The third objective analysed the effect of adoption of improved rice varieties on household net rice income per hectare using endogenous switching regression. Adopters of improved rice varieties increased their net rice income per ha by GH¢374.6 (a 56.9% rise). However, the potential gain in net rice income per ha to the non-adopters, had they adopted would have increased by GH¢867.5 (a 247.9% rise). Thus, households were better off as adopting improved rice varieties as a way of raising their incomes and reducing poverty. This is finding is similar to Tambo and Wünscher (2014) who found households that adopted agricultural innovation in the Upper East of Region of Ghana increased their farm income by 11% whereas the potential again for the non-adopters would have been 51%. Meanwhile, Zakaria *et al*. (2020) reported profits of GH¢2442.30 and GH¢576.20 under irrigated and rain-fed rice cultivation systems amongst smallholder farmers in Northern Ghana.

Lastly, the fourth objective applied in-depth interviews and focus group discussions to assess the importance of rice cultivation to farmers, rice varietal diffusion, access and adoption, farmers' perceptions of varietal traits, constraints to rice cultivation and how to ease these constraints. Agricultural extension agents and colleague farmers were sources of knowledge about improved rice varieties. Interviews with agricultural extension agents and agricultural input dealers revealed government subsidised improved rice varieties such as jasmine 85 and AGRA were available for farmers to purchase. Similarly, government is encouraging trained seed growers to expand production of certified improved rice varieties. Improved rice varieties were cultivated because of higher yield and disease resistance. Previous studies such as Buah *et al*. (2011) and Coffie *et al*. (2016) revealed Ghanaian farmers preferred higher yield, early maturity, disease and pest-resistance, good taste, easy to thresh and mill in adopting improved rice varieties. Nonetheless, traditional rice varieties were cultivated because of their demand in the local market, perceived resistance to bird infestation because of longer maturity period and higher yield. Consumer demand for jasmine 85 is low in the local market due to improper parboiling by rice processors. They require training on correct parboiling of jasmine 85 to increase its local consumption.

Labour constraint affected farmers' ability to perform recommended practices [direct seed planting, transplanting, bund construction etc.]. This is consistent with the findings of Nin-Pratt and McBride (2014) that labour constraints stifled the adoption of labour-intensive cultivation practices in Ghana. The government of Ghana is facilitating access to tractors, power tillers, rotovators and combined harvesters to farmers to mitigate the labour-intensity of rice cultivation (MoFA, 2019). Other constraints to rice cultivation were weed infestation, incidence of birds eating grains during the ripening and drying stage on rice fields, intermittent flash flooding and drought. This corroborates the findings of Kranjac-Berisavljevic' (*et al*., 2003), Faltermeier and Abdulai (2009) and Armah *et al*. (2011) that erratic rainfall and floods, pests and weeds infestation negatively affected rice cultivation in Ghana.

13.4 Recommendations for future studies

This study focused on the effect of adoption of improved rice varieties on output and technical efficiency and how that translated into household net rice income. It also identified specific constraints to rice cultivation in the study area. However, there are a number of ways in which this study could be extended, and they include:

1. A study on allocative efficiency could shed further light on the efficiency studies by examining the input use relative to input cost decisions of rice producing households. A rice farmer is allocatively efficient when inputs are used up to the level at which their marginal value product is equal to the marginal factor cost or price of input. This is because technical efficiency only analyses how a farmer could produce additional output without changing input levels used if it were to operate on the production frontier that is determined by the best-practice rice farms.

2. It would also be interesting to examine both technical efficiency and allocative efficiency by the use of panel data from the study area to ascertain how these efficiency levels would change over time with adoption since this study relied on cross sectional data only.

3. The limitations to the secondary data obtained from IFPRI permitted the estimation of household net rice income per hectare as proxy for effect of adoption of improved rice varieties on household welfare. The IFPRI data collected did not have production information on all crops cultivated by the household, animals and many of the

components that constitute household income and expenditure such as income from other activities, food, education, housing, energy, transportation, communication, purchases of consumer durables and non-durables and transfer payments made by households which affect its welfare. A future study can examine the effect of adoption of improved rice varieties on household welfare using both household income and expenditure data.

4. Lastly, it will be important to apply a quantitative approach to validate the findings from the qualitative interviews in this study.

13.5 Conclusions and recommendations

First and foremost, community involvement in rice projects, agricultural extension agents, agricultural input dealers and colleague farmers were sources of knowledge about improved rice varieties. Adoption under incomplete exposure under-estimated the adoption rate as 55.9%, producing a non-exposure bias of 11.3%. The exposure rate and adoption rate of improved rice varieties were 82.5% and 67.2% respectively. Although, subsidized improved rice varieties provided higher yield and disease resistance and easily accessible, traditional varieties cultivated had localized market demand, perceived resistance to bird infestation due to longer maturity period and higher yield. Local market demand for jasmine 85 is low because of improper parboiling by local rice processors. Training rice processors on its correct parboiling can increase consumption in the local market. Meanwhile, labour constraints, weed infestation, incidence of birds eating grains during the ripening and drying stage on rice fields, intermittent flash flooding and drought hampered rice cultivation.

Regarding rice production, the cultivation of improved varieties, farm size, fertilizer, farm labour and herbicide application increased the output of adopters whereas farm size and fertilizer had positive effect on the rice output of non-adopters. A vibrant private sector seed development and distribution system would also go a long way to increase availability and ensure timely access to high yielding rice varieties in order to reduce the rampant planting of farmer saved seed. Meanwhile, the Ministry of Food and Agriculture (MoFA) can regulate seed certification to ensure quality of varietal releases.

Fertilizer application had positive effect on the rice output of both adopters and non-adopters of improved rice varieties. Ammonia fertilizer application also reduced the technical inefficiency of non-adopters. Although, a fertilizer subsidy exists with the involvement of wholesale and retail actors, there is need to ensure timely access as delays in application can negatively affect yield. Herbicide application led to increased output and technical efficiency for adopters of improved rice varieties as opposed to manual hand hoe weeding. The Plant Protection and Regulatory Division of MoFA, the Food and Drugs Authority and the Environmental Protection Agency should play lead roles in regulating and educating farmers on the correct and safe application of these chemicals taking into consideration public and environmental safety.

Relative to improving farmer efficiency, access to agricultural extension services increased the technical efficiency of adopters of improved rice varieties. A well-resourced agricultural extension service plays the dual role of promoting the adoption of improved rice varieties as well as the complementary cultivation practices to reduce technical inefficiency in rice production. Male headed households amongst the adopters of improved rice varieties were more technically efficient than females. Support in the form of access to economic resources and farmer education will help reduce female technical inefficiency in rice production. Similarly, easy access to tractors and combined harvesters can mitigate the labour constraints and reduce the drudgery involved in rice cultivation. This study acknowledges the establishment of the agricultural mechanization services enterprise centres by government. However, the number of centres needs to be increased to cover many locations to provide timely tractor services to farmers in line with the national agricultural engineering policy.

More importantly, the adoption of improved rice varieties increased rice yield which translated into increased household net rice income per ha. Adopters raised their net rice income per ha by GH¢ 374.6, whereas the potential gain to the non-adopters, if they had adopted would have been GH¢ 867.5. Therefore, households were better off as adopters than as non-adopters of improved rice varieties.

In conclusion, this study has provided evidence that the adoption of improved rice varieties is an effective strategy to raising household net rice income and reducing poverty through increased rice yield. The study recommends the adoption of improved rice varieties while improving technical efficiency, and mitigating bird infestation on rice fields, intermittent flash flooding and drought as well as labour constraints through expanded access to agricultural mechanization services.

13.6 Study limitations

This study acknowledges the concerns of estimating household welfare without including other factors such as leisure, good health, and dietary diversity amongst others that contribute to improved welfare. This is due to the limitations of the secondary data used in this study. Lastly, although the qualitative analysis covers in more depth aspects of this research that are not contained in the quantitative data, the data collection was limited to two regions out of the eight regions that the secondary data covered due to resource constraints.

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APPENDICES

Tables A1 & A2: Results of Heckman probit selection model

Table A1: Results of the exposure to improved rice varieties selection model

Variable	Coefficient	Standard error
Constant	0.691***	0.097
Community participation in rice projects	0.409**	0.202
Presence of agro-input shop in community	0.268*	0.148
Model farmer	0.159	0.194
Block farming	0.038	0.261
FBO membership	0.125	0.130
Agricultural extension	0.230	0.163
Average exposure rate	0.833***	0.015
Log-likelihood	-250.849	
Chi-squared test statistic	17.35***	
No. of observations	576	

***, indicate values statistically significant at 1% and 10% respectively.

Table A2: Heckman Sample Selection results of joint exposure and adoption of improved rice varieties

Variable	Coefficient	Marginal effect
Constant	0.351	-
	(0.419)	
Community participation in rice projects	0.443	0.113*
	(0.280)	(0.067)
Presence of agro-input shop in community	0.123	0.035

	(0.186)	(0.054)
Model farmer	0.789***	0.179***
	(0.290)	(0.061)
Block farming	0.580*	0.134**
	(0.350)	(0.066)
Agricultural extension	0.581**	0.150**
	(0.235)	(0.065)
Sex of respondent	0.061	0.017
	(0.185)	(0.052)
Forest zone	-0.584*	-0.191*
	(0.303)	(0.113)
Guinea savannah zone	-0.848***	-0.229***
	(0.280)	(0.082)
Lowland rain-fed production	0.368	0.112
	(0.281)	(0.092)
Irrigated production	1.502***	0.316***
	(0.362)	(0.079)
Higher rice yield	0.379**	0.112*
	(0.182)	(0.060)
Rice market demand	0.064	0.018
	(0.173)	(0.050)
Own consumption of rice	0.107	0.030
	(0.181)	(0.050)
Rice seed recycling	-0.057***	-0.016**
	(0.021)	(0.007)
Farm size	-0.023	-0.007
	(0.014)	(0.004)
Rho (ρ)	-0.498 (0.670)	
Log-likelihood	-449.936	
Chi-squared test statistic	41.95***	
LR test of indep. Eqns (rho, $\rho = 0$)	0.160 (0.691)	
No. of observations	576	

***, **, *, indicate values statistically significant at 1%, 5% and 10% respectively. Figures in brackets are the standard errors. [a] standard error calculated using the delta method.

Table A3: Results of probit selection model for the stochastic frontier

Table A3: Results of the adoption selection model for the stochastic frontier

Variable	Unmatched sample	Matched sample
	Coefficient	Coefficient
Constant	0.225	0.029
	(0.381)	(0.405)
Community participation in rice projects	0.509*	0.535*
	(0.264)	(0.296)
Presence of agro-input shop in community	0.136	0.024
	(0.169)	(0.184)
Being a model farmer	0.822***	0.594*
	(0.278)	(0.316)
Participation in block farming	0.638*	0.513
	(0.354)	(0.406)
Agricultural extension	0.662***	0.565***
	(0.194)	(0.212)
Sex of respondent	0.060	0.110
	(0.194)	(0.202)
Forest zone	-0.619**	-0.372
	(0.256)	(0.334)
Guinea savannah zone	-0.908***	-0.571**
	(0.255)	(0.291)
Lowland rain-fed production	0.335	0.266
	(0.280)	(0.283)

Irrigated production	1.154***	1.142***
	(0.336)	(0.363)
Higher rice yield	0.391**	0.296
	(0.179)	(0.188)
Rice market demand	0.089	0.096
	(0.179)	(0.190)
Own consumption of rice	0.084	0.108
	(0.189)	(0.199)
Growing farm saved seed	-0.06***	-0.059***
	(0.019)	(0.020)
Farm size	-0.025**	-0.023*
	(0.013)	(0.014)
Log-likelihood function	-204.556	-190.897
Chi-squared test statistic	219.025***	75.634***
No. of rice plots	496	330

***, **, *, indicate values statistically significant at 1%, 5% and 10% respectively. Figures in brackets are the standard errors.

A1: Qualitative research participant information sheet

I am a PhD student at the University of Reading. As part of my studies, I am conducting research into the dissemination and adoption of improved rice varieties in Ghana. For this reason, I am carrying out personal interviews with, farmers, agricultural extension agents and agricultural input dealers in the Upper East Region and the Volta Region to identify issues regarding dissemination and access to improved varieties, and what measures need to be put in place to improve adoption rates. I am inviting you as an agricultural extension agent to participate in an in-depth interview on the dissemination and adoption of improved rice varieties in Ghana. The information obtained from this interview will help design strategies by Government and other non-government organizations to increase adoption rates of improved rice varieties for increased yield to improve farmer welfare through increased net rice income.

I am not collecting names as part of the interview and your identity will not be revealed to anyone. You can choose to participate or not in this interview and stop at any time. Although this interview will be tape-recorded, your responses will be transcribed and remain anonymous and confidential. Once transcribed, the original recording will be deleted. The findings from this interview will be written up into my PhD thesis.

Any contribution can be withdrawn up until the point at which the data is aggregated and results are analysed before 31/05/2020. After then, it will not be possible to withdraw your contribution. If you wish to withdraw, please use my contact details below, quoting the reference number at the top of this page.

All data I collect will be securely stored on a password-protected. The data will be destroyed at the end of the research no later than 17/09/2020. This research project has been reviewed according to the procedures specified by the University Research Ethics Committee, and has been given a favourable ethical opinion for conduct. By taking part in this interview, you are acknowledging that you understand the terms and conditions of participation in this study and that you consent to these terms.

Thank you very much for taking time to take part in this survey!

A2: Rice farmers' in-depth interview guide

Study on improved rice adoption and farmers perceptions of varietal traits

1. Name of Region...…………………………………………………….
2. Name of District ………………………………………………………….
3. Name of Community…………………………………………………………
4. Age of Respondent………………………
5. Sex of Respondent 1) Male 2) Female
6. Why does your household cultivate rice?
7. For how many years has your household been cultivating rice?
8. What rice cultivation system do you practice? (Upland, rain-fed lowland or irrigated rice).
9. What is the total rice area (ha) cultivated by your household?
10. Does your household know of any improved rice varieties?

11. How did your household know about (source) the improved rice varieties?

 (1=MoFA, 2=Research institute, 3=Project (NGO, donor), 4=farmer organization, 5=colleague farmer, 6=input dealer/supplier, 7=certified seed producer).

12. Which rice varieties did your household cultivate this season?
13. Kindly list the characteristics/traits that **you like** about the rice varieties you currently cultivate.
14. Kindly list the characteristics/traits that **you do not like** about the rice varieties you currently cultivate.
15. Kindly list the traits that **you wished** the rice varieties you currently cultivate possessed.
16. How many years has your household continuously cultivated this rice varieties?
17. What other varieties has your household cultivated in the last five years?
18. Which of the following do you practice in rice cultivation?

 Ploughing, harrowing, use of herbicide, recommended plant density of 100-126kg/ha for broadcasting, or 45-50kg/ha for dibbling, fertilizer application rate of 200–300kg/ha of NPK compound fertilizer and 150kg/ha of sulphate of ammonia or 75kg/ha of urea, bund construction, farrowing, puddling, or levelling.

19. List any constraints to the adoption of improved rice varieties in your household.
20. If your household ever cultivated improved rice varieties and stopped, can you give the reasons for dis-adoption?
21. What suggestions do you propose to increase your household's rice output/yield?

A3: Agricultural extension agent in-depth interview guide

The dissemination and adoption of improved rice varieties in Ghana

1. Name of Region...…………………………………………………….

2. Name of District ……………………………………………………………

3. Name of duty station in District ……………………………………….

4. For how many years have you been working as an agricultural extension agent?

5. Can you please share with me your experience working in the dissemination of improved rice varieties to farmers over the years?

6. Can you please tell me your general assessment about how farmers have adopted improved rice varieties over the years?

7. Can you please tell me the challenges if any, regarding access and adoption of these varieties by farmers?

8. What do you think should be the way to easing these challenges to the dissemination and adoption of improved rice varieties?

A4: Improved seed supplier's in-depth interview guide

Study on the dissemination and adoption of improved rice varieties in Ghana

1. Name of Region...……………………………………………………….

2. Name of District ……………………………………………………………

3. Name of community…………………………………….

4. For how many years have you been working as an improved seed supplier/seller?

5. Can you please share with me your experience including the sale of improved rice seed over the years?

6. Can you please tell me the constraints if any, you encounter in obtaining improved rice varieties for sale to farmers?

7. In your experience, can you tell me, if any, the challenges farmers face in trying to access improved rice varieties over the years?

8. What do you think should be the way to increasing the dissemination and adoption of improved rice varieties by farmers?

A5: Rice farmers focus group discussion guide

Study on the dissemination and adoption of improved rice varieties in Ghana

1. Kindly explain the importance of rice cultivation to this community.

2. List the rice varieties mostly cultivated by farmers in this community.

3. Why do you cultivate the only varieties mentioned above and not the other varieties?

3. Kindly list the characteristics/traits that **you like** about the rice varieties you currently cultivate.

4. Kindly list the characteristics/traits that **you do not like** about the rice varieties you currently cultivate.

5. Kindly list the traits that **you wished** the rice varieties you currently cultivate possessed.

6. List the constraints to the adoption of improved rice varieties in this community.

7. What can be done to ease these constraints to adoption of improved rice varieties?

A6: Ethical clearance approval of interview guides for the qualitative data collection