IMPROVED RICE VARIETIES ADOPTION AND TECHNICAL EFFICIENCY OF SMALLHOLDER RICE FARMERS IN OGUN STATE, NIGERIA

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DECLARATION

I, Bello Lateef Olalekan, declare that:

(i) The research reported in this thesis is my original research work;

(ii) This thesis has never been submitted for any degree or examination at any other university or institution of higher learning;

(iii) This thesis does not contain other authors' data, pictures, tables, graphs or other information, unless specifically acknowledged as being sourced from those authors. Where other written sources were quoted:

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Signed: Date: 29 July 2019

Bello Lateef Olalekan

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As the candidate's main supervisor, I, Professor Lloyd Baiyegunhi, agree to the submission of this thesis.

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ABSTRACT

Rice (*Oryza sativa*) is an essential food crop and the most consumed staple crop in the majority of the urban and rural households in Nigeria. Rice consumption in Nigeria is the highest in Africa; also, the country is one of the largest producers of rice on the continent and simultaneously one of the largest rice importers in the world (FAO, 2016). The high importation is due to the inconsistency and variability in production of rice in Nigeria. Rice yield in irrigated and rain-fed land is 3.0–3.5 mt/ha and 1.5-3.0 mt/ha which is below the potential output of 7-9 mt/ha and 3-6 mt/ha respectively. Low adoption of improved rice varieties (IRVs) is one of the major constraints leading to this low yield encountered by the resource-poor smallholder farmers. The main objective of this study was to examine the factors influencing adoption of IRVs and its impact on productivity and to estimate the differences in technical efficiency among adopters and non-adopters of IRVs in Ogun State, South West, Nigeria. A multi-stage random sampling technique was used to select 250 rice farmers and data was collected through a well-structured questionnaire. The Probit regression model was used to analyse the determinants of IRVs adoption while the stochastic frontier production function was used to model the determinants of rice output and technical efficiency.

The results of the probit model showed that education, rice farming experience, access to extension services, access to credit and seed access had a significant influence on adoption of IRVs. The estimates of the average treatment effect (ATT) from the PSM method indicated that the adoption of IRVs increases productivity of smallholder rice farmers by 452kg/ha. The implication of the results suggests that priority must be given to the use of improved agricultural technology such as IRVs in order to enhance rice production.

The estimate of the stochastic frontier analysis (SFA) indicates that smallholder rice farmers are producing below their potential output, however, adopters of IRVs are more technically efficient than the non-adopters. The mean technical efficiency of adopters and non-adopters of IRVs is 0.97 and 0.84, respectively. The study determined the sources of farmers' technical inefficiency from a combined effect of farm-specific, socio-economic, socio-institutional factors and predicted probability of IRVs. The findings of the study suggest that adoption of IRVs plays a crucial role in improving the technical efficiency of smallholder rice farmers.

The study, therefore, recommends an agricultural policy aimed at promoting farmers' education, through effective extension services, providing sustainable credit facilities and efficient relationship between farmer-based organizations and seed companies (private, NGOs and government) to enhance easy accessibility of IRVs by the rural smallholder rice farmers.

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To God alone can be all the Glory! You are more than enough.

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LIST OF ACRONYMS

AfDB	African Development Bank
ATA	Agricultural Transformation Agenda
ATT	Average Treatment effect on the Treated
COLS	Corrected Ordinary Least Squares
CMP	Conditional Recursive Mixed-process
DEA	Data Envelopment Analysis
DFA	Distribution Frontier Approach
DMUs	Decision Making Units
ESR	Endogenous Switching Regression
FAO	Food and Agricultural Organisation
FBO	Farmers-based Organisation
FDH	Free Disposal Hull
GPS	Generalized Propensity Score
GDP	Gross Domestic Product
GR	Green Revolution
IITA	International Institute of Tropical Agriculture
IRVs	Improved Rice Varieties
IPSW	Inverse Propensity Score Weighing
IV	Instrumental variable
KBM	Kernel-Based Matching
LATE	Local Average Treatment Effect
NAFPP	National Accelerated Food Production Program

NERICA	New Rice for Africa
NCRI	National Cereal Research Institute
NGOs	Non-government Organisations
NIRI	National and International Research Institute
NNM	Nearest Neighbour Matching
NPK	Nitrogen Phosphorus Potassium
PSM	Propensity Score Matching
Rbounds	Rosenbaum bounds
RM	Radius Matching
SFA	Stochastic Frontier Analysis
SSA	Sub Saharan Africa
SVS	Seed Voucher System
TEs	Technical efficiencies
TFA	Thick Frontier Approach

CHAPTER 1
INTRODUCTION

1.1 Background to the Study

Agriculture is an important sector that contributes significantly to the Nigerian economy. In the early 1960s, the sector accounted for the largest share of the Gross Domestic Products (GDP). The sector provides employment opportunities, enhance food security and promote the growth of the country. However, despite all these contributions to the economy, there has been a major setback in the agricultural sector leading to a decline in its contribution to the GDP; in the year 1960-1969, the agriculture's annual share was 58%, but the contribution to GDP declined to 31% between 1970-1979, during the oil boom (CBN, 2010; Abba and Isa, 2015). The average contribution to GDP within the year 1980-2011 was 36.6%, the highest GDP in this periods was 43.6% and 43.9% in 1992 and 2005 while the lowest was 20.6% in 1980 (Ihugba *et al.*, 2013). At present, agriculture accounts for 22.8% of the GDP in Nigeria (NBS, 2018). The decrease in agricultural share to the GDP was due to the rise in crude oil revenue in the early 1970s. Agricultural sector accounted for 65-70% of the total value of exports in the 1960s; it reduced to 40% in the 1970s, declined to less than 2% in the late 1990s and 0.60% in 2017 (Olajide *et al.*, 2012; NBS, 2017). Sequel to the drastic decline in agricultural output over the years, the government had come up with several policies and programs to revive the agricultural sector and also bridge the high gap between local production and importation of food commodities such as wheat and rice (FAO, 2017).

Rice is one of the most valuable cereal crops cultivated and consumed all over the world. It is a staple food in several African nations and constitutes a large portion of the diet on a regular basis (Merem *et al.*, 2017). Rice is cultivated in mostly all agroecological zones in Nigeria but on a relatively small scale (Ogundele and Okoruwa, 2006). Longtau (2003b) asserted that in Nigeria, rice [grown on 1.77 million hectares (ha)] ranks sixth after sorghum (4.0 million ha), millet (3.5million ha), cowpea (2.0 million ha), cassava (2.0 million ha) and yam (2.0 million ha), but it is still the most consumed staple crop in most homes in urban and rural areas. Rice consumption in Nigeria is the highest in Africa, also the country is one of the largest producers of rice on the continent and simultaneously one of the largest rice importers in the world (FAO, 2016). Nigeria imported 3.4 million metric tonnes (mt) of rice in 2011, making the country the world's largest rice importer that year (Ogunya *et al.*, 2017). Rice production has been expanding at the rate of 6% per annum in Nigeria, with 70% of the production increase due mainly to land expansion and only 30% being attributed to an increase in yield (Nguezet *et al.*, 2011).

There have been inconsistency and variability in the production of rice in Nigeria. Production increased from 2.92 million tonnes in 1995 to 4.18 million tonnes of paddy rice in 2008 but also reduced to 3.22 million tonnes in 2010 (GRiSP, 2013). FAO (2017) reported that there is a 4% slight increase of 4.95million tonnes in rice production in 2016 compared to 4.75 million tonnes output in 2015. The output of rice increased not because of the increase in efficiency of the farmers but due to more farmers engaging in rice production, which invariably led to the expansion of land area under rice cultivation. Despite the increase in rice production, yields are still low. In Nigeria, rice yield in the irrigated land is 3.0 -3.5 metric tonnes per hectare (mt/ha) compared with the potential of 7–9 mt/ha, while in the rainfed lowland environment, rice yield is 1.5–3.0 mt/ha compared to a potential of 3.0–6.0 mt/ha. Also in the upland areas, yields range from 1.0 to 1.7 mt/ha compared with a potential of 2.0–4.0 mt/ha (GRiSP, 2013).

To resolve the issue of underproduction, a series of research has been conducted towards providing agricultural technology to enhance rice productivity. Mulugeta and Hundie (2012), asserted that new agricultural technologies and improved practices play a major role in increasing agricultural production which in turn enhances national food security in developing countries. Evidence of success in the Green Revolution program in Asia has led to an effort directed towards the adoption of improved agricultural technology in increasing agricultural productivity in Africa (Awotide *et al.*, 2016). In view of this backdrop, the West African countries established the West African Rice Development Association (WARDA) in 1971 with the support of international organizations (Oladele and Somorin, 2008). The aim of WARDA was to implement the adoption of improved agricultural technologies (focusing on rice technologies) developed in Asia to improve food security and alleviate poverty in West Africa.

In respect of the significant contribution of rice to consumers and farm households, the government of Nigeria has prioritized the development of improved varieties of the crop to boost its productivity (Awotide *et al.*, 2016). For example, research institutes such as National Cereal Research Institute (NCRI), International Institute of Tropical Agriculture (IITA) and International Rice Research Institute (IRRI) have developed over 52 varieties of rice in the past and still working on more (Ologbon *et al.*, 2012). The rice varieties developed (such as FARO 15, 44, SIPPI, ITA 306), possess numerous qualities which include adaptive features to different rice environments (production systems) in Nigeria such as rain-fed upland, rainfed lowland, irrigated low land, deep inland water and mangrove swamp. Also, some IRVs are developed as flood and drought-tolerant varieties, suitable for farmers in high rainfall and low rainfall ecological zones in Nigeria. Apart from the adaptive features, the most important features of the IRVs are the high yielding qualities; with a potential yield ranging from 2-8 paddy tonnes/ha and the maturity period ranges from 95-140days (Ologbon *et al.*, 2012).

The introduction of improved varieties has made rice cultivable in mostly all agroecological zones of the country. However, despite the intensive research towards enhancing the productivity of rice, there is still a high yield gap. An explanation to this is that Nigerian agricultural sector dominated by resource-poor smallholder farmers is characterized by low level of technology adoption. It is expected that the adoption of IRVs and improved management practices would increase productivity and lower the cost of production for farmers (Awotide *et al.*, 2016).

Ogundele and Okoruwa (2006) observed that the quantity of seeds sowed by farmers adopting IRVs was low compared to farmers that planted traditional varieties but there was a yield gap between both groups of farmers; farmers planting traditional varieties having a lower yield than IRVs adopters. This 'gap' refers to the difference in productivity on 'best practice' in farm operations with comparable resources and under similar condition (Abedullah *et al.*, 2007)**.** Therefore, the low level of productivity reflects a low level of technical efficiency, i.e., the ability to get maximum output from a given set of input. One of the enormous challenges of achieving food production for the growing population is how to raise productivity and efficiency in the agricultural sector (Osawe *et al.*, 2008). However, the efficiency approach emphasizes the crucial need for improving the labour productivity of both men and women in any economic system (Rahman, 2008).

Determining the factors influencing adoption of IRVs and estimating the difference between actual and technical feasible output among smallholder farmers will have a great impact in increasing food and agricultural production through improvements in productivity (Abedullah *et al.*, 2007). Generally, it is believed that resources are underutilized in the agricultural sector especially in the underdeveloped countries. The major concern of farmers is to make a profit from the business which solely depends on the resource use efficiency. Measurement of production efficiency in agricultural production especially in developing countries like Nigeria helps to identify the source(s) of inefficiency, which can serve as a guide for optimal utilization of resources (Betonio *et al.*, 2016).

1.2 Statement of the Research Problem

Nigeria has a land area of 3.4 million hectares potentially suitable for rice production, but only about 1.7 million hectares is being utilized. In addition, less than 50,000 hectares of land is used to cultivate irrigated rice out of 3.14 million hectares of land suitable for irrigation (GRiSP, 2013). The small number of hectares under cultivation is an indication that food sufficiency through rice production has not yet been realized as rice production is left in the hand of smallholders whose output is inadequate and paddy processing is substandard (Longtau, 2003b). Nigeria's rice is produced by more than 90% of resource-poor smallholder farmers, while the remaining 10% is produced by corporate or commercial farmers. Also, about 95% of rice processors are in small-scale with low-capacity and obsolete mills (GRiSP, 2013). Despite the dominance and important role played by smallholder farmers in rice production, they are still faced with some challenges which includes poor distribution of agricultural inputs such as quality seed, lack of credit facilities, lack of irrigation facilities, low fertilizer application, unavailability of appropriate small farm machinery for harvest and post-harvest operation and poor extension services (GRiSP, 2013), which have farmers have contributed to the low productivity of the farmers.

Poverty could be alleviated through small-scale based agricultural growth through the adoption of improved agricultural technology. According to Awotide *et al.* (2016), agricultural innovations played a significant role in reducing poverty, lowering per-unit costs of production and increasing incomes of rural farmers. Adoption of IRVs has been found in the literature to have significant and positive impacts on welfare, poverty reduction and productivity of rice farmers (Adekambi *et al.*, 2009; Nguezet *et al.*, 2011; Awotide *et al.*, 2016). However, the adoption of improved rice technologies in

Nigeria has been low over the years due to the challenges encountered by farmers. Ogunya *et al.* (2017) noted that unavailability of fertilizer and improved seeds are the major constraints affecting adoption of improved rice technologies in Ogun State, South west, Nigeria. Awotide *et al.* (2016) also observed that high cost of seed and excessive distance to the source of seed are the major challenges faced by farmers in accessing IRVs in Nigeria. The disparity in the levels of technology adoption has been identified as a major setback in rice-based production systems in most developing economies especially in Nigeria which in turn has led to inefficiency among rice farmers (Ologbon *et al.*, 2012; Ogunya *et al.*, 2017).

Rice is an important crop that has attracted several studies in Nigeria. Some studies focused on the consumption and marketing of rice (Adeyeye *et al.*, 2010; Bamidele *et al.*, 2010); whilst others focused on resource use efficiency (Goni *et al.*, 2007; Amaechina and Eboh, 2017); technical efficiency (Ayinde *et al.*, 2009; Kadiri *et al.*, 2014) and adoption of improved rice variety (Bzugu *et al.*, 2010; Awotide *et al.*, 2012; Adedeji *et al.*, 2013). These studies have been conducted in different regions of Nigeria, however, there is still a deficit in research on adoption of improved rice varieties and technical efficiency differentials among smallholder rice farmers in Ogun State, Nigeria. Therefore, there is a need for information on adoption of improved rice varieties and technical efficiency of smallholder rice farmers in the study area. It is against this backdrop that these pertinent research questions are raised:

(i) What are the determinants of adoption of improved rice varieties and its impact on productivity among smallholder rice farmers in the study area?

(ii) Are there differentials in technical efficiency among improved rice varieties adopters and non-adopters smallholder rice farmers in the study area?

1.3 Objectives of the Study

The main objective of the study is to analyse the factors influencing adoption of improved rice varieties, and technical efficiency differentials among smallholder rice farmers in Ogun State, Nigeria.

The specific objectives of the study are to;

(i) examine the determinants of adoption of improved rice varieties and its impact on productivity among smallholder rice farmers,

(ii) estimate differentials in technical efficiency among improved rice varieties adopters and non-adopters.

1.4 Justification for the Study

The production of rice (quantity of rice produced) has been inconsistent in mostly all the agroecological zones of Nigeria. This has made the demands for rice exceed the local production which invariably leads to the high rate of rice importation in the country. Increasing domestic rice production to satisfy the growing rice consumption and to also reduce rice importation has become a top priority to the Nigeria Government and great concern in the global world (Ayinde *et al.*, 2009). Due to the high dependence on foreign rice which places a huge burden on the country's foreign reserves, the Nigeria Government has contributed largely to rice research and developmental programs to boost rice production. Programs such as the National Accelerated Food Production Program (NAFPP), Green Revolution (GR), African Rice Initiative (ARI) and Agricultural Transformation Agenda (ATA) among others were introduced to attain self-sufficiency in rice production. Some of these programs such as ARI promotes the distribution of IRVs to the rice farmers. However, there is still a low level of awareness and adoption of IRVs among rice farmers. Nguezet *et al.* (2011) noted that 6 years after the dissemination of an IRV (New rice for Africa [NERICA]), the level of farmer’s awareness and adoption is still low. According to Ologbon *et al.* (2012) production of rice can be increased to a sustainable level in Nigeria when farmers in all agroecological region adopt and cultivate IRVs with appropriate management practices.

The decision of the smallholder rice farmers to use these IRVs could be based on different factors. These include the ability of the farmers to understand the costs and benefits as well as other attributes of the technology. Also, constraint such as labour, capital and credit could also influence farmer’s decision in adopting a technology.

According to Just and Zilberman (1988) and Ghimire *et al.* (2015), the adoption of high yielding crop varieties such as IRVs could increase the productivity of smallholder rice farmers, stimulates the growth of agro-processing enterprise and facilitates the transition from a low productive subsistence agriculture to a high productive agro-industrial economy which in turns boost the agricultural sector contribution to the economy and increase exportation of food commodity. Therefore, for rice production in Nigeria to be increased to meet the demands of the people and exportation, there is a need for empirical research on adoption of IRVs and assessment of factors that contribute to inefficiency of smallholder rice farmers to generate sustainable information to be addressed in policy making to enhance adoption of IRVs which would in turn improves productivity and efficiency in rice production.

Recently, there is an increasing rate of smallholder farmers engaging in rice production due to the current ban placed by the Nigeria government on the importation of rice. Access to productive resources, adoption of improved technologies (including IRVs) and understanding the appropriate use and strategic combination of input for rice production by smallholder farmers could lead to an increase in yield and growth of the sector on the economy. This could also lead to the reduction of poverty among the rural poor smallholder farmers. The study, therefore, provides useful information for the

Nigerian government and policymakers on how to formulate policies and strategies that will enhance adoption of improved rice varieties and technical efficiency of smallholder farmers by making the appropriate decision in the combination of resources to achieve the desired output.

The study contributes to general knowledge on the factors influencing adoption of IRVs, productivity and inefficiency among smallholder rice farmers. The study also contributes to impact evaluation literature by providing insights on the impact of adoption of improved agricultural technology on smallholder farmers.

1.5 Outline of the thesis

Chapter 1 of the thesis includes the introduction, background, research problem, objectives and justification of the study. In chapter 2, literature review of theories and empirical studies relevant to the study are presented while in chapter 3 results of the first objective of the study which is adoption of improved rice varieties (IRVs) and its impact on productivity was presented using probit model and propensity score matching estimation technique. In Chapter 4, the differences in technical efficiency among adopters and non-adopters of IRVs was estimated using stochastic frontier analysis. In chapter 5, a summary, conclusion and policy recommendations, based on the empirical results were presented.

CHAPTER 2
LITERATURE REVIEW

2.1 Introduction

This chapter reviews relevant literature in relation to the background of the research problem and the objective of the study discussed in Chapter 1. The chapter starts with an overview of rice production in Nigeria followed by explanations and discussion of some key concepts used in the study which include adoption, impact, productivity and efficiency. Theoretical and empirical evidence on measurement of adoption and impact of agricultural technology were documented. Subsequent discussions focused on the types of efficiency with preference to technical efficiency. The different approaches of measuring efficiency are discussed, followed by a discussion on the empirical application of stochastic frontier analysis and data envelopment analysis.

2.2 Rice production in Nigeria

Nigeria has favourable soil suitability that supports the cultivation of rice, thus rice is grown in almost all agro-ecological zones of the country. There are various rice varieties grown across various ecological zones in Nigeria ranging from the traditional varieties to the improved varieties. The main rice varieties cultivated before the development of improved varieties are *Oryza glabarima* and *Oryza sativa.* The cultivation of rice in Nigeria started in 1500 BC with the cultivation of indigenous red grain species *Oryza glabarrima* in the Niger Delta belt of the country (Ologbon *et al.*, 2012). The white grain species (*Oryza sativa*) was introduced in the 1850's through missionary activities in Abeokuta, Ogun State, and to other region in Nigeria such as Epe area of Lagos in 1970's, Abakaliki and Ogoja in the South after the second world war in 1945, Shaki area of Oyo State in 1945, Oshogbo area of Osun State in 1954 and Niger Delta region in the early 1960's (Longtau, 2003b). The improved varieties such as the New Rice for Africa (NERICA) are hybrids (between *Oryza glabarima* and

Oryza sativa) that are developed through the collaboration between local and international research institutes.

According to Oladele and Somorin (2008), research on improved varieties of rice in Nigeria started in 1953 with the establishment of federal rice station (now NCRI) at Badegi in Niger State. The aim was to produce rice varieties of improved grain quality, uniform grain shape and sizes that will be suitable for less breakage during milling. The research institute produced 13 improved varieties of rice, comprising 2 uplands, 8 shallow swamps and 3 deep flooded rice between 1954 and 1970. Research activities from 1971 concentrated on developing high yielding and disease-resistant varieties, efficient use of nutrients and good soil management which were achieved through the adaptation and release of the new varieties.

Rice is grown under different production systems in Nigeria which include rain-fed upland, rain-fed lowland, irrigated low land, deep inland water, Hydromorphic and mangrove swamp. The characteristic features of rice growing environment and the features of rice production systems in Nigeria is presented in Table 2.1 and Table 2.2 respectively.

Table 2. 1: Characteristics of rice growing environments in Nigeria

Agro-climatic zone	Agro-ecological zone	Length of growing period (Days)	Annual Rainfall (mm)	Rainy Season	Rice Growing Season
Arid	Sahel	<75	<550	Jul-Aug	IL, DW
Semi-arid	Sudan Savannah	75-150	550-900	Jul-Sept	IL, RU, RL, DW
Sub-humid	Northern Guinea Savannah	151-180	900-1200	Jul-Oct	RU, RL, DW, H
Sub-humid	Southern Guinea Savannah	211-270	1200-1500	Jun-Oct	RU, RL, DW, H
Sub-humid	Derived Savannah	211-270	1500-2000	May-Oct	IL, RU, RL, H
Humid	Humid forest	>270	>2000	Mar-Nov	IL, RU
Mid- altitude	Moist savannah	181-270	1200-1500	April-Oct	RU, RL

Source: Longtau (2003b)

Rain-fed upland (RU), Rain-fed lowland (RL), Irrigated low land (IL), Deep inland water (DW), Hydromorphic (H) and mangrove swamp (M).

Table 2. 2: Features of rice production systems in Nigeria

Type	Characteristics	Geographical spread
Upland	Rain-fed rice grown on free-draining fertile soils. This is also called dry uplands.	Widespread, except coasts, high rain forests and Sahel. They are found in Ogun, Osun and Oyo state.
Hydromorphic	Rain-fed rice grown on soils with shallow ground water table or an impermeable layer. This is also called wet uplands.	Very widespread at the fringes of streams and intermediate zone between upland and swamps of rivers in the Savannah. Found in Anambra, Ebonyi, and Bayelsa state.
Lowland	Rain-fed or irrigated rice in aquatic conditions or medium ground water table. Water covers the soil completely at some stage during the cropping season. These are called shallow swamps or fadama	Very widespread from high rain forest to Sahel. Found in Ogun, Osun and Oyo state.
Deep Inland Water	Rain-fed rice grown on soils with deep water tables. The rice crop floats at some stage and harvesting may be done from a canoe. These are also called deep fadamas or floodplains	Found in the Sokoto-Rima Basin and Chad Basin, floodplains of the Niger, Benue, Kaduna, Gbako, Hadejia and Komadugu-Yobe.
Mangrove Swamps	Rice grown at the coast or swamps of the high rain forest.	Coastal areas and Warri area in Delta state.

Source: Longtau (2003b)

2.2.1 Rice production trends in Nigeria

According to Ologbon *et al.* (2012), paddy rice boom in Nigeria was first experienced in the period 1965-1970 when the average yield of paddy rice was 321,000 metric tonnes. Average land area used for rice cultivation was 234,000 hectares while the average national yield was 1.36 mt/ha during this period. The output also increases to an average of 2.1 million mt/ha, while the average area cultivated was 1.1million ha in the period 1986-1990. The distribution of rice paddy production and consumption in Nigeria is shown in Figure 2.1 and Figure 2.2.

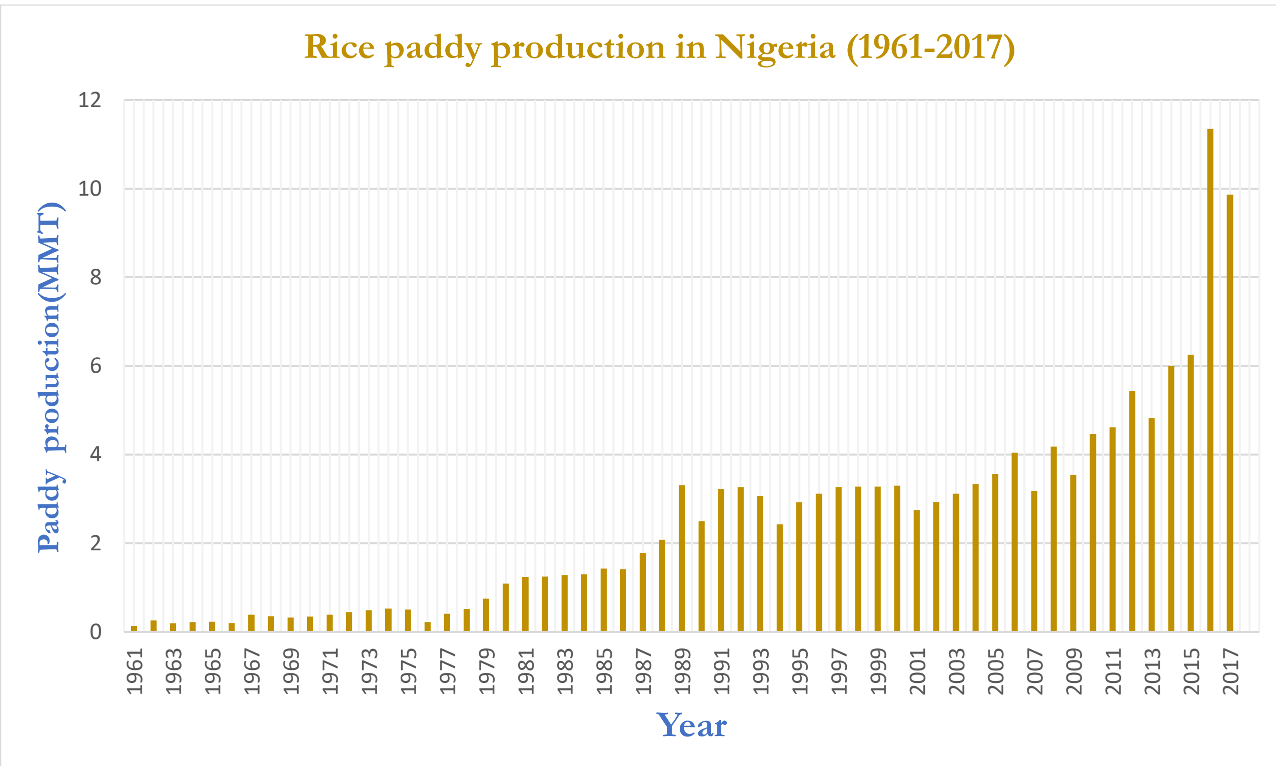

Figure 2. 1: Rice paddy production (million metric tonnes) in Nigeria.
Source: Authors computation adapted from FAOSTAT (2019)

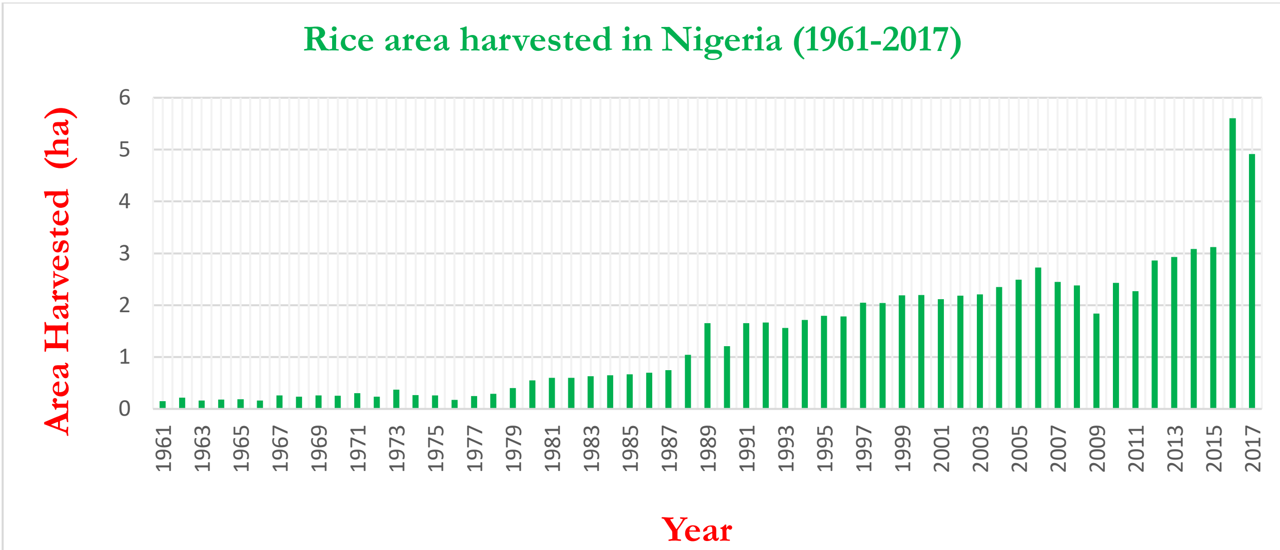

Figure 2. 2: Rice area (million hectares) harvested in Nigeria.
Source: Authors computation adapted from FAOSTAT (2019)

Nigeria is yet to be self-sufficient in rice production, although there is an increase in output over the years, it remains behind the increasing demand of the populace. Bamiro and Aloro (2013) reported that Nigeria experienced a decreasing trend in rice self-sufficiency in the 1980s, with a decline in production of 49.9% from 98.9% in the 1970s and further to 30% in early 1990s. The decline in self-sufficiency in the 1980s was due to the oil boom in the late 70s which diverted the attention of the government from the agriculture sector to the oil sector. The revenue from crude oil enhances the GDP of the country which in turn has a positive effect on the income level of the people, which also increase their preference to the staple crop (rice) among other food.

The demand for rice has continued to exceed production due to factors such as an increase in population and rural-urban migration (Cadoni and Angelucci, 2013; Amaechina and Eboh, 2017). The demand for rice was estimated to be 6.3 million tonnes in 2016 while the national supply was 2.3 million tonnes (FMARD, 2016). The quantity of milled rice production and consumption is presented in Figure 2.3.

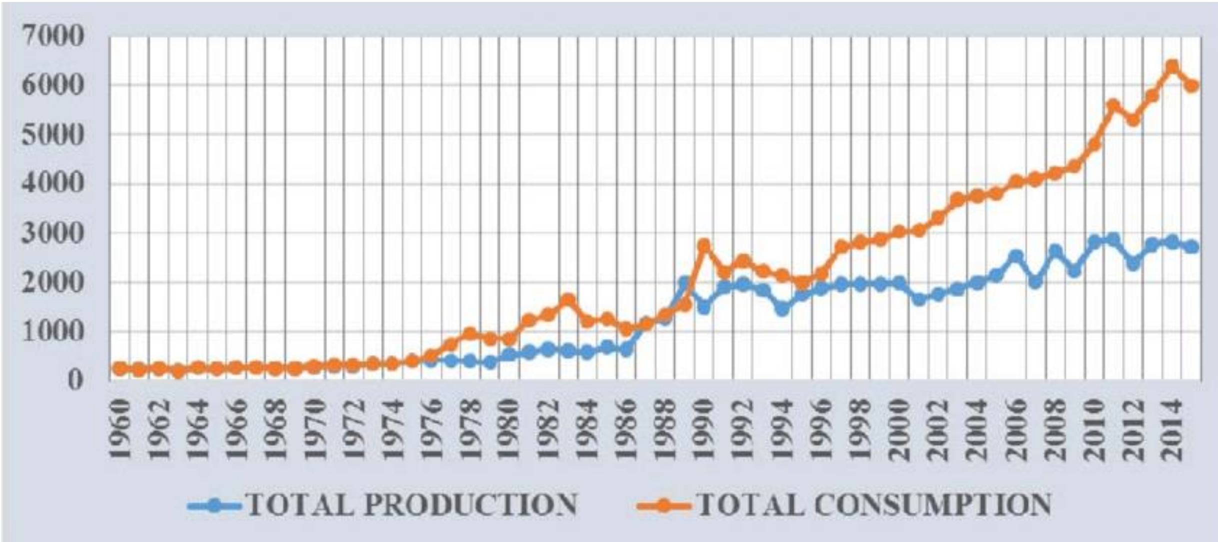

Figure 2. 3: Rice production (milled rice/ tonne) and consumption in Nigeria (1960-2015)
Source: Ayinde *et al.* (2016)

The huge gap between demand and national production was bridge by the importation of rice into the country. The importation of rice also increased over the years from 600,000 tonnes in 1981 to one million tonnes in 1982 and in the year 2011 Nigeria was the largest rice importer in the world with an estimate of 3.4 million tonnes rice importation (Bamiro and Aloro, 2013; Ogunya *et al.*, 2017).

2.3 Concepts of agricultural technology adoption

Agriculture serves as a source of livelihood for most rural dweller in developing countries like Nigeria, and therefore development, adoption and diffusion of new agricultural technology offer an opportunity to increase productivity, efficiency and farmers income substantially (Feder *et al.*, 1985). Economists and researchers have been attracted to technology innovations in agriculture and they have tried to explain farm technology adoption.

Rogers and Shoemaker (1971) defined adoption as the decision to apply an innovation and continuously utilizing it. However, adoption is not a permanent behaviour. This implies that an individual may decide to discontinue the use of an innovation for a variety of personal, institutional, and social reasons one of which might be the availability of another practice that is better in satisfying farmers' needs (Mulugeta and Hundie, 2012). Adoption process is a mental process an individual pass through from first hearing about an innovation to final adoption (Rogers, 2003). This decision-making process comprises a sequence of stages with a distinct type of activity taking place during each stage. According to Rogers (2003) adoption process passes through five main stages;

i. **Awareness:** the farmer is exposed to new technology but doesn't have complete information about it. The farmer knows little or nothing about its special qualities its potential usefulness and how it would work.
ii. **Interest stage**: The farmer develops an interest in the technology and seeks additional information about it.
iii. **Evaluation stage**: The farmer applies the new technology to his present and the anticipated future situation on expected returns and decides whether to try it or not.
iv. **Trial stage**: The farmer experiments the new technology (on a relatively small-scale to assess its suitability in practice). Here he put the changes in practice i.e. he must learn how, when, where, how much, etc. For example, a rice farmer may decide to use a plot of land to cultivate an Improve Rice Variety (IRV) from his 10 plots of rice farm as an experiment. The plots of land allocated for IRV could be increased if the experiment was successful and the farmer is convinced of the benefits of the IRV.
v. **Adoption stage**: the farmer is totally convinced and thus make cultivate IRV on all the farm plots which signify a full-scale adoption.

Feder *et al.* (1985) emphasized the need for a quantitative definition of adoption for theoretical and empirical analysis. They conceptualize adoption in two forms namely; individual (farm-level) and aggregate adoption. Farm-level adoption is defined as the degree of utilization of new technology in long-run equilibrium when the farmer has full information about the new technology and its benefit.

Aggregate adoption, on the other hand, is the application of new technology within a geographical area. The spread of this new technology within a locality or region is known as "diffusion". Rogers (1995) defined diffusion as the process by which an innovation is communicated through certain channels over time among the members of a social system.

2.3.1 Approaches to farm technology adoption measurement

Several scholars across the world have over the years used different approaches (models) to analyse the determinant of agricultural technology adoption. Many studies (Asfaw *et al.*, 2012; Willy *et al.*, 2014; Ghimire *et al.*, 2015; Khonje *et al.*, 2015; Ali and Behera, 2016; Awotide *et al.*, 2016; Danso-Abbeam and Baiyegunhi, 2017) have used models such as Probit, Logit, Tobit, Heckman and Double hurdle model to determine factors influencing adoption of agricultural technology.

Probit and logit are dichotomous choice models classified as a quantal response (all or nothing) and are usually used for qualitative and categorical data. For example, they are used to measure technologies that are not divisible such as the utilization of a tractor which is dichotomous (use or no use) and assumes that factors influencing adoption decision can be personal or external (Danso-Abbaem, 2018). Probit and logit models are based on normal and logistic cumulative distribution functions, respectively. Both Probit and Logit model are similar, but the main difference is that the logistic distribution has slightly fatter tails (Lopes, 2010). The drawback of the dichotomous model is that they can only measure the probability of adoption but cannot explain the intensity of adoption. For example, a dichotomous measure of IRV adoption is not adequate to determine the intensity of adoption about the quantity of IRV a farmer used per plot or hectare.

Tobit model developed by Tobin (1958) is a hybrid of the discrete and the continuous dependent variable and shows the link between a non-negative exogenous variable and an independent variable (or vector). Tobit model is employed when the dependent variable is constrained or censored. It is mostly used to determine the factors influencing both the probability and intensity of adoption thereby estimating the joint effect. However, the drawback of the Tobit model is that probability and intensity may not be joint decisions.

In providing a solution to this drawback, Heckman (1976) developed a two-step process model (Heckman model) to estimate the probability (discrete decision) and intensity (continuous decision) separately. The model involves estimation of a probit model for the probability of a decision, followed by the insertion of a correction factor (the inverse mills ratio) calculated from the probit model into the second model which is Ordinary Least Square (OLS) (Bushway *et al.*, 2007). The OLS is used to estimate the continuous decision. Heckman models help to resolve the endogeneity resulting from sample selection but do not account for independent variables that are endogenous for other reasons (Certo *et al.*, 2016). However, the double-hurdle models allow for two independent decisions made by the production units. The double-hurdle model has two separate hurdle equations which determine the adoption decision and intensity of use of a technology with an assumption of independence between the stochastic error terms (Beshir, 2014). In relation to this assumption, the double-hurdle is like the combination of a binary model (probit or logit) and truncated regression model (Danso-Abbaem, 2018).

2.4 Concepts and impact evaluation of farm technology

Impact can be defined as the attainment of goals of intervention. Impact evaluation is an assessment of the significance (outcome) of an intervention. Impact evaluation has involved different methods and approaches to determine and establish a causal link between the intervention and its outcome. According to Kedir (2017), there are two common interrelated challenges encountered by impact evaluation, which are; estimating a viable counterfactual and attributing the impact to an intervention.

Evaluating the impact of a developed farm innovation technology (such as IRVs) on farmers' livelihood is important in determining the converse effects of the technology (Asfaw *et al.*, 2012). The measurement of impact requires a valid counterfactual (control group) of what those outcomes would have been in the absence of adopting the technology compared with the adopters of the technology (treatment group). The comparability of both control and treatment group is done with respect to observed and unobserved characteristics to ensure that outcome effect of the variable of interest such as productivity and income for the treatment group is solely due to the adoption of the technology.

The fundamental problem that occurs in the measurement of impact evaluations is selection bias and endogeneity. This may be due to the non-random selection of treatment groups. When this occurs the decision to adopt a technology may be influenced by both inherent and non-observable characteristics (such as farmers' motivation and risk attitude) and observable heterogeneity that may be correlated with the outcome variable (Danso-Abbaem, 2018). The next section discusses the various techniques of measuring impact evaluations.

2.4.1 Techniques for estimating impact of farm technology

Theoretically, impact evaluation could be estimated using three main methods, such as the randomization/pure experimental design; non-experimental design and quasi-experimental design (Kedir, 2017). These methods involved the use of econometrics approach to providing a solution to selection bias and endogeneity in cross-sectional data. These econometrics techniques include Instrumental variable (IV), Endogenous Switching Regression (ESR), Conditional Recursive Mixed-process (CMP), Generalized Propensity Score (GPS) matching in a continuous treatment framework and Propensity Score Matching (PSM). The Propensity score matching technique is used in this study and will be discussed in the next section.

i) Propensity score matching (PSM)

Rosenbaum and Rubin (1983) initiated the basic idea of propensity score matching. The authors observed that self-selection bias can be removed through adjustment in propensity scores of treated and untreated groups. The propensity score matching method has been widely used in agricultural research to evaluate the impact of agricultural technology adoption on the outcome variable. PSM helps to address self-selection problem by matching the treatment to the control groups that have similar characteristics using propensity score.

The propensity score assumes a conditional independence, which considers the decision to adopt as a random condition on observed covariates. The PSM also assumes common support condition, which involves comparison in covariates between treated and control groups. In this situation among the farmers that are compared have a similar probability of being both an adopter and non-adopter. If both conditional independence and common support assumptions are met, thus the average treatment effect on the treated (ATT) can be calculated. The average treatment effect is defined as the mean difference between the treatment group matched with the control group who are balanced on the propensity scores and fall within the regions of common support.

The PSM technique is estimated in a two-step procedure; firstly, the use of probit or logit model to calculate the propensity score for each farmer while in the second stage, each adopter is matched with non-adopter with similar propensity score to estimate ATT (Abadie and Imbens, 2006). Thus, PSM ensures that the estimated technology effect is only due to the treatment (adoption) and not because of other covariates by taking care of self-selection bias. However, the estimated treatment effect could have hidden bias due to unobserved heterogeneity (Willy *et al.*, 2014). The next section discusses on instrumental variable.

ii) Instrumental variable (IV) estimation

The instrumental variable (IV) estimation underlies the assumptions about the structure of the cause-effect relationship and about the correlations between treatment participation and outcomes (Zeng, 2014). IV approach is designed to deal with the problem of observed and unobserved biases and endogeneity. IV involves introducing a variable (instrument) that is highly correlated with the treatment participation but uncorrelated with unobserved characteristics affecting outcomes. An IV plays an important role in inducing a change in the behaviour of the treated group (adopters) in a way that it will influence the response variable. However, if instruments are not selected carefully, weak instrument can result in bias of estimates if the instruments are correlated with unobserved characteristics affecting the outcome. This drawback can be address by testing for weak instrument. The main strategies to deal with identification of average treatment effects within the framework of IV approach include Local Average Treatment Effects (LATE) and Endogenous Switching Regression (ESR) (Danso-Abbaem, 2018).

2.5 Empirical studies on agricultural technology adoption and impact

Literature in agricultural production across the world has provided evidence on the significance of agricultural technology adoption in increasing productivity and efficiency of farmers which in turn lead to increase in income and improvement in the livelihood of farmers. Mulugeta and Hundie (2012) employed the propensity score matching to analyse the impact of improved wheat technologies on households' food consumption in South-eastern Ethiopia. The results indicated that wheat technologies had a robust and positive impact on farmers' food consumption levels. The authors found out that the level of food consumption of farmers was higher by 21% for the adopters. The mean food consumption for adopters was 2694kcal compared to 2217kcal for non-adopters. The study identified factors affecting adoption of improved wheat technologies to be age, education, farm experience, participation in off-farm activities, access to credit, extension contact, and livestock holding. Willy *et al.* (2014) applied propensity score matching and exogenous switching regression to estimate the joint effect of multiple soil conservation practices among smallholder farmers in the Lake Naivasha basin area of Kenya. The findings indicate that there is a significant positive effect of implementing multiple soil conservation practices on crop productivity.

In analysing the impact of modern technologies on farm productivity in Philippine. Villano *et al.* (2015) employed propensity score matching and stochastic frontier to estimate the impact of modern rice technologies on farm productivity while disentangling technology gaps from managerial gaps. The empirical results indicated that the adoption of certified seeds has a significant and positive impact on productivity, efficiency and net income in rice farming. Khonje *et al.* (2015) utilized propensity score matching and endogenous switching regression models to analyse the adoption and impacts of improved maize varieties in Eastern Zambia. The findings show that the adoption of improved maize leads to significant gains in crop incomes, consumption expenditure, and food security. The results also show that that improved maize varieties have significant poverty-reducing impacts in eastern Zambia. In a similar study, Mmbando *et al.* (2015) employed propensity score matching, and endogenous switching regression techniques to examine the welfare impacts of smallholder farmers' participation in maize and pigeon pea market in Tanzania. The results indicated that maize and pigeon pea market participation and the level of participation had a positive and significant influence on the welfare of rural households. The result further shows that maize and pigeon pea market participation increased consumption expenditure per capita in the range of 19.2–20.4 % and 28.3–29.4 %, respectively.

Abate *et al.* (2016) used a propensity score matching technique to evaluate the effects of institutional financial services on farmers' adoption of agricultural technology in Ethiopia. The results reveal that access to institutional finance has a significant positive impact on both the adoption and extent of technology use. Ali and Behera (2016) analyzed the factors influencing farmers' adoption of energy-based water pumps and impacts on crop productivity and household income in Pakistan, using a multivariate probit model and propensity score matching approach. The empirical results indicated that educated, younger, and wealthier farmers are more likely to adopt alternate energy-based water pumps for irrigation. Furthermore, access to credit facilities and frequent hours of load shedding were identified as the major factors influencing a farmer's decision to adopt alternative energy-based water pumps rather than relying on electricity.

In assessing the adoption of agrochemical management practices among smallholder cocoa farmers in Ghana. Danso-Abbeam and Baiyegunhi (2017) employed multivariate probit and tobit models to examine the determinants of agrochemical inputs adoption and the extent of adoption, respectively. The result of the study showed that agrochemical management practices are complementary, and the adoption of an agrochemical input is conditional on the adoption of others. Factors such as household characteristics, household assets, institutional variables, and the perception of soil fertility status and the incidence of pests and diseases were found to influence the adoption of individual agrochemical inputs. The result also indicated that the intensity of agrochemical adoption is also influenced by extension services and farmers' visits to demonstration farms.

Adoption of agricultural technology has attracted many studies (Saka and Lawal, 2009; Awotide *et al.*, 2013; Nguezet *et al.*, 2013; Oladeji *et al.*, 2015) in Nigeria over the years. Saka and Lawal (2009) employed adoption index, logit model and stochastic frontier model to examine the determinants of adoption and productivity of improved rice varieties in South-western Nigeria. The results show that farmers responded to an intervention program that promotes the use of improved rice varieties with an adoption rate of 68.7% which leads to an increase of 19.4% in production. The rice yield of farmers adopting IRVs (1.90 tonnes/ha) was significantly higher than that of non-adopters (1.07 tonnes/ha). The estimated average technical efficiency score of the rice farmers was 78.4%, indicating that rice farmers have the potential to increase their productivity by increasing their farm size, the quantity of improved seed and fertilizer in south-western Nigeria.

Applying the Average Treatment Effect (ATE), Nguezet *et al.* (2013) examined the actual and potential adoption rates and determinants of improved rice variety (New Rice for Africa (NERICA)) among rice farmers in Nigeria. The results indicated that the potential NERICA adoption rate in Nigeria will be 54% if the entire population is aware and up to 62% if they have access to NERICA seed. They also found that the actual observed adoption rate (19%) implies a population adoption gap of 35% and 43% because of lack of awareness and access to NERICA seed, respectively.

Oladeji *et al.* (2015) utilized probit regression and Heckman two-stage sample selection model to examine the determinants of awareness and adoption of Improved Rice Varieties (IRVs) in North Central, Nigeria. The empirical results show that 95.3% of the sampled households were aware of improved rice varieties while 87.25% had grown at least one of the IRVs at the time of visit. They also found out that access to credit, access to media, farm size, gender, household size and agricultural income significantly influence the probability and intensity of adoption of IRVs. In another study, Awotide *et al.* (2013) employed inverse propensity score weighing (IPSW) and the local average treatment effect (LATE) to estimate the impact of seed vouchers on poverty reduction among smallholder rice farmers in Nigeria. The findings revealed that the Seed Voucher System (SVS) has a positive and statistically significant impact on annual household income and per capita consumption expenditure.

The above studies reviewed shows that there have not been sufficient studies evaluating the impact of IRVs adoption on productivity in Nigeria. Therefore, this study aims to contribute to the gap in impact of adoption of agricultural technology in Nigeria.

2.6 Agricultural productivity and efficiency

Production system and efficiency in resource use in the farm determine the nature and amount of agricultural resources that would be made available for farmers to enhance their productivity. According to Coelli *et al.* (2005), the terms productivity and efficiency are often used interchangeably, but they are not precisely the same thing. Productivity is an absolute concept which includes partial factor productivity and total factor productivity and is measured by the ratio of outputs to inputs. The total productivity is a productivity measure that involves all factors of production while the partial productivity measures are in terms of specific inputs such as capital, labour and land productivity.

Productivity is a measure of how efficient and effective resources are used as inputs to produce products and services needed by society in the long run. The increase or decrease in production can be attributed to the factor used. Thus, if production increases more than the factor used then this is referred to as increased productivity, but not efficiency. A firm may be technically efficient, but still not able to enhance its productivity through other sources such as scale economies. Thus, efficiency is one of the sources of productivity changes just like technological changes when the time is incorporated. When a firm (farm or other agro-allied enterprises) increases its productivity from one period to another, the increment may not be due to efficiency improvement alone but may have been due to technological change or exploitation of scale economies or from some combination of these three factors (Coelli *et al.*, 2005).

Efficiency is a relative concept and is measured by comparing the actual ratio of outputs to inputs with the maximum ratio of outputs to inputs (Dao, 2013). Efficiency measurement begins with the seminal work of Farrel (1957) who defined a measure of a firm efficiency. According to Farrel (1957), efficiency of a firm is defined as the ability to produce the largest possible output from a given set of inputs. He further explained that this definition is accepted provided that all inputs and outputs are correctly measured. Farrel (1957) disintegrates efficiency into economic efficiency, technical efficiency and allocative efficiency. Efficiency is an important economic concept for the measurement of economic performance of a production unit. Production efficiency is concerned with the relative performance of the process used in transforming inputs into outputs.

According to Ọlayide and Heady (1982), agricultural productivity is a measure of efficiency since the aggregate productivity of an economic system is proportional to the efficiency of production of the components within the systems. Among other scholars, Bravo-Ureta *et al.* (2007) identified the importance of an economic concept of farm efficiency and the use of frontier production models to compare the efficiency of farms. They were able to achieve this by reviewing the concepts, models and measurement of technical efficiency and production frontier technology stimulated by Farrel (1957). Therefore, this thesis applies a frontier production approach (best practice frontier) to explore the technical efficiency of smallholder rice farmers. The next section explains the different types of efficiency such as technical efficiency and allocative or economic efficiency.

2.6.1 Technical efficiency

According to Briec (1997), the research of productive efficiency originated with the work of Koopmans (1951), Debreu (1951), and Farrel (1957). In economic literature, there are two main definitions of technical efficiency. According to Koopmans (1951) who first explain technical efficiency, a producer is technically efficient if an increase in an output requires a reduction in at least one other output or an increase in at least one input, and if a reduction in any input requires an increase in at least one other input or a reduction in at least one output. Debreu (1951) introduced an output-oriented technical efficiency which he called a coefficient of resource utilization. The output-oriented technical efficiency considers a firm to produce a maximum output without an increase in the use of a given set of input. Farrel (1957) later implemented the Debreu measure and provided the measurement of input-oriented technical efficiency which considers the minimal utilization of inputs by a firm without a reduction in its output. The second definition of technical efficiency by Debreu (1951)and Farrel (1957) known as Debreu-Farrell measure is defined as one minus the maximum equi-proportionate reduction in all inputs that still allows the production of given outputs, a value of one indicates technical efficiency and a score less than unity indicates the severity of technical inefficiency. Technical efficiency is the degree in which a farmer produces maximum output from a given set of inputs or uses the minimum amount of inputs to produce a given level of output (Cooper *et al.*, 2004). A farmer is said to be technically efficient if he produces the highest level of output with a given set of input i.e. ability to operate on the production frontier

2.6.2 Allocative and economic efficiency

Allocative efficiency also termed as price efficiency, is the ability of a firm to use the inputs in optimal proportions, given their respective prices (Cooper *et al.*, 2004). This is the degree at which the farmer maximizes his profit by utilizing his resources (input) with respect to the price of the input. Coelli *et al.* (2005) explain allocative efficiency as an input selection which involves selecting the mix of inputs (e.g. labour and capital) that produces a given quantity of outputs at a minimum cost (given the input price which prevails).

Economy efficiency is the combination or product of technical and allocative efficiency, which is also referred to as overall efficiency (Farrel, 1957). Nargis and Lee (2013) explained that economic efficiency is different from technical and allocative efficiency, even though it is the product of both. They define Economic efficiency as the ability of a production unit to produce a well-specified output at minimum cost. An economically-efficient firm should be both technical and allocative efficient. The concept of economic efficiency denotes that the firm is concerned about maximizing profit and minimizing cost for a given level of output. Therefore, the firms or farms strive to achieve a substantial level of production by either reducing the cost of output or increasing the output with a certain level of costs. The next section explains the techniques used in measuring efficiency level.

2.7 Approaches to efficiency measurement

The frontier function models have been used extensively to measure the level of efficiency/inefficiency of farms. The different frontier models that have been developed based on Farrell's work can be categorized into parametric and non-parametric. The parametric approach is composed of the stochastic frontier approach (SFA), the thick frontier approach (TFA) and the distribution-free approach (DFA). Non-parametric models encompass of data envelopment analysis (DEA) and the free disposal hull (FDH). DEA is a linear programming technique, which uses data on inputs and outputs to construct a best practice production frontier over the data. The main difference between the parametric and non-parametric is that the parametric approach specifies a functional form i.e. the random errors and the probability distribution for the inefficiency while the non-parametric does not. In addition, the parametric approach relies on econometric techniques, which include stochastic frontier analysis and simple regression analysis while the non-parametric approach uses mathematical programming techniques.

The stochastic frontier analysis (SFA) and the data envelopment analysis (DEA) are the most commonly used parametric and non-parametric approach. However, there is no agreement by researchers on the best method for measuring efficiency. This study focuses on the stochastic frontier analysis which is discussed in the next section.

2.7.1 Stochastic frontier analysis

Stochastic frontier production function was independently proposed by Aigner *et al.* (1977) and Meeusen and Van Den Broeck (1977). The model has been reviewed and developed in the work of Forsund *et al.* (1980); Schmidt (1986); Bauer (1990); Battese (1992) and Greene (1993). The stochastic frontier production function allows for technical inefficiencies of production of firms involved in producing an output. The model also acknowledges the fact there are other sources of inefficiency that is beyond the control of producers that can affect output. Kumbhakar *et al.* (1991); Reifschneider and Stevenson (1991) and Huang and Liu (1994) improved the models for the technical inefficiency effects involved in stochastic frontier functions. The parameters of the stochastic frontier and the inefficiency model are estimated simultaneously, given proper distributional assumptions associated with cross-sectional data on the sample firms. Stochastic frontier analysis (SFA) uses the maximum likelihood estimation or corrected ordinary least squares (COLS) technique to estimate the frontier function in a given sample (Richmond, 1974). This depends on whether an explicit distribution for the error term of the efficiency component is assumed or not (Bravo-Ureta and Pinheiro, 1993). Explicit, exponential, gamma or half-normal distributions are commonly used when assumptions are made (Alemu *et al.*, 2017).

The main advantage of SFA is its ability to distinguish deviations from production function as comprising both random error and inefficiency components. This provides a distinction between a random symmetrical component which accounts for measurement errors in the output variable and stochastic effects (e.g. weather influences) and a symmetric deviation component which represents the inefficiency (Bezat, 2009). However, the stochastic frontier model also has its drawback. The main disadvantage is that there is no a priori justification for the selection of any distributional form for the inefficiency component of the error term (Greene, 1990). Also, the wrong choice of production function may influence the result of the analysis.

The model used in this study has a high application preference than the data envelopment analysis in an agricultural research context. The main reason is that the DEA attributes all deviation from the frontier is due to farmers' inefficiency which is not acceptable because in agricultural production there are some factors that are beyond the farmers control such as weather, pest and diseases (Mango *et al.*, 2015). Several studies (Battese and Coelli, 1995; Longtau, 2003a; Ogundari, 2008; Mango *et al.*, 2015) have used the stochastic frontier model to estimate technical efficiency in their empirical studies.

The measurement of efficiency in agricultural production has remained an important area of research in both developing and developed countries. Farrell's (1957) paper has led to several empirical studies of efficiency measures to evaluate the performance of farms. The first application of the stochastic frontier model to farm level data was done by Battese and Corra (1977) who estimated deterministic and stochastic Cobb-Douglas production frontiers for the grazing industry in Australia. The variance of the farm effects was found to be a highly significant proportion of the total variability of the logarithm of the value of sheep production in all states. However, their study did not directly address the technical efficiency of farms.

Bagi (1984) used the stochastic frontier Cobb-Douglas production function model to analyse the differences in technical efficiencies of small and large crop and mixed enterprise farms in West Tennessee. The study found that the variability of farm effects was highly significant. The average technical efficiency of mixed enterprise farms was found to be smaller (76%) than for crop farms (85%). Battese and Coelli (1995)employed the Cobb-Douglass stochastic frontier to estimate the source of technical inefficiency on paddy rice farms in Aurepalle India using panel data for ten years.

They concluded that older farmers where more inefficient than the younger ones, also farmers with greater years of schooling were more efficient but declined over a period of ten years. In a study by Sharma and Leung (1998) on technical efficiency of carp production in Nepal. The estimated average technical efficiency is 77% with intensive farms being more efficient than extensive farms. They also concluded that the adoption of regular fish, water, and feed management activities has a strong positive effect on technical efficiency.

Seyoum *et al.* (1998) used a translog stochastic production frontier to analyse technical efficiency of maize producers in Eastern Ethiopia for farmers within and outside the Sasakawa Global 2000 project. The mean technical efficiency of farmers within the SG 2000 project was estimated to be 0.937 while the estimate of the farmers outside the project was 0.794. They concluded in the study that younger farmers are more technically efficient than older farmers. Also, farmers with more years of school were more technically efficient. However, those that obtained information from extension advisers tended to reduce the technical inefficiency.

Abdulai and Eberlin (2001) employed the translog stochastic frontier model to estimate the technical efficiency of maize and beans in Nicaragua. The average technical efficiency was 69.8 and 74.2% for maize and beans, respectively. Also, the human capital, access to formal credit and farming experience contribute positively to production efficiency, while farmers' participation in off-farm employment tended to reduce production efficiency. Fleming and Coelli (2004) employed the stochastic frontier model to assess the performance of a nucleus estate and smallholder scheme for oil palm production in West Sumatra. The mean technical efficiency of the farmers was 0.66 which suggests that 0.34 of oil palm yield was lost due to inefficiency. Al-Hassan (2008) used translog stochastic frontier analysis to analyse the technical efficiency of rice farmers in Northern Ghana. The rice farmers were found to be technically inefficient, producing below the frontier with an average efficiency level of 53%. Khai and Yabe (2011) used a Cobb-Douglass stochastic production frontier to analyse technical efficiency of rice production in Vietnam. The mean technical efficiency of the farmers was 81.6% which suggests that 18.4% of paddy rice was lost due to inefficiency.

In measuring the technical efficiency of smallholder maize production in Zimbabwe. Mango *et al.* (2015) used a Cobb-Douglas stochastic frontier production function to determine the production elasticity coefficients of inputs, technical efficiency and the determinants of efficiency. The technical efficiency analysis suggests that about 90% of farmers in the sample were between 60 and 75% efficient, with an average efficiency of 65%. The significant determinants of technical efficiency were the gender of the household head, household size, frequency of extension visits, farm size and the farming region. The results imply that the average efficiency of maize production could be improved by 35% through better use of existing resources and technology. Alemu *et al.* (2017) employed the Cobb-Douglas stochastic frontier model to estimate the technical efficiency of apple production in Ethiopia. The average technical efficiency was 40% and 52% for production of apple fruits and seedlings which suggest that 60% and 48% of apple fruits and seedlings were lost due to inefficiency.

The stochastic frontier analysis has been applied in agricultural empirical studies in Nigeria. Udoh (2000) used the Maximum Likelihood Estimation of the stochastic production function to examine the land management and resource use efficiency in South-Eastern Nigeria. The study found a mean output-oriented technical efficiency of 77%. Amaza and Olayemi (2002) investigated technical inefficiency in food crop production among farmers in Gombe State, Nigeria. The average technical efficiency was 69%. In analysing the resource use efficiency of urban farmers in Uyo, South Eastern, Nigeria. Umoh (2006) employed the Maximum Likelihood Estimation stochastic production frontier approach. The average technical efficiency of urban farmers is 72%. Idiong (2007) estimated the farm level technical efficiency of small-scale Swamp Rice Production in Cross River State of Nigeria, using the Cobb-Douglass stochastic frontier production approach. The results show that the rice farmers were not fully technically efficient. The mean efficiency obtained was 77% indicating that there was a 23% allowance for improving efficiency. The result also shows that farmers' educational level, membership of cooperative/farmer association and access to credit significantly influenced the farmers' efficiency positively. Ogundari (2008) estimated the technical efficiency of rice farmers in Nigeria, using the translog stochastic frontier approach. The mean technical efficiency of the farmers was 0.75 which suggests that 0.25 of rice yield was lost due to inefficiency.

Omonona *et al.* (2010) used the Cobb-Douglass stochastic frontier production function to analyse the technical efficiency of cowpea farmers in southwest Nigeria. The farmers' average technical efficiency is 87%, which suggest an appreciable use of inputs in productivity. The average technical efficiency of the irrigated and rain-fed rice farmers was 76% and 71% respectively. Abba and Isa (2015) applied the Cobb-Douglass stochastic frontier model to estimate the technical efficiency of rice farmers in Adamawa state, Nigeria. They estimated the average technical efficiency of irrigated and rain-fed rice farmers to be 76% and 71% respectively. Okoye *et al.* (2016) analysed the differentials in technical efficiency among smallholder cassava farmers in Central Madagascar using a Cobb Douglas stochastic frontier production approach. The average technically efficiency of the farmers was 79%, suggesting that opportunities still exist for increasing efficiency among the farmers. The next section continues with the other approach of measuring efficiency.

2.7.2 Data envelopment analysis (DEA)

Among other scholars, Charnes *et al.* (1978) were the first to introduce DEA in estimating efficiency based on seminal work by Farrel (1957). Charnes *et al.* (1978) developed DEA to analyse the performance of public sector organization whose goals are not profit maximization (Oberholzer and Van der Westhuizen, 2009). DEA is a linear programming technique used to estimate a non-parametric production frontier for the peer decision-making units (DMUs). It gives a piece-wise linear frontier that "envelopes" the observed input and output data (Coelli *et al.*, 2002). In agricultural context, the DMUs are the farmers.

DEA model can be input and output oriented based on DMUs (De Koeijer *et al.*, 2002). If the DMUs have more control over inputs variable than the output variables, the DEA model should be input model if otherwise, it should be output model. The DEA estimates the efficiency of a farm as the ratio of its weighted output to its weighted input where the ratio of the farm is not greater than 1 (Mardani and Salarpour, 2015).

The main advantage of DEA is that it does not require a specific functional form for the frontier to be specified. Also, it can be used in estimating technical, allocative, cost and scale efficiency. However, DEA has a drawback of attributing all deviations from the production frontier to inefficiencies of the farmers which denotes that it doesn't account for random error (such as measurement error, pest and diseases).

DEA has been applied to many agricultural studies. Llewelyn and Williams (1996), analyse the technical, pure technical and scale efficiencies of food crops in Indonesia using DEA. They estimated the efficiencies for three production seasons which are the rainy, middle and dry season. The results indicated that average overall technical efficiency, pure technical efficiency and scale efficiency of farms was estimated to be 98.1%, 98.8% and 99.2% during the rainy season; 95.5% and 97.7%, 97.7% during the middle season and 97.7%, 98.9% and 98.7% during the dry season. They further observed that majority of the farmers are efficient but farmers that are operating inefficiently do so more because of scale inefficiencies rather than technical inefficiency.

Coelli *et al.* (2002) employed DEA to estimate the technical, allocative, cost and scale efficiencies of rice cultivation in Bangladesh. They estimated the efficiencies for two production seasons (dry and wet season). The mean technical, allocative, cost and scale efficiencies during dry season was estimated to be 69.4%, 81.3%, 56.2%, 94.9 and 66.2%, 78.0%, 51.7%, 93.3 % for the wet season.

Solomon *et al.* (2015) applied DEA to examine gender differentials in scale and technical efficiencies among improved wheat variety growers in Ethiopia. The DEA results indicated that the women farmers are more efficient than the men farmers with an average technical efficiency of 80.8% and 70%, and average scale efficiency of 78% and 81.6% respectively

2.8 Factors affecting agricultural productivity and efficiency

This section aims to discuss the factors influencing agricultural productivity and efficiency. The determinants of agricultural productivity and efficiency are categorized into production factors and inefficiency factors. The production factors are the resources used in agricultural production while the inefficiency factors are variables that contribute to the inefficiency of the farmers such as socio-economic and socio-institutional factors are. The determinants are discussed in detail in the next section;

2.8.1 Resource use in rice production

Agricultural resources used in producing a farm output includes land, fertilizer, seed, agrochemicals and labour. The efficient combination of these resources yields the desired output. This section reviews literature on resource use in rice production.

i) Land

According to Kagoda (2008), land is the most valuable form of property in agrarian societies because of its economic, political and ritual importance. Land is one of the most important resources used in agricultural production because other resource depends on land for an output to be produced. The size of land area used in farming has an influence on output. Efficient use of land combined with other farm inputs will enhance the productivity of rice. For instance, (Abadie and Imbens, 2006); Tu *et al.*

(2018), indicated that farm size increases the technical efficiency of rice farmers in Vietnam. They reported that rice farmers were efficient in the utilization of farmland even though agricultural land ownership were limited to 3 hectares per household by Vietnamese land law. Some empirical studies in Nigeria (Ogundele and Okoruwa, 2006; Ogundari *et al.*, 2010; Akighir and Shabu, 2011; Ohen and Ajah, 2015; Amaechina and Eboh, 2017) has also found farm size to be significant and positively related to rice yield.

ii) Fertilizer

The depletion of large quantities of soil nutrients has been caused by smallholder farmers without sufficient quantities of organic or inorganic fertilizer to replenish the soil over the decades (Sanchez, 2002). Soil nutrients depletion can be overcome using mineral fertilizers. The deficit in mineral fertilizer application by resource-poor small-scale farmers is due to the high cost. Sanchez (2002), reported that fertilizer cost in Africa is between two to six times the cost in Europe, North America or Asia which result in Africa being one of the lowest fertilizer consumption continents. The quantity of fertilizer usage also varies across different African countries, for example, GRiSP (2013) reported that fertilizer application rate of 13kg/ha used by farmers in Nigeria is one of the lowest in sub-Saharan African (SSA).

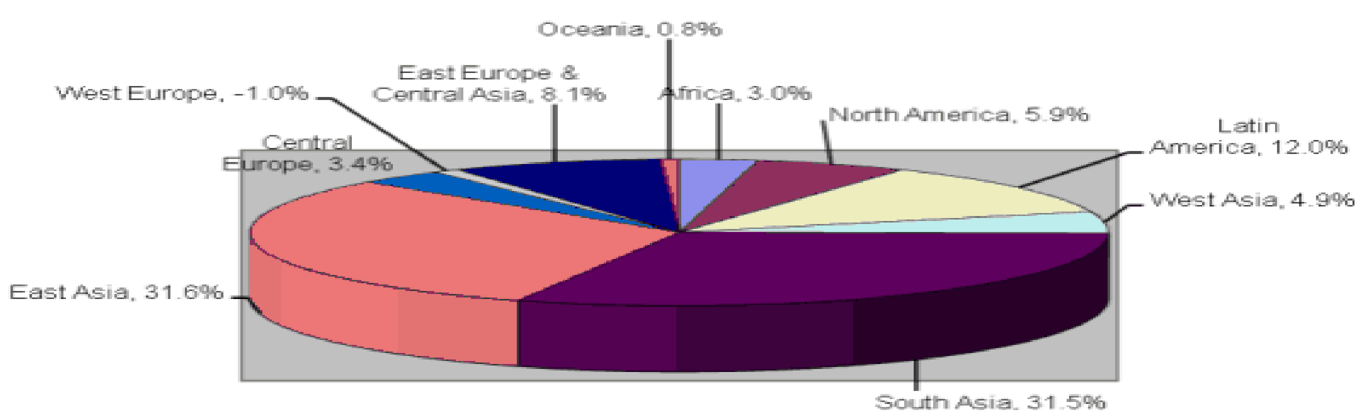

Figure 2. 4: World share in consumption of nitrogen fertilizer
Source: FAO (2011).

Ahmed *et al.* (2017) in a study comparing rice production in Nigeria to China, observed that the yield in rice production in China is higher than that of Nigeria due to increase in the use of chemical fertilizers. Other empirical studies conducted in different part of the world including Africa has shown that fertilizer has a significant and positive relation to rice yield (Akighir and Shabu, 2011; Hussain, 2013; Villano *et al.*, 2015; Ishani *et al.*, 2016). In contrary to these studies, Llewelyn and Williams (1996) observed a negative relationship between fertilizer and yield of crop (including rice) farmers in Indonesia. They explain that the farmers using high quantity of fertilizer are less efficient and this may be due to a high fertilizer subsidy during the study period and thus the farmers might be using above the recommended rate. In a similar study, Abedullah *et al.* (2007) found fertilizer to be significant and negatively related to rice yield in Pakistan. They argued that this is due to an inappropriate combination of different fertilizer nutrients (NPK, P, P_2O_5) rather than over utilization of fertilizer because the total amount of fertilizer (NPK) used by the farmers is below the recommended rate.

iii) Seed

According to Cassman (1999), the gap between average yields achieved by farmers and potential yield is determined by the quality of crop varieties or hybrids and the efficiency of farmers on crop and soil management practices. Seeds used in rice production are classified into two, which are local and improved varieties. Different varieties of rice seeds have been developed over the years. Rice seed varieties are planted based on their adaptive features to the different production system. However, accessibility to high yielding rice seeds variety will enhance productivity and efficiency in rice production. Ishani *et al.* (2016) conducted a study on resource use efficiency in rice production in India, they observe that a percentage increase in the quantity of seed sown will result in 10% increase in rice yield. Ogundele and Okoruwa (2006) observed that farmers with improved seed have a higher yield than farmers that planted local rice seed in Nigeria. Ogundari *et al.* (2010) also provide evidence that seed has a positive and significant impact on the yield of rain-fed rice farmers in Nigeria. In contrary Huynh-Truong (2009), observe that an increase in the quantity of seed will decrease the yield of rice farmers in Vietnam. This is because of the adoption of advanced rice farming practices in the area which are intended to minimize the quantity and cost of input used in production to maximize output. For example, practicing row seeding will lead to a reduction in the quantity of seed sowed by 80 – 120kg/ha which in turn reduces labour requirement also.

iv) Agrochemicals

The occurrence of weeds, pests and diseases along with soil fertility depletion is a major biophysical cause of low per capita food production in Africa (Sanchez, 2002). One of the production challenges encountered by rice farmers is the invasion of weeds, pests and diseases on rice plot which might be caused by poor farm management practices. Agrochemicals such as pesticide and herbicide are important inputs used in rice production to enhance productivity and efficiency. Ogundari (2008) conducted a study on resource-productivity, allocative efficiency and determinants of technical efficiency of rain-fed rice farmers in Nigeria, the study showed that herbicide is statistically significant and positively related to rice yield. The study also found out that herbicide contributed most among other inputs to paddy rice yield of the farmers. In contrary, Heong *et al.* (1994), observed that application of insecticide does not increase rice yield in Philippines and Vietnam. They observed that the insecticide used does not affect the leaf borers hence not effective in enhancing rice production. Similarly, Nimoh *et al.* (2012) also found agrochemicals application to be statistically significant and negatively related to rice yield in Ghana.

v) Labour

Labour is an important resource used in rice production process. The advancement of technology has resulted in the substitution of human labour for machinery to perform different farm operations in most developed countries. Despite this, human labour cannot be eradicated because they are needed to operate these machines. However, in many African countries where there is low use of machinery on farms, small scale farmers depend on labour forces to carry out their farm operations such as land clearing, ridging, seed planting, agrochemicals application and harvesting. In agriculture, human labour comprises of family and hired labour. Family labour are members of the farmers' household while hired labour are individuals paid to work on the farm. Hired labour can be of two forms the skilled and unskilled labour. The skilled labourers are used in some sensitive production process such as agrochemicals application and use of farm technology while unskilled labourers are used in other manual farm operations such as weeding and harvesting. Family labour is more used by resource-poor farmers than hired labour because of the high cost of hired labour (Masterson, 2007).

The efficient utilization of human labour has effect on rice productivity. Empirical studies (Al-Hassan, 2008; Huynh-Truong, 2009; Khai and Yabe, 2011; Villano *et al.*, 2015) has provided evidence that labour had a statistically significant and positive impact on rice yield in Africa and Asia. Khai and Yabe (2011) observed that labour is one of the most important factors having positive effect on technical efficiency level of rice farmers in Vietnam.

2.8.2 Factors influencing inefficiency in agricultural production

The inefficiency factors are variables influencing the level of efficiency and productivity of the farmers. The inefficiency factors can be categorised into socio-economic and socio-institutional factors. Literature on inefficiency variables are discussed below.

2.8.2.1 Socio-economic factors

The socio-economic variables found to influence the level of technical efficiency of rice farmers in literature include age, gender, household size and farming experience.

i) Age

The age of farmers is important in determining the farmer's efficiency level. A positive or negative impact on efficiency depends on whether older farmers are more experienced or slower in adopting new technologies than younger farmers (Tipi *et al.*, 2009). Abedullah *et al.* (2007) found age to be positive and significantly influence the technical inefficiency of rice farmers in Pakistan. This implies that older rice farmers are technically inefficient than young farmers. This is maybe due to the reason that they are physically less active in performing different farm operations. In estimating gender differences among men and women rice farmers in Nigeria, Oladeebo and Fajuyigbe (2007) observed age to be negatively related to the inefficiency of both men and women farmers. They explained that young rice farmers are more efficient than older farmers because they are likely to be more progressive and willing to adopt new practices which in turn enhances their technical efficiency in rice production.

ii) Gender

Gender difference in farm productivity and efficiency in subsistence farming has been an issue of interest in public policy in developing countries (Dossah and Mohammed, 2016). Determining the efficiency level of both male and female farmers is significant in enhancing food security in Africa where there is high disparity in cultural and religious believe. Addison *et al.* (2016) reported that female farmers are more technically inefficient than male rice farmers in Ghana. This finding is also consistent Adesina and Djato (1997) who observed that inefficiency of women rice farmers was due to constraints in accessing productive inputs. In a similar study, Omondi and Shikuku (2013) provide evidence that male farmers are more efficient than female rice farmers in Kenya. Kinkingninhoun-Mêdagbé *et al.*, (2010) observe a significant difference in paddy rice yield of men and women rice farmers in Benin. However, they indicated that there is no significant difference in technical efficiency of men and women farmers. They further explained that the higher productivity of men farmers than their female counterpart is due to the possession of larger land holding size allocated for rice farming by men farmers.

iii) Household size

The significance of household size in agriculture cannot be overemphasized. Household size contributes largely to subsistence farming in most Sub-Saharan countries where farmers depend on household members for about 80% of labour required for farm operations due to high cost of the hired labour (Ogundele and Okoruwa, 2006). Empirical studies (Oladeebo and Fajuyigbe, 2007; Al-Hassan, 2008; Ayinde *et al.*, 2009; Nwosu *et al.*, 2015) provide evidence that household size increases efficiency and productivity of rice farmers. For example, Nwosu *et al.* (2015) provide evidence that household size is significant and has a positive relationship with paddy rice output and farmers' income in Nigeria. In contrary, Ayinde *et al.* (2009) observed that household size has a negative influence on technical efficiency of rice production in Nigeria.

iv) Farmers experience

Empirical studies (Bozoğlu and Ceyhan, 2007; Bäckman *et al.*, 2011; Omondi and Shikuku, 2013; Tu *et al.*, 2018) indicated that farmers experience has a positive influence on technical efficiency. For example, Bäckman *et al.* (2011) provide evidence that rice farmers with more farming experience are more technically efficient than farmers with less farming experience in Bangladesh. However, Huynh-Truong (2009) observed that farming experience is positive and significant in explaining technical inefficiency of rice farmers in Vietnam. This implies that farming experience does not contribute to increasing the efficiency level of the farmers. The author explained the reason for this was that farmers with high farming experience neglected the traditional farm practices and might follow the innovation on advanced farm technologies taught by agricultural technicians inappropriately.

2.8.2.2 Socio-institutional Factors

This section discusses literature on socio-institutional factors that influence technical inefficiency. The socio-institutional variables include education, extension service and farmer-based organisation.

i) Education

The role of education in enhancing farmers' productivity and efficiency is widely known because it enables farmers to understand the socio-economic conditions guiding their farming operations and to learn how to collect, retrieve, analyse and disseminate information (Al-Hassan, 2008). In estimating technical efficiency of rice farmers in Northern Ghana, Al-Hassan (2008), observe that education is significant in increasing the efficiency level of irrigated and non-irrigated rice farmers. The author explained that farmers with high level of education can form farmer's organisation which in turns enable them to have easy access to credit facilities from government or non-governmental organisation.

Khai and Yabe (2011) provide evidence that primary school and secondary school education is positive and significantly influence the technical efficiency of rice farmers in Vietnam. They explained that farmers with secondary education level and above are more productive than those without education or primary education level. Llewelyn and Williams (1996) found out that high school education has a significant and positive relationship with the efficiency level of rice farmers during the rainy, middle and dry season in Indonesia. Ogundele and Okoruwa (2006), also indicated that education decreases the inefficiency level of rice farmers in Nigeria.

ii) Extension services

Extension services are important in small and large-scale farming as it provides relevant information to farmers that in turns enhances their productivity and efficiency. Al-Hassan (2008), provide evidence of a negative relationship between extension contact and technical inefficiency of the farmers. This implies that farmers that have contact with extension agent are more technically efficient than farmers with no contact. He explained further that extension contact increases technical efficiency because farmers are able to adopt modern farm techniques involved in different rice farming operation such as land preparation, seed planting and application of agrochemicals. Conversely, Oladeebo and Fajuyigbe (2007) observe a significant and positive relation between extension contact and technical inefficiency of upland men and women rice farmers in Nigeria. They explained that inefficiency of farmers that have access to extension agent might be due to the farmers not adhering to instructions or slow in adopting innovations taught by the extension agent.

iii) Farmer-based organisation

Farmers' organisation plays a crucial role in enhancing the productivity of farmers as it provides farmers with relevant information related to farming operations and serves as a link in accessing credit facilities and productive inputs from government and non-governmental organization (NGO). Several studies (Kuwornu *et al.*, 2013; Abba and Isa, 2015; Danso-Abbeam *et al.*, 2015) had observed the relationship between farmer-based organisation and efficiency of farmers. For example, Abba and Isa (2015) observed farmer association to be significant in reducing the technical inefficiency of rice farmers under irrigation production system in Nigeria. In contrary, Kuwornu *et al.* (2013) indicated that members of farmer-based organisation are technically inefficient than non-members of a farmer-based organization in Ghana. The authors explained that the reason for this might be due to members focusing more on other activities in meetings such as how to acquire inputs from government and

NGOs rather than learning improved farming practices during their meetings. However, Chiona *et al.* (2014) observe no significant relationship between farmers association and technical inefficiency of smallholder farmers in Zambia.

2.9 Chapter summary

Agricultural technology such as IRV adoption is important in reducing hunger and promoting food security in SSA including Nigeria. This chapter presented an overview of rice production in Nigeria and the relevant concepts related to the study. A review of approaches and econometric techniques for measuring adoption and technical efficiency were also presented. The Chapter indicated the advantages and drawbacks of the econometric techniques. In farm impact technology adoption literature, it was deduced that the two major estimation techniques used are; Instrumental Variable and PSM. The two important efficiency estimation techniques (SFA and DEA) were also discussed, emphasising more on the SFA. The Chapter explains the link and differences between Agricultural productivity and efficiency. The Chapter concludes with the review of resource use in rice production and some important variables influencing farm technology adoption, productivity and efficiency.

CHAPTER 3

ADOPTION OF IMPROVED RICE VARIETIES AND ITS IMPACT ON PRODUCTIVITY AMONG SMALLHOLDER RICE FARMERS

3.1 Introduction

In this chapter, the methodologies and the empirical results regarding the factors influencing the adoption of improved rice varieties (IRVs) and its impact on productivity of smallholder rice farmers are presented and discussed. The rest of the chapter is structured as follows: Section 3.2 presents the conceptual framework, estimation techniques and the description of variables used in the empirical models. Section 3.3 constitutes the description of the study area, data collection, and sampling techniques. In section 3.4, the empirical results and discussions are presented while section 3.5 concludes the chapter with a summary of the results as well as policy recommendation.

3.2 Conceptual and analytical framework

Agriculture serves as a source of livelihood for must rural dwellers in developing countries like Nigeria, and therefore development, adoption and diffusion of new agricultural technology offer an opportunity to increase productivity, efficiency and farmers income substantially (Feder *et al.*, 1985). Smallholder farmers in Nigeria are involved in a series of decision making (which include adoption of farm technology) during production. Rogers and Shoemaker (1971) defined adoption as the decision to apply an innovation and continuous utilization of it. Adoption of IRVs coupled with combining efficient production input and best management practices could enhance productivity (reducing the gap between potential and actual output) and income of smallholder rice farmers in Nigeria.

Following Baiyegunhi *et al.* (2019) and Khonje *et al.* (2015) the decision to adopt technology (IRVs) can be analysed and modeled in a random utility framework. The model assumes that a utility maximizing farmer will adopt an IRV if the expected net utility (rice yield) from adoption (U_{iA}) is greater than non-adoption(U_{iN}). If N^* denotes the expected net utility, a farmer will choose to adopt IRVs if $N^* = U_{iA} - U_{iN} > 0$. The net utility is unobserved and can be expressed as a function of observable elements in the latent variable model below:

$$N_i^* = Z_i\alpha + \varepsilon_i \text{ , with } N_i = 1, \text{ if } N_i^* > 0 \tag{3.1}$$

where N_i is a binary dummy variable that equals 1 if farmer i adopts IRVs and 0 otherwise; α is a vector of parameters to be estimated; Z_i is a vector of household and farm characteristics and ε_i is the random error term. The farmers' performance indicator is the net yield of paddy rice. The treatment variable was a binary indicator of whether a farmer adopts IRVs or not.

Evaluating the impact of a developed farm innovation technology (such as IRVs) on farmers' productivity is important in determining the converse effects of the technology (Asfaw *et al.*, 2012). The measurement of impact requires a valid counterfactual (control group) of what those outcomes would have been in the absence of adopting the technology compared with the adopters of the technology (treatment group). The comparability of both control and treatment group is done with respect to observed and unobserved characteristics to ensure that outcome effect of the variable of interest (productivity) for the treatment group is solely due to the adoption of the technology.

The fundamental problem that occurs in the measurement of impact evaluations is selection bias and endogeneity. This may be due to the non-random selection of treatment groups. When this occurs the decision to adopt a technology may be influenced by both inherent and non-observable characteristics (such as farmers' motivation and risk attitude) and observable heterogeneity that may be correlated with the outcome variable (Danso-Abbaem, 2018). The potential selection bias can be addressed by

Propensity Score Matching (PSM) techniques estimating the average treatment effect (ATT). PSM ensures that the estimated technology effect is only due to the treatment (adoption) and not because of other covariates by taking care of self-selection bias.

3.3 Empirical model specification and estimation technique

This study used the propensity score matching (PSM) to estimate the impact of adoption of IRVs on smallholder rice farmers' yield. The basic idea of PSM was introduced by Rosenbaum and Rubin (1983) who observed that self-selection bias can be removed through adjustment (matching) using propensity score between the treated (adopters) and untreated (non-adopters) groups. PSM has been applied in many studies (Asfaw *et al.*, 2012; Willy *et al.*, 2014; Khonje *et al.*, 2015; Villano *et al.*, 2015; Ali and Behera, 2016) to control for self-selection bias.

In this study, self-selection problem (bias) may occur since adoption of IRVs by farmers is not random but based on factors influencing farmers' decision. Thus, farmers who adopt IRVs may systematically differ from non-adopters based on several factors such as farm-specific, and socio-economic characteristics which might influence the rice yield of farmers. In order to estimate the impact of IRVs on the productivity of smallholder farmers the self-selection bias problem must be addressed (Willy *et al.*, 2014). The self-selection problem is solved by implementing PSM which involves the use of a binary choice model to generate a propensity score for each farmer in the study. In PSM, each farmer receiving treatment (adopters) is matched with untreated farmers (non-adopters) based on observable covariates in a quasi-experimental approach to mimic random assignment to treatment and then measure the average differences in the productivity (rice yield) between the adopters and non-adopters of IRVs. The PSM can be expressed as;

$$p(X) = \Pr[D = 1|X] = E[D|X]; \quad p(X)=F\{h(X_i)\}, \tag{3.2}$$

where $p(X)$ is a propensity score, and Pr is the probability of adopting IRVs (taking a treatment, $D = 1$ and 0 otherwise) conditional on the vector of observed covariates (pre-treatment characteristics), X and $F\{.\}$ can be a normal or logistic cumulative distribution.

A probit model was employed in the study to estimate the predicted probabilities (propensity scores) of adopting IRVs. Following Greene (2003); Verbeek (2008) and Willy *et al.* (2014)the probit model is expressed as;

$$Pr(D = 1|X) = G(z) = \int_{-\infty}^{X'\beta} \emptyset(z)dZ = \boldsymbol{\phi}(X'\beta) \tag{3.3}$$

where $G(z)$ is a function taking values between 0 and 1, $\emptyset$ is the standard normal probability density function, z is the vector of covariates and $\boldsymbol{\phi}$ is the standard normal cumulative distribution function. The probabilities were estimated using the maximum likelihood method specified as;

$$\ln L = \sum_{y_i=0} \ln[1 - \boldsymbol{\phi}(X'\beta)] + \sum_{y_i=1} \ln \boldsymbol{\phi}(X_i'\beta) \tag{3.4}$$

The empirical probit model estimated is expressed below;

$$Y_i^* = +u_i, \quad u_i \sim N(0,1), i = 1 \dots., N \; and \; Y_i = \begin{cases} 1 \; if \; Y_i^* > 0 \\ 0 \; if \; Y_i^* < 0 \end{cases} \tag{3.5}$$

where Y_i^* is a latent variable representing the decision to adopt IRVs, Y_i is the observed status of adopting IRVs for each farmer, X is a matrix of explanatory variables which include farmer and farmer and farm characteristics, socio-economic and institutional factors, the βs are the parameters to be estimated and u_i is a normally distributed error term.

The predicted probabilities obtained by estimating the model above (equation 3.5) are used as propensity for matching the samples of IRVs adopters and non-adopters. After propensity scores estimation, a matching algorithm was used to match each adopter with a non-adopter with similar propensity score. This study employed three matching methods, nearest neighbour matching (NNM), Kernel-based matching (KBM) and radius matching (RM) techniques to estimate the impact of IRVs on yield of the smallholder rice farmers. The nearest neighbour matching methods consist of matching each adopter farmer with the non-adopter farmer that has the closest propensity matching score. It can be applied with or without replacement of observations. The NNM may result in bad matching if the closest neighbour is far away. This can be corrected using a radius matching technique which imposes a maximum tolerance on the difference in propensity scores (Mulugeta and Hundie, 2012). However, some treated units may not be matched if the dimension of the radius is too small to control units. The kernel based matching methods involves matching all adopter farmers with a weighted average of all non-adopter farmers using the weight that is inversely proportional to the distance between the propensity scores of the farmers in adopter and non-adopters group (Becerril and Abdulai, 2010). The common support was imposed to construct the matching estimates. The common support condition involves selecting comparable observations from the adopters and non-adopters groups in the analysis. Thus, all the observations outside the common support were excluded from the analysis in the study.

The balancing property of the sample was necessary to be observed in the analysis to ensure that all farmers within the common support area have the same distribution of observable characteristics, irrespective of whether the farmer adopts IRVs or not (Villano *et al.*, 2015). The balancing property indicates the matching quality of the samples. This study employed the standardized bias method to observe the matching quality, which calculates the bias in the mean difference of covariates for the adopter and non-adopter groups after matching. If the average bias in mean difference is less than 5%, it denotes the samples are matched well. After the propensity scores have been estimated, the causal effect of adoption of IRVs on rice yield was calculated using the average treatment effect on the Treated (ATT). The average treatment effect is defined as the mean difference between the treatment group matched with the control group who are balanced on the propensity scores and fall within the regions of common support. The ATT is specified as follows;

$$ATT = E(Y_1|D = 1) - E(Y_0|D = 0) \quad (3.6)$$

where Y_1 and Y_0 are rice productivity measured as rice yield in kg/ha for adopter and non-adopter farmers, D is a dummy variable which takes two values: $D = 1$ if farmers adopt IRVs and $D = 0$ if farmers did not adopt IRVs.

The study tested for sensitivity of the estimated ATT to hidden bias due to unobserved heterogeneity using the Rosenbaum (2002) bounds sensitivity test. The bounds test indicates the point at which the estimated results would no longer be valid i.e. how robust the ATT is to unobserved heterogeneity (Willy *et al.*, 2014). The sensitivity bounds test approach has been used in previous impact evaluation studies (Abebaw and Haile, 2013; Willy *et al.*, 2014; Tilahun *et al.*, 2016) to test for hidden bias in impact estimates.

Finally, the study examined how the estimated impacts of adoption of IRVs vary across farm households by regressing ATT of the individual outcome indicators generated from the PSM on some socioeconomic factors of the smallholder farmers using the ordinary least squares (OLS).

3.4 The study area, sampling and data collection technique

The study was carried out in Ogun State because it is one of the major rice producing states in south west Nigeria. The state has twenty local government, which are grouped into 4 agricultural zones namely Abeokuta, Ikene, Ijebu and Ilaro. The state is covered by tropical rain forest and has wooded savanna in the northwest. The major occupation of the inhabitants is farming. The major food crops produced are rice, maize, cassava, yam and banana.

A multi-stage random sampling technique was employed to select 250 smallholder rice farmers interviewed for the study. In the first stage, five major rice producing local government areas (LGAs) namely (Obafemi Owode, Ifo, Yewa north, Ewekoro and Ogun waterside) were purposively selected based on prior knowledge that smallholder farmers in the LGAs are actively involved in rice production. In the second stage, five rice growing communities/villages were randomly selected in each of the five LGAs. In the third stage, 10 household heads who are smallholder rice farmers were randomly selected from each of the communities/villages to make a total sample of 250 respondents for the study. Farmers that cultivate at least one IRV were considered adopters while non-adopters are those that did not cultivate any IRVs. Primary data was obtained from these sampled respondents through the administration of structured questionnaire consisting of open and close-ended questions relating to socio-economic characteristics of respondents, factors of production such as land, labour, materials such as fertilizers, seed, agrochemicals and marketing information like procurement of input and sales of paddy rice. A pre-test of the questionnaire was done, and some few modifications were made in the questionnaire to get more relevant information and enhance the reliability of the data.

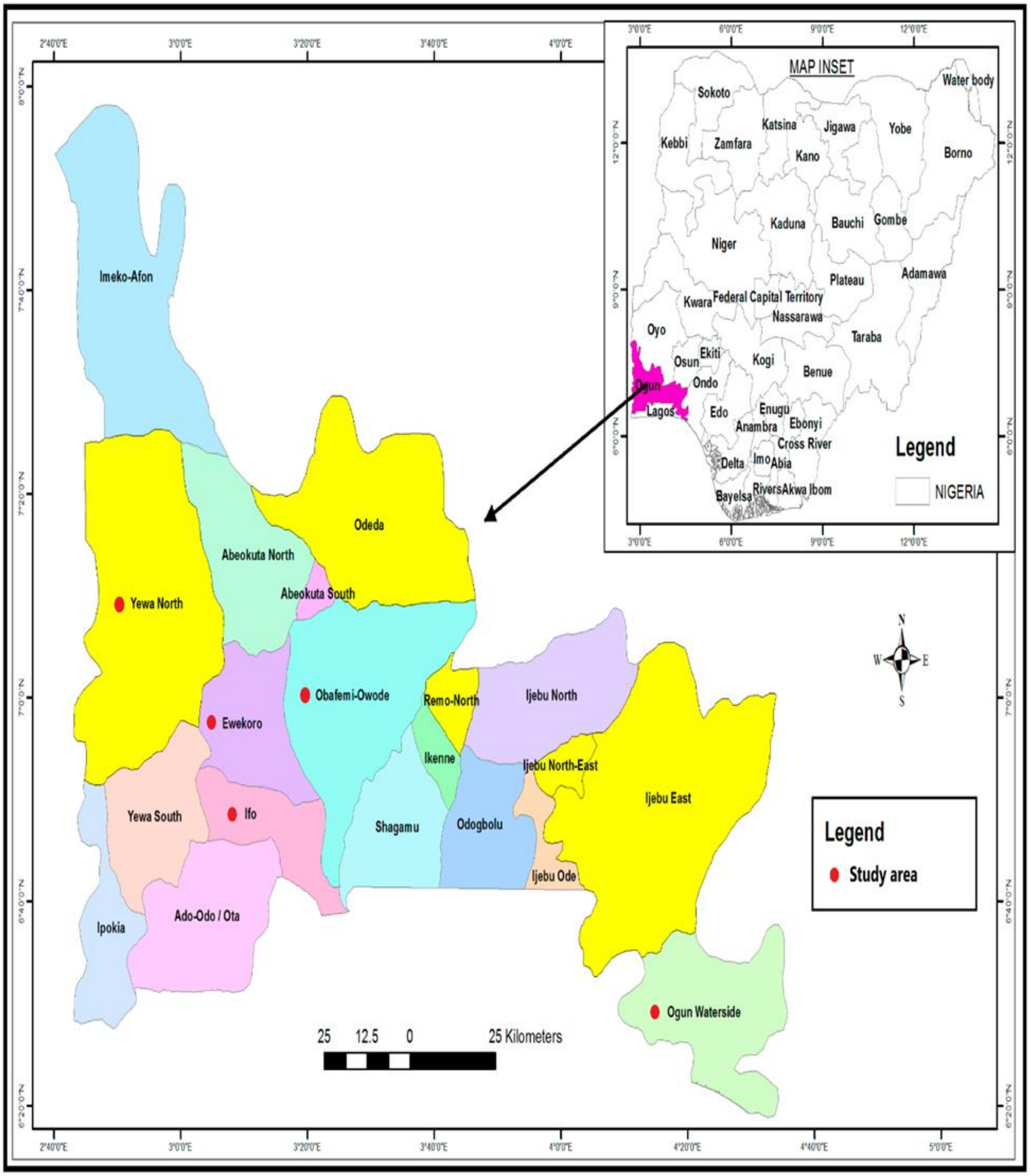

Figure 3.1: Map of Ogun state showing the study areas.

3.5 Definition of variables and summary statistics

The definitions of variables and summary statistics of the sampled farm household in the study are presented in Table 3.1

Table 3.1: Descriptive statistics of explanatory variables used in estimations.

Variable	***Full sample*** $(n = 250)$		***Adopters*** $(n = 110)$		***Non-adopters*** $(n = 140)$		***T-test*** (χ^2)
	Mean	***SD***	***Mean***	***SD***	***Mean***	***SD***	
Socioeconomic characteristics							
Gender (1=male, 0 = female)	0.58		0.65		0.52		2.13^{**}
Age (year)	48.22	8.27	48.38	7.80	48.09	8.66	0.27
Formal education (year)	5.35	5.96	5.27	5.96	5.41	5.98	0.84
Rice farming experience (years)	15.28	5.12	15.45	5.38	15.14	4.92	0.48
Farm size (hectare)	2.23	0.58	2.26	0.54	2.20	0.62	0.82
Off-farm income (1=yes, 0= no)	0.53		0.55		0.51		0.74
Institutional/Policy variables							
FBO membership (1=yes, 0= no)	0.67		0.75		0.61		2.21^{**}
Access to extension (1=yes, 0= no)	0.28		0.49		0.11		3.77^{***}
Access to credit (1=yes, 0= no)	0.36		0.55		0.22		5.59^{***}
Access to seed (1=yes, 0= no)	0.76		0.99		0.57		8.73^{***}

Source: Field Survey, 2017. *Note: SD denotes standard deviation*, ***, **, *and* * *denote significance levels at 1%, 5%, and 10.*

The results from Table 3.1 showed that the proportion of male-headed households (0.65) in the adopters' group are significantly higher than that in the non-adopters sample (0.52). Adopters and non-adopters of IRVs have a similar average age of 48 years respectively, which implies that most of the sampled farmers are within their active and productive age. The education level for both adopters and non-adopters is relatively low; with an average of 5 years of formal education for both groups. Rice farming experience of adopters and non-adopters were also found to be similar; consisting of about 15 years of rice farming experience for both groups.

Adopters of IRVs have larger farm size than non-adopters but not statistically significant. Farmers with larger farm size can allocate more land for cultivation of improved varieties. Thus, farmers who have more land have a comparative advantage over their counterpart in adopting IRVs. Other empirical studies (Smale and Mason, 2013; Khonje *et al.*, 2015) also found similar results. Khonje *et al.* (2015) noted that adopters of improved maize varieties have larger land than non-adopters.

Farmers-based organisation/groups/cooperative (FBO) is often suggested as an important institutional factor where farmers share and access information relating to agricultural activities. Membership in FBO differs significantly between adopters and non-adopters (75% vs 61%) respectively.

The smallholder farmers in the study area have limited access to extension service; on average, about 28% of the sampled farmers have access to the extension agent. However, adopters of IRVs differs significantly than non-adopters in having access to extension agent. The low access to extension service might influence the level of awareness and adoption of IRVs among smallholder rice farmers in the study area. Similarly, majority (64%) of the farmers does not have access to credit. The constraint in accessing credit could affect IRVs adoption and productivity because smallholder farmers are known to be resource constraint with low income. Accessibility to credit could help farmers to purchase adequate quantity of inputs needed for farm operations.

About 76% of the sampled smallholder rice farmers have access to seed. However, access to IRVs seed is significantly higher among adopters of IRVs than non-adopters of IRVs. Khonje *et al.* (2015) posited that efforts aimed at promoting modern agricultural technologies adoption (such as IRVs) should be geared towards increasing farmers' access to institutional supports services such as extension, input supply and credit.

About 53% of the smallholder rice farmers generate income from off-farm activity; on average, about 55% and 51% of IRVs adopter and non-adopters engaged in off-farm activity.

3.6 Empirical results and discussion

This section presents and discusses the empirical findings concerning the determinants of adoption of improved rice varieties and its impact on productivity.

3.6.1 Determinant of improved rice varieties adoption

In explaining the different effect of explanatory variables on the dependent variable, the estimated coefficients and the marginal effects of the probit estimates are indicated in Table 3.2. The likelihood ratio (LR) chi-square value, the probability of chi-square, and pseudo-R-square values reported at the bottom of Table 3.2 show that the model specification provides a reasonably good fit for the data. The estimated marginal effects were used to interpret the results because the coefficient of parameters is not suitable for interpreting magnitudes in probability models. The sign of the marginal effect values indicates the direction of the influence of the explanatory variables on the dependent variable (adoption of IRVs) while the magnitude shows the size of the probability of effects (Danso-Abbaem, 2018).

The estimated parameters of the probit model of the determinant of adoption of improved rice varieties are presented in Table 3.2.

Table 3.2: Probit model estimates of improved rice varieties adoption

Variable	Estimated coefficient	Standard error	Marginal effect
Gender	0.062	0.213	0.024
Age	-0.111	0.012	-0.001
Education	0.070^{***}	0.022	0.028
Farm size	0.207	0.179	-0.044
Rice farming experience	0.039^{*}	0.022	0.016
FBO Membership	0.323	0.255	0.127
Access to extension service	0.465^{**}	0.215	0.183
Access to credit	1.254^{***}	0.223	0.454
Access to seed	2.450^{***}	0.492	0.553
Off farm income	0.207	0.212	0.082
Constant	-4.023^{***}	0.899	
Pseudo R^2	0.3725		
LR χ^2 (10)	127.75^{***}		

Source: Field Survey, 2017. ***, **, * denote significance level at 1%, 5% and 10%.

The estimated coefficient of education is positive and statistically significant for the probability of IRVs adoption. The partial effect of a unit increases in level of education on conditional probability of adopting IRVs is 0.028, which suggests that the likelihood of adopting IRVs increases by about 2.8% with an additional year of smallholder rice farmer's education. This implies that the more educated farmers are; the more they are likely to adopt IRVs. This is because educated farmers might be able to access, understand, process and interpret information efficiently than the uneducated farmers. This result is consistent with Asfaw *et al.* (2012) and Ghimire *et al.* (2015).

The estimated coefficient for rice farming experience is positive and statistically significant for the probability of IRVs adoption. The partial effect of a unit increase in rice farming experience on conditional probability of IRVs adoption is 0.016, which suggest that an additional year of rice farmers' experience will cause a 1.6% increase in IRVs adoption. Rice farming experience increases IRVs adoption because the experienced farmers are more likely to have practical knowledge about the inherent benefit of a farm technology than the unexperienced farmers. Similar results were reported by Tiamiyu *et al*. (2009) for IRVs adoption in Nigeria and for improved groundnut varieties in Malawi (Simtowe *et al.*, 2012).

As expected, access to extension agent was associated with increasing probability of IRVs adoption. The partial effect of an increase in access to extension on conditional probability of IRVs adoption is 0.183, which suggest a 18.3% increase in probability of IRVs adoption by smallholder rice farmers. Agricultural extension is an important socio-institutional factor that involves building human capital development of farmers through teaching, training and giving information on farm operations and exposing the farmers to farm technologies such as IRVs which in turn have an impact on increasing the productivity of the farmers (Asfaw *et al.*, 2012). This implies that farmers that have access to extension agent are more likely to have awareness and information about the benefit of modern agricultural technologies which would in turn have a positive influence on their decision to adopt the technology. The positive influence of access to extension variable is in line with the findings of Ghimire *et al.* (2015) for IRVs adoption in Nepal and Khonje *et al.* (2015) for improved maize varieties in Zambia.

The results further show that access to credit and seed increases the likelihood of IRVs adoption. The partial effect of an increase in access to credit on conditional probability of IRVs adoption is 0.454, which suggest a 45.4% increase in probability of IRVs adoption by smallholder rice farmers. This implies that farmers that have access to credit are more likely to adopt IRVs. Accessibility of credit could ease adoption of modern agricultural technologies such as IRVs because farmers would have funds to purchase these critical inputs such as IRVs, which will in turn enhance productivity. This result is in consonance with other findings such as Danso-Abbaem (2018) who reported that access to credit had a positive and significant effect on adoption of fertilizer among cocoa farmers in Ghana and for IRVs adoption in North central Nigeria (Oladeji *et al.*, 2015).

The estimated coefficient for access to seed is positive and statistically significant for the probability of IRVs adoption. The partial effect of an increase in access to seed on conditional probability of IRVs adoption is 0.553, which suggest a 55.3% increase in probability of IRVs adoption by smallholder rice farmers. A plausible explanation to the positive relationship between access to seed and IRVs adoption is that availability of IRVs seed in local agro allied stores close to the farmers would ease the purchase and cultivation of IRVs. However, during the scheduled interview of the sampled farmers, it was noted that most of the farmers travelled a long distance to purchase seed while some used seeds stored from previous seasons and others buy seeds from the local market. The use of uncertified and low-quality seeds could have a negative influence on the yield of farmers. The positive effect of access to seed variable is in agreement with other findings such as Asfaw *et al.* (2012) for improved pigeon pea and cowpea adoption in Tanzania and Ethiopia, and Ghimire *et al.* (2015) for IRVs adoption in Nepal.

Other variables in the probit model such as membership in farmer-based organisation and farm size are not significant but have a positive influence on adoption of IRVs.

3.6.2 Impact of improved rice varieties adoption on productivity

To estimate the impact of adoption of IRVs on the treated groups with PSM, the study performed two diagnostic tests to ensure quality of the matching process after predicting the propensity scores for both adopters and non-adopters of IRVs. First, we compare the situation before and after matching to ensure that there are no remaining differences in covariates conditioning on propensity score. Following Caliendo and Kopeinig (2008) and Sianesi (2004), we compared the *Pseudo-*R^2 generated before and after matching. The *Pseudo-*R^2 shows how well the independent variables included in the model explain the probability of IRVs adoption. After matching, there should be non-existence of significant differences in the distribution of the independent variables for both adopters and non-adopters, which will lead to small *Pseudo-R^2* value and the rejection of the joint significance of the covariates. Thus, *t-test* was employed to evaluate the quality of the matching to ensure that the distribution of covariates is equal between the treated and control samples independent of the treatment (Willy *et al.*, 2014). Second, we check for hidden biases that may arise from unobserved characteristics that may concurrently affect both adoption of IRVs and productivity. We employed Rosenbaum (2002) sensitivity analysis procedure to evaluate the effect of the hidden biases on the magnitude of the impacts obtained. Once these two quality conditions are satisfied, the matched comparison group is considered as plausible counterfactual and the estimates are reliable (Ali and Abdulai, 2010).

The density distribution of the propensity scores of adopters and non-adopters of IRVs is presented in Figure 3.1. The figure shows that common support condition was satisfied, as there was considerable overlap in the distribution of propensity scores for adopters and non-adopters of IRVs. The upper and bottom part of the histogram revealed the distribution of the propensity scores of the adopters and non-adopters. The distribution densities of the scores are shown on the y-axis (vertical axis).

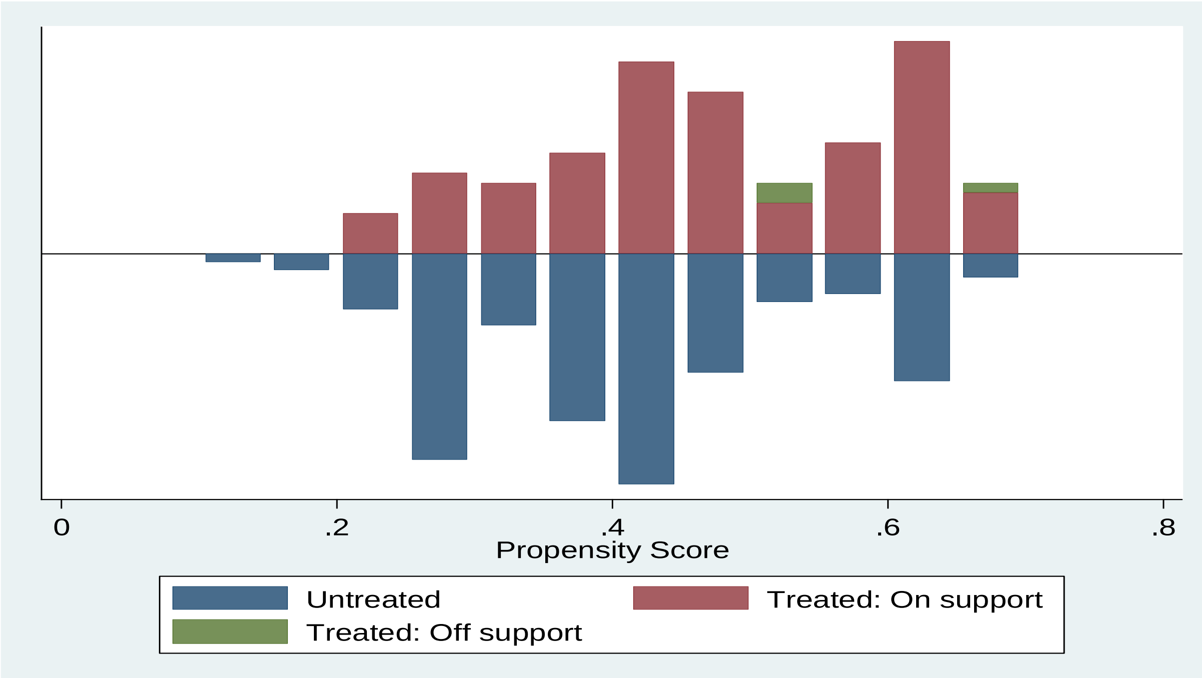

Figure 3.2: Propensity score distribution and common support for propensity score estimation.
Note: Treated: On support indicates adopters of IRVs have a suitable comparison group (non-adopters), while Treated: Off-support indicates the adopters of IRVs that did not have a suitable comparison group (non-adopters).

Source: Field Survey, 2017.

In ensuring the reliability of the estimates in Table 3.3, the test of balancing property based on nearest-neighbour matching technique (considering only those observations that were on common support) was conducted to ensure that adopters and non-adopters of improved rice varieties have similar pre-exposure characteristics. The test of balancing property of mean equality across the covariates is presented in Table 3.3.

Table 3.3: Test of equality of means of variables before and after matching

Variables	Unmatched sample			Matched sample			
	Adopters	Non-adopters	Diff: p-value	Adopters	Non-adopters	Diff: p-value	% reduction bias
Gender	0.65	0.52	0.034**	0.66	0.64	0.846	90.5
Education	5.27	5.41	0.860	5.37	4.50	0.273	90.8
Age	48.38	48.09	0.785	4.62	4.61	0.941	83.2
Farm Size	2.26	2.20	0.411	2.26	2.12	0.694	52.0
Rice farming experience	15.46	15.14	0.634	15.59	14.82	0.371	-147.3
FBO Membership	0.75	0.61	0.028**	0.74	0.72	0.711	82.8
Access to extension	0.49	0.11	0.152	0.48	0.10	0.541	63.6
Access to credit	0.55	0.22	0.000***	0.38	0.49	0.178	65.2
Access to seed	0.99	0.57	0.000***	0.99	0.99	1.000	100.0
Off-farm income	0.55	0.51	0.458	0.56	0.53	0.728	38.1

Source: Field Survey, 2017. Note: ***, ** denote significance level at 1% and 5%.

The *t-statistics* obtained in Table 3.3 ($p > 0.1$) shows that satisfactory matching quality was achieved for all covariates included in the model. Thus, there is no significant difference between the mean covariates after matching, which implies that farmers that adopt IRVs and their counterparts that did not adopt IRVs are comparable and thus have similar characteristics. Therefore, the two groups have same features regarding gender, education, age, farm size, rice farming experience, membership in the farmer-based organization, access to extension service, access to credit, access to seed, and off-farm income.

The summary of the covariates balancing test is presented in Table 3.4. The *p-values* of the likelihood ratio test indicate that the joint significant cannot be rejected before matching (*p-value = 0.000*) but rejected after matching (*p-value = 0.544*). There is also a substantial reduction in the value of the *Pseudo* R^2, from 0.372 before matching to 0.045 after matching.

Table 3.4: Overall matching quality indicators before and after matching using Nearest-neighbour matching

Sample	Pseudo R^2	LR (χ^2)	P>(χ^2)	Mean standardized Bias	Bias	Total % bias reduction
Unmatched (before matching)	0.372	127.75	0.000***	38.0	161.3	
Matched (after matching)	0.045	8.87	0.544	4.21	50.4	68.75

Source: Field Survey, 2017. Note: *** *, denotes significance level at 1%.*

The standardized mean bias also reduced considerably from 38.0 before matching to 4.21 after matching leading to a total bias reduction of 68.75. The high total bias reduction, the low standardized mean bias, and the insignificant p-value of LR after matching show that the matching process has been successful; hence, the PSM is appropriate to assess the impact of IRVs on farm productivity in the study area (Danso-Abbeam and Baiyegunhi, 2019).

The results of the *rbounds* test are shown in Table 3.5 to check the robustness of the estimates to unobservable covariates.

Table 3.5: Rosenbaum bound test

	Wilcoxon statistics	
Gamma(Γ)	**Upper bound significance level**	**Lower bound significance level**
1	0.000	0.000
1.5	0.004	0.000
2	0.000	0.000
2.5	0.000	0.000
3	0.002	0.000
3.5	0.008	0.000
4	0.023	0.000
4.5	**0.051**	**0.000**
5	0.092	0.000

Note: The numbers in bold refer to the Rosenbaum bounds critical gamma cut-off value

The rbounds test suggest that the estimates are found to be unbiased. The estimates are found to be robust or insensitive to an unobserved bias that would have increased the odds of adoption of IRVs by at least 4.5 folds. This is because an increase in the critical value to 4.5 produces an upper bound significant level of 0.051. This result suggests that the inferences made concerning impact of IRVs on productivity is insensitive to hidden biases and that an increase in productivity is because of improved varieties adoption rather than differences in some unobserved variables or factors.

The propensity score matching (PSM) estimates of improved rice varieties (IRVs) adoption impact on productivity are presented in Table 3.6. The impacts were estimated using the kernel, radius and nearest neighbours matching methods to ensure robustness.

Table 3.6: Impact of adoption of improved rice varieties on productivity-PSM

Matching estimators	ATT for outcome variables	t-test
Kernel-based matching (KBM)	439.599 (69.642)	6.312^{***}
Radius matching (RM)	387.868 (46.992)	8.254^{***}
Nearest neighbour matching (NNM)	531.136 (101.811)	5.217^{***}

Source: Field Survey, 2017. *** denotes significance level at 1%.

The PSM (KBM, RM and NNM) results presented in Table 3.6 indicated that adoption of IRVs had a positive and statistically significant effect on productivity (rice yield). The estimated average impact of IRVs on yield ranges from about 388kg/ha to about 531kg/ha depending on the estimation technique. Thus, the average rice yield for non-adopters would be about 452kg/ha more if the farmers had adopted IRVs

3.6.3 Impact of heterogeneity among adopters of improved rice varieties

The estimated ATT reported in Table 3.3 assumes no variation in the impact of IRVs adoption for all smallholder rice farmers in the treatment group (adopters). However, there are differences in impact among treatment group because of differences in their socio-economic characteristics. The study analyses the existence of heterogeneity of the impact of IRVs adoption across the various socio-economic and institutional variables using ordinary least square (OLS) techniques.

Table 3.7: Heterogenous impacts among adopters of improved rice varieties

Variable	Estimated coefficient	Standard error
Gender	0.077***	0.021
Education	0.001	0.002
Age	-0.002	0.013
Farm size	0.163***	0.019
Rice farming experience	0.001	0.002
Membership in FBO	0.076***	0.022
Access to extension	0.001	0.019
Access to credit	0.006	0.019
Access to seed	0.081	0.102
Off-farm income	0.055***	0.198
Constant	-0.214	0.129
N	110	
R^2	0.598	
F	14.70***	

Source: Field Survey, 2017. ***, **, * denote significant level at 1%, 5% and 10%.

The results presented in Table 3.7 shows that productivity has heterogenous effect among IRVs adopters. The estimated results show that gender, farm size, membership in farmer-based organisation, and off-farm income were positive and statistically significant for rice yield among IRVs adopters. This implies that IRVs adoption increases productivity among male smallholder rice farmers, farmers with large farm size, who are members of FBO and farmers who get income from off-farm activity.

The positive and significant effect of gender on IRVs adopters' productivity implies that male adopters of IRVs are more productive than their female counterpart. This is because male farmers tend to own more vital production input such as land and capital than their female counterpart. This result is in line with (Kinkingninhoun-Mêdagbé *et al.*, 2015).

Farm size exerts a positive and significant influence on productivity of IRVs adopters. This implies that adopters of IRVs with large farm size have more yield per hectare (ha) than IRVs adopters with small farm size. An increase or expansion of farm size for crop production is expected to enhance productivity of farmer because returns on adoption are scale dependent (Baiyegunhi *et al.*, 2019). The positive influence of farm size on productivity of IRVs adopters is in consonance with the findings of Ojo *et al.* (2019) who reported a positive relationship between farm size and rice yield in south western Nigeria.

Membership in farmer-based organisation is positive and significantly influence productivity among IRVs adopters, which implies that IRVs adopters who have membership in farmer-based organisation are more productive than those with no membership. A plausible explanation for this is that farmers that belong to farmer-based organisation gets important information about improved farm technologies, farm input subsidy, credit, marketing among others than farmers with no membership in farmer-based organisation. This result is in consistent with Baiyegunhi *et al.* (2019).

Furthermore, the results show that off-farm income has a positive and significant influence on productivity among IRVs adopters. This implies that adopters of IRVs that engages in off-farm income activities have more yield that does that engages in only farm income activities. This is because farmers who are involved in off-farm activities can buy adequate quantities of inputs such as IRVs needed for their farm operations, as their engagement in off-farm income activities can overcome farm-related financial constraints. This finding is in tandem with Danso-Abbeam *et al.* (2017).

3.7 Chapter summary

The chapter examines the determinants of IRVs adoption among smallholder rice farmers and the link between IRVs adoption and rice productivity. The results of the probit regression model showed that some socio-economic and institutional characteristics of the farmers such as education, rice farming experience, access to extension service, access to credit and seed access are statistically significant determinants of IRVs adoption.

The econometric approach (PSM) used to analyse the impact of IRVs, shows that adoption of IRVs had a significant positive influence on rice productivity. The estimates of the average treatment effect (ATT) from the PSM method revealed that average rice yield for adopters would be about 452kg/ha less if the smallholder rice farmers had not adopted IRVs. Therefore, the findings support the view that adoption of IRVs is important in increasing rice productivity which in turn increases income and reduces poverty among smallholder rice farmers. The positive impacts of IRVs adoption on productivity suggest that, to boost rice production in the study area, priority must be given to the use of improved agricultural technology such as IRVs.

CHAPTER 4

DOES ADOPTION OF IMPROVED RICE VARIETIES EXPLAIN TECHNICAL EFFICIENCY DIFFERENTIALS AMONG SMALLHOLDER RICE FARMERS?

4.1 Introduction

This chapter provides the empirical findings on differentials in technical efficiency among adopters and non-adopters of improved rice varieties (IRVs) smallholder farmers in Ogun State, Nigeria. The methodologies, conceptual and analytical framework and estimation techniques for measuring technical efficiency differentials among smallholder rice farmers are discussed. In addition, the empirical findings from the study and chapter summary are also provided.

4.2 Conceptual and analytical framework

The theory of technical efficiency has remained an important measurement in estimating farm level performance. Farrel (1957) seminal work led to the theoretical framework of technical efficiency. Farrel (1957) defined technical efficiency of a firm as the ratio of input to output. Studies such as Kumbhakar *et al.* (1991) and Battese (1992)starts with the measurement of farm technical efficiency. In an agricultural context, technical efficiency is used to measure the ability of a farmer to produce maximum output from a given set of resources or input. A farmer's level of technical efficiency is characterized by the relationship between observed production and some potential production (Greene, 1980; Ogundele and Okoruwa, 2006). The technical inefficiency results from farmer's inability to produce the highest possible output from a given set of inputs used. Given the relationship of inputs in a production function, a technically efficient farmer will operate at its frontier production function. The farmer is technically inefficient if he operates below the frontier. Figure 4.1 shows a production frontier which is a measure of technical efficiency conditional on the levels of inputs used (Battese, 1992).

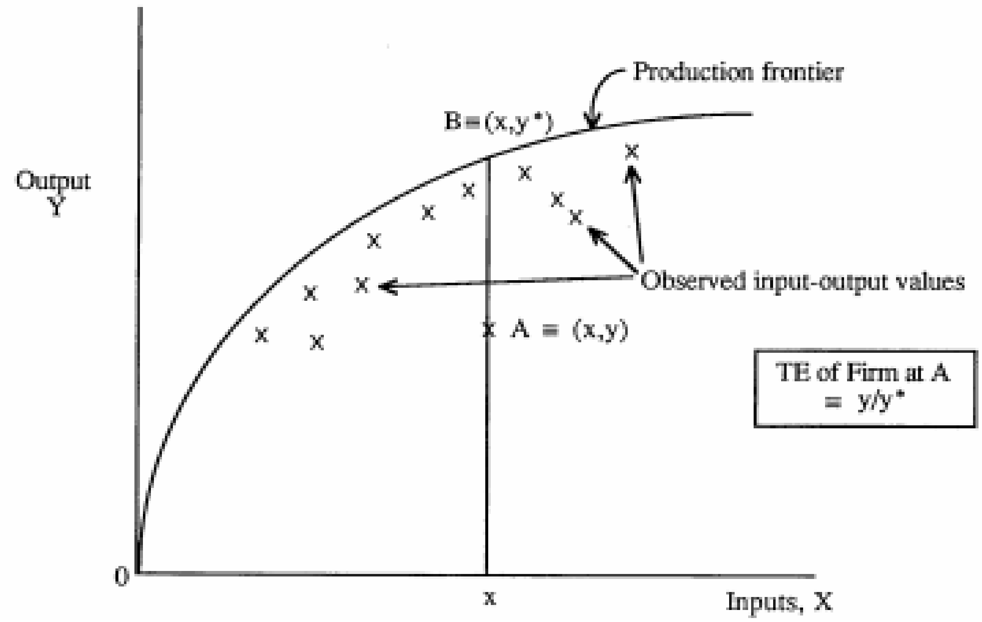

Figure 4. 1 Technical efficiency of firms in relative input-output space
Source: Battese (1992)

Previous studies (Ogundele and Okoruwa, 2006; Ogundari, 2008; Ayinde *et al.*, 2009; Kadiri *et al.*, 2014) have shown that rice farmers in Nigeria are producing below the potential output, that is the farmers are below their frontier production. This study aims to measure the different levels of technical efficiency among two groups; the adopters and non-adopter of IRVs in the study area. This study employed the stochastic frontiers technique (Aigner *et al.*, 1977; Meeusen and Van Den Broeck, 1977) to determine the technical efficiency and identify the factors influencing the technical inefficiency of rice farmers. The stochastic frontier and data envelopment analysis are the most common approaches in measuring production efficiency. The stochastic frontier approach is considered more appropriate than data envelopment analysis in agricultural production because it takes cognisance of both the farmers' inefficiency and systemic errors (due to weather conditions, diseases outbreak, etc.) which is beyond the farmers' control.

Following Battese (1992), the stochastic frontier production model is specified as:

$$Y_i = f(X_i, \beta)\exp(V_i - U_i) \tag{4.1}$$

where i = 1, 2…, n and Y_i represent the possible production level for the ith farmer; $f\ (X_i, \beta)$ is a suitable function (e.g., Cobb-Douglas or Translog) of the vector, X_i is the vector of inputs quantities used by the ith farmer, β is a vector of unknown parameters to be estimated, V_i is the random error that is due to factors beyond the control of farmers e.g. weather and disease outbreak. The distribution of the random error component V_i is assumed to be independently and identically distributed as N (0, σ_v^2) and independent of U_i. U_{is} are non-negative random variables, associated with technical inefficiency of production, which are assumed to be independently distributed, such that U_i is obtained by truncation (at zero) of the normal distribution with mean $Z_i\delta$ and σ_u^2 variance. Following Battese and Coelli (1995), the technical inefficiency effect, U_i in stochastic frontier production model (equation 1) can be expressed as;

$$U_i = Z_i\delta + W_i \tag{4.2}$$

where Z_i is a vector of explanatory variables associated with technical inefficiency of production of farms, δ is a vector of unknown coefficient, the random variable W_i is defined by the truncation of the normal distribution with zero mean and variance σ^2, such that the point of truncation is $Z_i\delta$ i.e. $W_i \geq Z_i\delta$.

The technical efficiency production of the i[th] farm is expressed as;

$$TE = \exp(-U_i) = \frac{Y_i}{Y_i^*} = \frac{f(X_i, \beta)\exp(V_i - U_i)}{f(X_i, \beta)\exp(U_i)} \tag{4.3}$$

where Y_i is the observed output and Y_i^* is the frontier production, if the ratio of Y_i and Y_i^* equals 1 it means the farm is 100% technical efficient i.e. TE = 1. Also, if U_i = 0, it means there is no indication of inefficiency, the farm is on frontier meaning it obtains its maximum output from a given set of input. If $U_i > 0$ or $TE < 1$ then production lies below the frontier, indicating an existence of inefficiency in the farm.

The maximum likelihood single-stage estimation procedure for estimating the frontier model (equation 4.1), inefficiency model (equation 4.2) and the farm-specific technical efficiency defined by the measure of efficiency of technical efficiency model (equation 4.3) are estimated using the computer software Frontier version 4.1 (Coelli, 1994).

The likelihood function is expressed in terms of variance parameters (Battese and Coelli, 1995);

$$\sigma_s^2 = \sigma_v^2 + \sigma_u^2 \tag{4.4}$$

$$\gamma = \frac{\sigma_u^2}{\sigma_s^2} \tag{4.5}$$

where σ_s^2 is the total variance, σ_v^2 is the variance of stochastic error, σ_u^2 is the variance of inefficiency and γ is the ratio of the variance of inefficiency to the total summation of the variance of the stochastic component. The value of γ ranges from 0 to 1, if $\gamma = 1$ it implies that the variation from the frontier is due to inefficiency and if $\gamma = 0$, it indicates the variation from the frontier is due to the stochastic error. Therefore, for $0 < \gamma < 1$, the variation in output is attributed to both stochastic error and technical inefficiency of the farmer.

4.3 Empirical model specification

This study employed the Cobb-Douglas functional form to estimate the stochastic frontier production function for adopters and non-adopters of IRVs in the study area because the test of hypotheses proved that the translog functional form was inadequate to represent the data obtained from both groups of smallholder rice farmers (adopters and non-adopters of IRVs). The Cobb-Douglas production function has been used to represent the stochastic frontier function previously by many studies (Simonyan *et al.*, 2011; Abba and Isa, 2015; Dang, 2017). The Cobb-Douglas Production function is linear in its activities, imposes severe restrictions on parameters to be estimated, constant elasticity of substitution and constant return to scale.

The Cobb-Douglas stochastic frontier model is specified as follows;

$$\ln Y_i = \beta_0 + \sum_{j=1}^{5} \beta_j \ln X_{ji} + V_i - U_i \tag{4.6}$$

where ln = natural logarithm, Y= total quantity of rice produced, i = ith rice farmer for i = 1, 2, 3… 250, X_{ji} =amount of input j used by i-th rice farmer. Where, X_1= farm size, X_2 = labour used (man-days/ha), X_3=seed (kg)/Ha; X_4 = fertilizer (kg)/Ha; X_5= agro-chemicals (kg/Ha or L/Ha); β_j= regression coefficient of the explanatory variables in the estimated stochastic production function; V_i = random errors from the stochastic frontier production and U_i= a vector of non-negative technical inefficiency component of the error term.

Following Asante *et al.* (2014), the study estimated the effect of IRVs adoption on technical efficiency by estimating the predicted probability of IRVs adoption (the propensity score) from the results of the probit model in Chapter 3. The propensity score was then included as an explanatory variable with other farm specific, socio-economic and institutional variables in the pooled stochastic frontier inefficiency model. The main advantage of using this approach is that it corrects for endogeneity in IRVs adoption before including it as an explanatory variable in the technical inefficiency estimation.

The significance and sign on the coefficient of the predicted IRVs scores is an indication of whether IRVs adoption has a negative or positive effect on technical efficiency of the smallholder rice farmers.

The technical inefficiency model is specified as;

$$U_i = \delta_0 + \sum_{j=1}^{7} \delta_j Z_{ji} \quad (4.7)$$

where U_i= technical inefficiency of the i-th; $\delta_j =$ regression coefficients of the explanatory variables in the estimated technical inefficiency model, j =1, 2……7; Z_1= Gender, a dummy variable which takes the value of unity for male and zero for female; Z_2= educational attainment (years); Z_3= Rice farming experience (years); Z_4 = membership in farmer-based organisation, a dummy variable which takes the value of unity for member and zero for non-member; Z_5= Access to extension services, a dummy variable which takes the value of unity for access and zero for non-access; Z_6= Record-Keeping a dummy variable which takes the value of unity for farm record and zero for no farm record; Z_7 = Predicted IRVs (propensity scores).

4.4 The study area, sampling and data collection techniques

The study area, sampling and data collection technique used for this study are the same as described in Chapter 3.

4.5 Definition of variables and summary statistics.

The descriptive statistics of sampled farm households are presented in Table 4.1. The variables described are inputs used in rice production, farm-specific, socio-economic and institutional factors.

Table 4. 1: Summary statistics of variables for the sampled smallholder rice farmers

Variables	Pooled (All) (n=250)		Adopters (n=110)		Non-adopters (n=140)	
	Mean	SD	Mean	SD	Mean	SD
Production function model						
Yield (kg/ha)	385.00	147.21	481.82	136.42	308.93	104.79
Farm size (ha)	2.27	0.58	2.26	0.54	2.20	0.62
Labour (man-days/ha)	206.16	50.68	210.45	46.71	202.79	53.52
Seed (Kg/ha)	67.82	5.00	68.32	4.65	67.43	5.24
Fertilizer(kg/ha)	234.60	51.02	234.55	54.92	234.64	47.94
Agrochemical (ltr/ha)	7.27	1.75	7.37	1.81	7.19	1.70
Inefficiency effects model						
Gender (dummy)	0.58		0.65		0.52	
Education (year)	5.35	5.96	5.27	5.96	5.41	5.98
Rice farming experience (year)	15.28	5.12	15.45	5.38	15.14	4.92
FBO membership (dummy)	0.67		0.75		0.61	
Farm record (dummy)	0.60		0.61		0.59	
Extension access (dummy)	0.28		0.49		0.11	

Source: Field Survey, 2017. Note: SD denotes standard deviation.

The results presented in Table 4.1 show that the average yield of rice produced by adopters and non-adopters of IRVs was 481.82kg/ha and 308.93kg/ha respectively. The yield of both groups of farmers is below the potential average yield of 2mt/ha and average national yield of 1.4mt/ha for rain-fed upland rice production system in Nigeria (GRiSP, 2013). Adopters and non-adopters of IRVs have a similar average farm size of 2.26ha and 2.20ha respectively.

The average labour (family and hired) used was 210.45 man-days/ha and 202.79 man-days/ha for adopters and non-adopters of IRVs respectively. The implication of high man-days recorded for labour of both adopters and non-adopters indicates the high dependency rate of human labour for most of the farm operations. This shows that Nigerian agriculture is labour intensive with low level of mechanized farming.

The adopters used IRVs seed for their production while the non-adopters planted the traditional rice varieties. The average amount of seeds used by adopters and non-adopters was estimated to be 68.32kg/ha and 67.43kg/ha respectively. The quantity of seed used by majority of the rice farmer (both adopters and non-adopters) in the study area was below the recommended seed rate of 100kg/ha for rain-fed (upland and lowland) rice production system (IRRI, 1995). This influences the yield of rice produced by the farmers.

The adopters and non-adopters of IRVs used an average fertilizer rate (NPK/urea) of 234.55kg/ha and 234.64kg/ha respectively. The fertilizer rate used by both groups was also below the recommended rate of 250-350kg/ha for upland and lowland swamp production system. This also has a significant impact on yield. The average agrochemicals used (comprising of pesticides and herbicides) by adopters and non-adopters of IRVs was estimated to be 7.37ltr/ha and 7.19ltr/ha respectively.

The male farmers constitute 65% and 52% of adopter and non-adopters of IRVs. The average years of schooling for adopters was 5.27 years while that of non-adopters was 5.41 years. Both adopters and non-adopters of IRVs have similar average rice farming experience of 15.45 and 15.14 years respectively. About 60% of the smallholder rice farmers keep farm record, with 61% and 59% of adopters and non-adopters keeping farm record. The majority (72%) of the smallholder rice farmers do not have access to extension agent, with 49% and 11% of IRVs adopters and non-adopters having access to extension agent.

4.6 Test of model specification

The generalized likelihood ratio test was used to test three null hypotheses in the study. The test of hypotheses was conducted for the pooled, adopters and non-adopters of IRVs separately.

The hypotheses are as follows;

1. $H_{01}: \beta_{ji} = 0$, the best functional form that fits the data is Cobb Douglass

2. $H_{02}: \gamma = \delta_0 = \delta_1 \ldots\ldots \delta_7 = 0$, the coefficient of the variables determining technical inefficiency in the model equals zero i.e. absence of inefficiency effects from the model at all level.

3. $H_{03}: \gamma = 0$, inefficiency effects are not stochastic i.e. the average response model estimation procedure is more adequate than stochastic frontier model.

The likelihood ratio test statistic is specified as;

$$\lambda = -2\{log[L(H_0)] - log[L(H_1)]\} \tag{4.8}$$

Where LH_0 is the likelihood of the null hypothesis and LH_1 is the likelihood of the alternative hypothesis. The generalized likelihood-ratio test statistic (λ) has approximately a chi-square (or mixed chi-square) distribution with the number of degree of freedom equals to the difference between the parameters estimated under H_0 and H_1 respectively. The critical value is obtained from the normal chi-square table. If LR (λ) is less than the critical value, the null hypothesis (H_0) will be accepted but rejected if otherwise. The p-value indicates if the critical value is greater or less than the LR test statistic. The results of the generalized likelihood test for the data obtained from smallholder rice farmers (adopters and non-adopters of IRVs) in the study area is presented in Table 4.2.

Table 4. 2: Result of the null hypotheses tested

Hypothesis	**Log-likelihood value**	**Test statistic** (λ)	**P-value**	**Decision**
Pooled				
Functional form test	100.81	7.62	0.868	Accept
Absence of inefficiency	97.01	17.15	0.004	Reject
Inefficiency are not stochastic	105.58	11.01	0.000	Reject
Adopters				
Functional form test	67.42	0.57	0.225	Accept
Absence of inefficiency	53.72	1.95	0.081	Reject
Inefficiency are not stochastic	61.01	27.42	0.011	Reject
Non-adopters				
Functional form test	52.94	2.43	0.9993	Accept
Absence of inefficiency	51.73	12.77	0.0000	Reject
Inefficiency are not stochastic	58.90	14.35	0.0135	Reject

Source: Field Survey, 2017.

From the Table 4.2, the first null hypothesis for smallholder rice farmers was accepted since the generalized likelihood-test was not statistically significant from zero. This indicates that the Cobb-Douglass frontier function best fits the data. The generalized likelihood-test was statistically significant from zero and the second hypothesis was rejected for the pooled, adopters and non-adopters of IRVs indicating that there is presence of technical inefficiency in the model. Similarly, the third hypothesis was also rejected, revealing that the frontier production function was more appropriate than the traditional average response function for the pooled and both categories of farmers.

4.7 Empirical results and discussion

In this section, the empirical findings on the factors influencing rice yield, technical inefficiencies and level of technical efficiency of smallholder rice farmers are discussed.

4.7.1 Stochastic frontier production estimates

The result of the maximum likelihood estimates of the Cobb-Douglass stochastic frontier production model for the pooled, adopters and non-adopters of IRVs is presented in Table 4.3. The pooled estimate is for the total sampled smallholder rice farmers, i.e., the combination of both adopters and non-adopters IRVs.

Table 4. 3: Maximum likelihood estimates of stochastic frontier production model for smallholder rice farmers

Variable	Parameter	Pooled (All)		Adopters		Non-adopters	
		Coefficient	t-ratio	Coefficient	t-ratio	Coefficient	t-ratio
Constant	β_0	0.155	7.17***	0.010	0.52	0.186	7.17***
Farm size	β_1	-0.098	-0.29	-0.105	-0.20	1.021	2.10**
Labour	β_2	0.211	1.53	-0.056	-0.29	0.349	2.05**
Seed	β_3	0.782	2.39**	1.010	1.94*	-0.314	-0.70
Fertilizer	β_4	0.347	3.78***	0.282	2.24**	0.316	2.29***
Agrochemicals	β_5	0.006	0.06	-0.122	-0.91	-0.088	-0.59
Variance Parameters							
Sigma squared	σ_s^2	0.0575		0.0475		0.074	
Gamma	γ	0.8070		0.8135		0.918	
Log-likelihood function	LLF	97.01		53.71		51.73	

Source: Field Survey, 2017. ***, ** and * denote significance level at 1%, 5% and 10%.

The result from Table 4.3 shows that farm size, labour, seed and fertilizer contributed significantly to the technical efficiency of the smallholder rice farmers. The regression coefficient denotes the output elasticity in a Cobb-Douglas production function. The estimated sigma squared of 0.0575, 0.0475 and 0.074 for the pooled, adopters and non-adopters of IRVs shows a good fit and the appropriateness of the specified distribution of assumption of the composite error term, rather than the average response specification. The estimated gamma value for adopters and non-adopters is 0.81 and 0.92 which indicates that 81% and 92% of the variation in paddy rice output among adopters and non-adopters of IRVs was due to technical inefficiency while 19% and 8% of the variation in paddy rice yield among adopters and non-adopters of IRVs was due to random factors which are beyond the farmers control which could be unfavourable weather condition, pest and disease infestation.

The estimated coefficient of seed and fertilizer are the statistically significant variables for the adopters of IRVs while farm size, labour and fertilizer are the statistically significant variables for non-adopters of IRVs. The estimated coefficient of seed (1.01) indicates that a percentage increase in the quantity of seed planted will lead to 1.01% increase in paddy rice output for adopters of IRVs. This implies that the use of IRVs seed has a significant and positive influence on productivity of rice farmers. However, the coefficient of seed (traditional variety) for non-adopters of IRVs is not significant in explaining the output of the farmers. The possible explanation of a significant positive relationship between IRVs seed and yield is that the farmers are planting below the recommended rate of 100kg/ha for upland and lowland rice production system as posited by IRRI (1995). Therefore, an increase in the use of IRVs up to the recommended rate will enhance rice yield of adopters of IRVs. This result is consistent with Mango *et al.* (2015) who observed that seed have a positive influence on maize yield in Zimbabwe.

The estimated coefficient of fertilizer (0.28 and 0.32) for adopters and non-adopters exert a significant positive effect on paddy rice output. This implies that a percentage increase in quantity of fertilizer will lead to 0.28% and 0.32% increase in paddy rice yield of adopters and non-adopters of IRVs. This could be attributed to the fact that both adopters and non-adopters applied below the fertilizer recommended rate of 250-300kg/ha in upland and lowland swamp rice production system (Ogundele and Okoruwa, 2006; GRiSP, 2013). The significant positive effect of fertilizer is consistent with the study of Zahidul Islam *et al.* (2012) who reported a positive effect of fertilizer on rice yield of both traditional and high yielding rice varieties adopters in Bangladesh. The result is also in line with that of Abba and Isa (2015) who observed that fertilizer has a positive and significant influence on rice yield in both irrigated and rain-fed production system in Nigeria.

The results further showed that farm size and labour have a positive and statistically significant influence on paddy rice yield of non-adopters of IRVs. The estimated coefficient of farm size (1.02) indicates that a percentage increase in land area allocated for rice production will lead to 1.02% increase in paddy rice yield of IRVs non-adopters. This implies that expansion of farm size plays a crucial role in enhancing farm productivity. This result conforms to that of Oladeebo and Fajuyigbe (2007) for rice production in Nigeria, Danso-Abbeam *et al.* (2012) for cocoa production in Ghana and Asekenye *et al.* (2016) for groundnut production in Kenya and Uganda.

The statistically significant and positive elasticity of 0.35 for labour indicates that rice yield of IRVs non-adopters will rise by 0.35% with a percentage increase in labour. This implies that an increase in labour employed for farm operation will lead to an increase in rice yield. A possible reason for this is that crop production such as rice is labour intensive and resource constraint smallholder farmers are known to be highly dependent on manual labour to carry out most of their farm operations. This finding is consistent with Ogundari *et al.* (2010) and Mango *et al.* (2015)

4.7.2 Technical efficiency level of smallholder rice farmers

The predicted technical efficiencies (TEs) of smallholder rice farmers from the maximum likelihood estimation are presented in Table 4.4.

Table 4. 4: Distribution of technical efficiency among smallholder rice farmers

TEs	**Pooled**		**Adopters**		**Non-adopters**	
Indices	**Frequency**	**Percentage**	**Frequency**	**Percentage**	**Frequency**	**Percentage**
<0.75	4	1.60	1	0.91	29	20.71
0.75-<0.85	8	3.20	6	5.45	29	20.71
0.85-<0.95	65	26.00	17	15.45	73	52.14
0.95-≤1	173	67.20	86	78.18	9	6.43
Total	250	100	110	100	140	100
Mean		0.95		0.97		0.84
Minimum		0.61		0.69		0.42
Maximum		1		1		0.97
Standard deviation		0.06		0.06		0.11

Source: Field Survey, 2017.

The results presented in Table 4.5 revealed that the average technical efficiency of the smallholder rice farmer is 95%. The technical efficiency indices of IRVs adopters ranges from 69% to 100% with an average of 97%. This implies that if the average farmer among the sampled adopters of IRVs had achieved the technical efficiency level of his/her most efficient peer farmer, then he/she would have realised an output gain of 3% $(1 - [97/100])$. Similarly, the most inefficient farmer among adopters of IRVs would have increased his/her output by as much as 31% $(1 - [69/100])$.

The technical efficiency indices of IRVs non-adopters ranges from 42% to 97% with an average of 84%. This implies that if the average farmer among the sampled non-adopters of IRVs had achieved the technical efficiency level of his/her most efficient peer farmer, then he/she would have realised an output gain of 13.4% $(1 - [84/97])$.Similarly, the most inefficient farmer among non-adopters of IRVs would have increased his/her output by as much as 42.3% $(1 - [42/97])$.

The average technical efficiency indices of both groups of farmers imply that the adopters and non-adopters of IRVs produced 97% and 84% paddy rice output respectively, at the current level of farm practice and input available. In addition, both adopters and non-adopters of IRVs are producing below 3% and 16% of the potential frontier output. Thus, there is an opportunity for the adopters and non-adopters of IRVs to increase their production by 3% and 16% respectively through the efficient utilization of production resources/inputs and adoption of improved farm technologies for rice production.

Furthermore, the result shows that there is a significant difference between IRVs adopters and non-adopters; with adopters of IRVs being more technically efficient than non-adopters.

4.7.3 Effect of improved rice varieties on technical inefficiency

The result of the maximum likelihood estimates of inefficiency model is presented in Table 4.5. A positive sign on a coefficient of the parameter denotes the variable reduces technical efficiency while a negative sign on a coefficient of the parameter means the variable increases technical efficiency.

Table 4.5: Maximum likelihood estimates of technical inefficiency model for smallholder rice farmers

Variables	Para-meter	Pooled (All)		Adopters		Non-adopters	
		Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio
Constant	δ_0	-4.396	-19.24***	-4.043	-26.78***	-4.928	-10.54***
Gender	δ_1	-2.187	-5.12***	-0.443	-0.34	-1.275	-2.50**
Education	δ_2	-0.004	-0.17	-5.131	-0.02	-0.004	-0.16
Rice farming experience	δ_3	-0.043	-1.66*	-0.247	-3.94***	-0.083	-3.06***
FBO membership	δ_4	-0.822	-2.44**	-27.704	-0.02	-0.548	-1.53
Farm record	δ_5	-0.622	-1.56	-5.846	-0.94	-0.565	-1.54
Extension access	δ_6	1.506	3.83	30.584	0.02	1.072	2.63***
Predicted IRVs scores	δ_7	-2.121	-3.92***	-	-	-	-

Source: Field Survey, 2017. Coeff. denotes coefficient. ***, ** and * denotes significance level at 1%, 5% and 10%.

The result from table 4.5 shows that the predicted probability of IRVs exerts a negative and significant effect on technical inefficiency of smallholder rice farmers. This result suggests that adoption of IRVs enhances the technical efficiency of smallholder rice farmers, which implies that IRVs adopters are more technically efficient than non-adopters. This result conforms to the result in table 4.4 indicating the differentials in technical efficiency level of adopters and non-adopters. The finding therefore, suggests that adoption of IRVs is important in improving the technical efficiency of smallholder rice farmers. This finding is in consonance with Asante *et al.* (2014) who observed a positive and significant effect of adoption of yam minisett technology on technical efficiency of yam farmers in Ashanti region of Ghana.

The results presented in Table 4.5 also revealed that other variables such as gender, rice farming experience, membership in farmer based-organisation, access to extension contributed significantly to smallholder rice farmers' technical inefficiency. The statistically significant variables for IRVs adopters is only rice farming experience while gender, rice farming experience and access to extension service are statistically significant for non-adopters of IRVs.

The estimated coefficient of rice farming experience is negative and statistically significant for both adopters and non-adopters of IRVs which implies that the more experienced farmers are less technically inefficient than others. A possible reason could be that farmers with longer years of rice farming are able to observe and learn from their past production operations to improve subsequent production. This finding conform to that of Asante *et al.* (2014) and Danso-Abbeam *et al.* (2015).

Gender has a significant and negative influence on technical inefficiency of IRVs non-adopters, which implies that the male farmers are more technically efficient than the female farmers. A plausible explanation for this is that the farm production decision in often made by majority of men and they are also in control of vital input such as land, labour and capital. This result is consistent with Mango *et al.* (2015) who observed that men headed-maize farmers are more efficient than their women counterparts farmers in Zimbabwe.

Surprisingly, the coefficient for access to extension services was positive and statistically significant for technical inefficiency of non-adopters of IRVs. This implies that non-adopters of IRVs with access to extension services are more technically inefficient compared with those without access to extension services. A possible reason could be that either the extension services offer poor service to the farmers or the farmers did not adhere to the instructions and innovations offered to them on their farm practices. This could also influence the decision of the farmers not to adopt IRVs. This finding is in consonance with Ojo *et al.* (2019) who reported a negative relationship between access to extension service and productivity of rice farmers in South West Nigeria. The result is also in line with Oladeebo and Fajuyigbe (2007) and Kuwornu *et al.* (2013) but contrary with Mango *et al.* (2015) and Abdulai *et al.* (2017).

The negative and significant value for the estimated coefficient of membership in farmer-based organisation for the smallholder rice farmers (pooled) implies that farmers with membership in farmer-based organization are more technically efficient than others with no membership. This is because farmers obtain some benefits through farmer-based organisation such as access to credit for financing the farm, access to farm inputs from NGOs and government and useful information relating to farm operations. This result is consistent with Danso-Abbeam *et al.* (2015) who observed that membership in farmer-based organization negatively influenced technical inefficiency of smallholder groundnut farmers in Northern region of Ghana.

4.8 Chapter summary

This chapter analysed the differentials in technical efficiency among adopters and non-adopters of IRVs in Ogun state, Nigeria, using the stochastic frontier model. The results of the study showed that production inputs such as farm size, fertilizer, seed and labour influence the productivity of smallholder rice farmers. The study also revealed that factors such as gender, rice farming experience, membership in farmer-based organisation, access to extension influence and IRVs adoption influence the technical inefficiency of the rice farmers.

The estimated technical efficiency score of both groups of smallholder rice farmers indicated that the farmers are producing below the potential output. The study also revealed that IRVs adopters are more technically efficient than non-adopters. Therefore, adoption of IRVs with good management and cultural farm practice will enhance the technical efficiency of smallholder rice farmers in Ogun state, Nigeria.

CHAPTER 5
SUMMARY, CONCLUSIONS AND RECOMMENDATIONS.

5.1 Summary

Rice (*Oryza sativa*) is grown in almost all agro-ecological zones of Nigeria due to its adaptability to the country's fertile land. Despite the huge land area suitable for rice production, less than half of the land is utilized. This has resulted in variability and inconsistency in the production of rice in the country. Moreover, rice is produced by over 90% of resource-poor smallholder farmers. Despite the dominance and important role played by smallholder farmers in rice production, they still encounter numerous challenges. Among the challenges faced is lack of credit facilities and accessibility to productive inputs such as fertilizer, agrochemicals and IRVs. The challenges faced by smallholder farmers have contributed to their low productivity. The low productivity has also been attributed to low adoption of improved rice varieties (IRVs). Although, the government has put in place different intervention programs and policies to increase in the national rice output in recent years yet domestic production has not been able to suffice the increasing demand, which in turn intensify the importation of rice in the country. However, rice yield per hectare is still below the potential output. Adoption of IRVs and understanding the appropriate utilization and combination of inputs is essential in increasing the productivity and efficiency of rice farmers. Nevertheless, there is an empirical gap in adoption of IRVs and technical efficiency in the literature of Nigerian rice sector.

The study's general objective was to analyse the adoption of improved rice varieties and technical efficiency among smallholder rice farmers. The first objective was to examine the determinants of adoption of IRVs and its impact on productivity of smallholder rice farmers. The second objective was to estimate the differences in technical efficiency among adopters and non-adopters of IRVs smallholder rice farmers.

This study was conducted in Ogun State, South West, Nigeria. Data were obtained in 2017 using a structured questionnaire administered to 250 rice farmers through multi-stage random sampling techniques. Datasets were analysed using descriptive and econometric techniques.

5.2 Conclusion

In Chapter three, the determinants of adoption of IRVs and its impact on productivity was analysed. The empirical results from the probit model indicate that education, rice farming experience, access to extension service, access to credit and access to seed had positive and statistically significant effects on the adoption of IRVs. The estimates of the PSM revealed that adoption of IRVs had a significant influence on productivity (rice yield). Thus, the findings of the study suggest that priority must be given to improved agricultural technology such as IRVs to boost rice production in the study area.

The empirical results from the stochastic frontier analysis in Chapter 4 indicate that the smallholder farmers are producing below their potential production output but adopters of IRVs are more technically efficient than the non-adopters. The study also observed that there are some vital production inputs such as fertilizer and seeds that are under-utilized by the smallholder rice farmers have a statistically significant and positive influence on rice yield. Appropriate utilization of these inputs at the recommended rate could increase the efficiency and productivity of the farmers.

In addition, adoption of IRVs and combined effect of some socio-economic and socio-institutional factors were found to be the sources of technical inefficiency of the smallholder rice farmers.

It can be concluded from this study that adoption of IRVs plays a vital role in enhancing productivity and technical efficiency of smallholder rice farmers.

5.3 Policy Recommendations

In view of this study, some essential findings have emerged that are pertinent for policy implication and recommendations towards enhancing the productivity and efficiency of rice production in Ogun State and Nigeria.

The study recommends that the ministry of agriculture strengthen the extension services by recruiting and training an adequate number of extension agents across the agricultural zones and local government area of the state. This will enhance regular visit and efficient delivery of extension service (which includes educating the farmers on the benefits of IRVs). Furthermore, availability/recruitment of non-governmental organisations (NGOs) and private organisation extension agents to supplement government extension agents will enhance awareness and adoption of IRVs in the study area.

Based on the findings that the farmers are using below the recommended rate of fertilizer and seed. There is a need for the provision of substantial and sustainable credit facilities by the government and private institutions to the smallholder farmers to enhance adoption of IRVs and the purchase of adequate quantities of the inputs needed for the production process.

Farmer-based organisation has been observed to have a positive influence on both adoption of IRVs and technical efficiency of the smallholder rice farmers, therefore the study suggests that extension agents should sensitize the farmers on the benefits of joining a farmer-based organization such as easy accessibility to production inputs, including IRVs. In communities where there is no farmer based-organisation, the extension agent should help them form some.

Policymakers need to encourage an efficient relationship between farmer-based organisations and seed companies (private, NGOs and government) to enhance easy accessibility of IRVs by the rural smallholder rice framers.

5.4 Limitations of the study and suggestions for further research

Rice is produced in different regions in Nigeria where there is diversity in cultures, religion and socio-economic characteristics of the people. The study is limited to a state in South West, Nigeria due to time and financial constraint for data collection. Therefore, the study recommends that further research of this kind should be conducted in more rice producing areas across the country. A larger sample size of the respondent is also suggested to generate more information that can be generalized about Nigeria.

Furthermore, this study did not focus on a specific improved rice variety cultivated by the smallholder farmers but focused on all type of IRVs planted in the study area. The study suggests that further studies could consider the adoption and technical efficiency among adopters and non-adopters of a/some specific IRVs. This could shed light on the need to focus on some specific IRVs that could increase the production of rice in the country.

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APPENDICES

APPENDIX I: Research Questionnaire Used for Data Collection

UNIVERSITY OF KWAZULU-NATAL

INYUVESI YAKWAZULU-NATALI

RESEARCH QUESTIONNAIRE

RESEARCH TOPIC: GENDER DIFFERENTIALS IN TECHNICAL EFFICIENCY AMONG SMALL SCALE RICE FARMERS IN OGUN STATE, NIGERIA.

Serial Number of Questionnaire …………………..

Local Government……………………………………

Community name……………………………………..

INTRODUCTION AND CONSENT

Dear Sir/Ma,

Please introduce yourself to respondent: My name is……………………………I am an enumerator collecting data on behalf of Lateef Olalekan Bello, a Post graduate student of University of KwaZulu-Natal, South Africa. The study aims to examine Gender differentials in technical efficiency among small scale rice farmers. Your cooperation in responding to these questions will be highly appreciated. The information so given will strictly be used for academic purposes, and in utmost confidence.

In the process of the interview, you are free to interrupt me and ask for any clarification. You have the liberty or legal right to call the principal researcher (Mr Lateef Olalekan Bello) on the mobile number +23480384448438 and ask for any clarification at any point in time. I respect all the responses you give and appreciate your cooperation.

Name of enumerator	
Name of respondent	
Date	

SECTION A. SOCIOECONOMIC CHARACTERISTICS OF RESPONDENTS

Household Basic Characteristics

Questions	*Responses*	
1.1 Are you the household head?	(1) Yes [ ] (2) No [ ]	
1.2 If no, state your relationship with the household head	(1) Spouse [ ] (2) Child/House-help/Farm care-taker [ ]	
Age of household head		
1.4 Gender of household head	(1) Male [ ] (2) Female [ ]	
1.5 Marital status of household head	(1) Married [ ] (2) Single/divorced [ ]	
1.6 Household (HH) size		
1.7 Household composition by Gender	(1) No of males ………. (2) No of females …………..	
1.8 No of people in the household in the following age category.	(1) < 18 … (2) 18 – 60 ……. (3) > 60……	
A19. What is the primary activity of the household head?		[1] Agricultural related activity [2] Formal private employment [3] Public sector employment [4] Artisans [5] Retired [6] Others
A20. What is the secondary activity of the household head?		
A21. What is the primary activity of the respondent?		
A22. What is the secondary activity of the respondent?		
1.10 No of years in crop farming		
1.11 No of years in rice farming		

Note: Household size includes all people, who usually eat from the same pot and sleep under the same roof. Include also members who are absent for less than two months

Educational Status (Human Capital)

Questions	*Responses*
2.1 Can the household head (HHH) read, construct and write a simple sentence?	(1) Yes [ ] (2) No [ ]
2.2 Highest level of education completed by the household head	(1) Primary school [ ] (2) JHS [ ] (3) SHS [ ] (4) Tech/Voc. [ ] (5) Training/Poly/Univ. [ ]
2.3 Number of years of schooling by household head	…………………..
2.4 Highest level of education completed by the spouse of the household head.	(1) Primary school [ ] (2) JHS [ ] (3) SHS [ ] (4) Tech/Voc. [ ] (5) Training/Poly/Univ. [ ]
2.5 Number of years of schooling by the spouse of the household head.	
2.5 Number of people in the household who are in school (e.g children and other relatives).	(1)Primary school ……………………. (2 JHS……… (3) Training/Polytechnic/University………..

2.6 Number of people who are learning other trade (e.g hair-dressing, carpentry).	

Other Knowledge Gained Through Social Network

Training attended/Membership of organization for the past 5 years	*Household head*		*Spouse*		*Any other member of the household*	
	Yes = Y No = N	*# of times*	*Yes [ ] No [ ]*	*# of times*	*Yes [ ] No [ ]*	*# of times*
3.1 Agricultural extension services						
3.2 Farmer seminar/workshop/conference						
3.3 Farmer field school						
3.4 Membership of any rice related NGO's						
3.5 Farmer-based-organization						
3.6 Any other agricultural related training received						
3.7 Any other capacity building training received (financial management, other skills).						
3.8 Membership of any socio-economic group (e.g credit union, community ass, etc)						
3.9 Membership of any religious group (e.g. church)						
3.10 Any leadership position held						
3.12Any relative in community leadership position (chief, etc)						

SECTION B. BUSINESS IDENTITY & STRUCTURE

Business Details

4.1	Name of Farm/Firm (optional)	
4.2	Business Form/Type	[1] Sole Proprietorship [2] Limited Liability [3] Partnership [4] Other (specify)________________
4.3	Business Address (optional)	
4.4	Telephone Number	
4.5	Are you in rice farming Full or Part time?	[1] Full time [2] Part time

4.6	How many persons does your business currently employ in full time or part time? (No)	Full Time [______________]	Part Time [_______________]
4.7	How many rice farm plot do you have	[_______________]	
4.8	What is/are their sizes (ha)		
4.9	What is the total size of your current land (ha)		
4.10	What was the annual sales/turnover of your previous production cycle? (₦)	[_______________]	
4.11	In the last 1 year, do you think your rice business in general has been profitable?	[1] Yes [2] No	
4.12	Do you keep record of activities on your enterprise?	[1] Yes [2] No	
4.13	What is the average monthly cash income from rice farming?		
4.14	What is the average monthly cash income from non-farming business		
4.15	Where do you turn to if you suddenly need money?		
4.16	Do you source for credit for your farm operation?	1] Yes [2] No	
4.17	If NO, please state the reason?		
4.18	What are your other source of financing your farm operations?		

SECTION C. RESOURCE INFORMATION

Fixed Costs

Please list the total fixed cost items used for all your operations in the last 12 months

	Fixed Costs for the last production in the last 12 months			Total Quantity (₦)	Cost/Unit (₦)
		Owned	Rented		
1	Land				
2	Warehouses/Space/Building				
3	Bowls				
	Machinery				
4	Tractor machine				
5	Ridger				
6	Sprayers				
7	Harvester				
8	Plough				
9	Wheelbarrow				
10	Water tank				
11	Bowls/Pans				
12	Parboiling pot/chamber				
13	Water borehole				
14	Pumps				
15	Funnels				
16	Weighing Scale				
17	Other 1 (specify)__________				
18	Other 2 (specify)__________				
19	Other 3 (specify)__________				
20	Other 4 (specify)__________				

6. Variable Cost

	Raw Material Costs used in the last 12 months
1	Seed (kg)
2	Fertilizer (kg)
3	Herbicide (ltrs)
4	Pesticide (ltrs)
5	Irrigation water (ltrs)

6	Other 1 (specify)________________
7	Other 2 (specify)________________
8	Other 3 (specify)________________
9	Other 4 (specify)________________

7. Labour Structure – Hired

Farming Activities	*No. of labourers Hired*		*Number days hired*		*Wage per day per person*		*Other Cost of input application*	
	Male	*Female*	*Male*	*Female*	*Male*	*Female*	*Fuel*	*Machine*
Farm clearing								
Ploughing								
Seed planting								
Weeding								
Fertilizer Application								
Pesticides application								
Herbicides Application								
Bird Scaring								
Harvesting								

8. Labour Structure - Family

Farming Activities	*Number family labourers*				*Number of days worked*			
	Adults (18 years and above)		*Children (Below 18 years)*		*Adults (18 years and above)*		*Children (Below 18 years)*	
	Male	*Female*	*Male*	*Female*	*Male*	*Female*	*Male*	*Female*
Farm clearing								
Ploughing								
Seed planting								
Weeding								
Fertilizer Application								
Pesticides application								
Herbicides Application								
Bird Scaring								
Harvesting								

SEED, FERTILIZER AND AGROCHEMICALS

9.1. Seed

What type of seed do you plant? (a) Local [ ] (b) Improved [ ]

Are you aware of improved rice variety? (a) Yes [ ] (b) No [ ]

Are you planting of improved rice variety? (a) Yes [ ] (b) No [ ]

If Yes in Q2 above, Year of awareness ………………………………..

If Yes in Q3 above, Year of planting ………………………………..

Why do you prefer the variety (ies) ……………………………………………………….

What is the total farm size planted with improved rice? …………………………………

What is the quantity of improved rice seed planted? ………………………………………

What is the total farm size planted with local rice? …………………………………

What is the quantity of local rice seed planted? ………………………………………

Do you have access to improved rice seed? (a) Yes [ ] (b) No [ ]

If Yes, how frequent? (a) Very frequent [ ] (b) Not frequent [ ]

Please state the source of the seed by percentage?

Local Government ………………………………

NGOs ……………………………………………

Government agency …………………………….

Research Institute ………………………………

Farmers' group ………………………………….

Others (state) ………………………………

If you are not planting improved rice seed, why?

…………………………………………………………………………………….

Seed Type (specify the name local/improved variety)	*Quantity/kg*	*Price/unit*

9.2. Fertilizer and Agrochemicals

Fertilizer Application: Y [ ] N [ ]			*Pesticide Application: Y [ ] N [ ]*			*Herbicide Application: Y [ ] N [ ]*		
Type	*Quantity (Bag/kg)*	*Price/ Unit*	*Type*	*Quantity/ litre*	*Price/ Unit*	*Type*	*Quantity/ litre*	*Price/ Unit*

If you don't apply fertilizer and other agrochemicals, why? …................................

………………………………………………………………………………………..

Has the use of Fertilizer and Agro-chemicals improved the output of rice farm?

(a) Yes (b) No ____

If Yes, by how many tonnes has it increased the output?

If No, why are you not using…………………………………………………

SECTION D. REVENUE

10. Sales Volume & Price

Item	*Total Quantity Produced/acquired (Bag/kg)*	*Total Quantity used for home consumption/gift (Bag/kg)*	*Total quantity sold (Bag/kg)*	*Price (Bag/kg)*
Paddy rice				

THANKS FOR YOUR COOPERATION