

**TECHNICAL EFFICIENCY ANALYSIS OF GROUNDNUT PRODUCTION IN
GHANA: A BAYESIAN APPROACH**

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DEDICATION

This work is dedicated to my loved one: Miss Alice Nbebi Binyiti

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The commencement and accomplishment of this work is due the prowess and sovereignty of the Lord Almighty God, without whom the success of this work would have not seen the light of the day. To God be the glory.

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ABSTRACT

Groundnut has been identified as the most important leguminous crop in Ghana both in terms of volume of production and export. Its production has faced numerous challenges over the past decades in Ghana as the productivity of groundnut continues to decline despite the abundant resources that support its growth. The question is, what then is responsible for the declining productivity levels of groundnut in Ghana? The study sought to estimate the productivity levels and technical efficiency levels of groundnut farmers in Ghana as well as analyse the determinants of inefficiencies among the farmers. In a single stage approach, a Bayesian stochastic frontier model was analysed with the translog functional form. Cross-sectional data from three-hundred (300) groundnut farmers sampled across three regions in Ghana were used for the study. A relatively non-informative priors were chosen for the parameters of the models with a prior median efficiency of 0.8. Groundnut farmers were found to be producing at an increasing return to scale of 1.10. Average technical efficiency score of the farmers was found to be 70.5% which ranges from a minimum of 13% to a maximum of 95.13%. Frequency of extension visit, educational level and gender of the farmers were identified to significantly explain inefficiency of the farmers. The study concludes that groundnut farmers in Ghana are producing at an increasing return to scale and at an average technical efficiency level of 70.5%. Extension visit, educational level and gender were found to be responsible for inefficiencies among groundnut producers. The study therefore recommends increase in scale of production by groundnut farmers, empowering the farmers to produce at an efficient level by districts assemblies and improving upon the extension services and information delivery to enhance farmer learning ability through department of agriculture.

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LIST OF ACRONYMS

AARS	Africa Agriculture Status Report
AE	Allocative Efficiency
AEAs	Agriculture Extension Agents
AP	Average Productivity
CAADP	Comprehensive Africa Agriculture Development Program
GDP	Gross Domestic Product
HA	Hectare
MT	Metric Tons
NEDAP	New Partnership for Africa Development
SFA	Stochastic Frontier Analysis
TE	Technical Efficiency
DEA	Data Envelopment Analysis
EE	Economic Efficiency
EU	European Union
FAOSTAT	Food & Agriculture Organization (Statistics Department)
FBO	Farmer Base Organization
GHS	Ghana Cedi
GSS	Ghana Statistical Service
IITA	International Institute of Tropical Agriculture
KG	Kilogram
MCMC	Markov Chains Monte Carlo
MFP	Multiple Factor Productivity
ML	Maximum Likelihood
MoFA	Ministry of Food and Agriculture
MP	Marginal Productivity
NGO	Non-Governmental Organization
NHST	Null Hypothesis Significance Testing
OLS	Ordinary Least Square
PFP	Partial Factor productivity

PHC	Population and Housing Census
ROPE	Region of Practical Equivalence
RTS	Return to Scale
SFM	Stochastic Frontier Model
SFP	Single Factor productivity
SSA	Sub-Saharan Africa
TE	Technical Efficiency
TFP	Total Factor Productivity
US	United States
USDA	United States Department of Agriculture

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CHAPTER ONE

INTRODUCTION

1.1 Background to the Study

Groundnut (*Arachis hypogaea L.*) is noted to be an important leguminous crop that is mostly produced in the northern part of Ghana. It serves as a source of both livelihood and nutrition to the producers (Danso-Abbeam et al., 2015). Globally, groundnut is reported to be the fourth oil seed crop, third most significant source of vegetable protein after soybean, followed by cotton seed and it is the thirteenth most important food crop (Taphe et al., 2015). Girei et al. (2013) also asserts that in terms of the proportions of nutrients, groundnut seeds contain 20% carbohydrates; 25% digestible protein and 50% high quality edible oil. There is virtually no part of groundnut, thus, either the plant or fruits that is not put into use for human benefit. The fruits and/or nuts can be eaten raw, by boiling when it is harvested fresh or roasted when it is dried. The nuts (seeds) are ground into paste and is used in diverse ways including, soup preparation, cake (locally called kulikuli), and extracted for oil. The paste is sometimes used as butter for eating bread. The by-product of groundnut (fodder) serves as feed for livestock and the cake also serves as an important ingredient in animal feed (Tsigbey & Clottey, 2003). From the agronomical point of view, it aids in weed control, soil water conservation and improves soil fertility by adding some organic matter into the soil. Just as any other leguminous crop, groundnut fixes atmospheric nitrogen into the soil.

Ministry of Food and Agriculture (MoFA) reported that groundnut is the most important legume that contributes partly to the agriculture share of Ghana's Gross Domestic Product (GDP). The enormous role that agriculture plays in terms of its contribution to the gross

domestic product of the Ghanaian economy cannot be over emphasized as it contributed about 26% on the average (over the last decade) to the annual GDP of Ghana (MoFA, 2016). Following the report of the 2018 annual budget statement of Ghana, it can be noted that the share contribution of agriculture to Ghana's GDP continues to decline year after year. For example, the provisional estimates for the year 2017 revealed agriculture share contribution to GDP as 18.5% compared to 18.9% in 2016. Ghana Statistical Service (GSS) reported that despite the decline of agriculture contribution to GDP, it continues to be the leading employer in the Ghanaian economy as it employs about 44.7% of the labour force (MoFA, 2015).

Out of the five (5) sub-sectors of agriculture in Ghana (crops, livestock, cocoa, forestry and fisheries), the crop sub-sector is known for its greater share of agriculture contribution to GDP (GSS, 2015). For instance, in 2012 and 2013, the agriculture sector contributed 22.9% and 22.4% respectively to Ghana's GDP, out of which the crops-sub sector alone had a share contribution of 17.2% and 17.4% respectively.

The contribution of agriculture to the economy is not limited to Ghana but extends to most parts of the world at large. Lipton (2005) asserts that with the exception of nations that are more of cities, almost all significant reduction in poverty since 1700 started with high records of employment and self-employment income as a result of increased productivity levels of small family farms. Africa Agriculture Status Report indicated that in the light of agricultural contribution to development, agricultural transformation in most parts of the world has generally been a significant component of the broader economic transformation (AASR, 2016). Badiane & Makombe (2015) and AASR (2016) emphasized that the Maputo Declaration serves as a signal for strong political resolution of African leaders to

revitalize agriculture as a driver of economic growth, reducing poverty and food and nutrition insecurity.

Despite all these efforts that have been geared towards agricultural production, productivity has for the past decades not seen the light of progressive growth rate in Sub-Saharan Africa (SSA) (Norton, 2004 and Adzawla *et al.*, 2015). For example, yield gaps of 67% for maize, 78% for groundnuts and 67% for sorghum, has been reported in Kenya (Asekenye, 2012). In Ghana, the average yield of maize, groundnut, rice and yam, were estimated at 1.7Mt/ha, 1.5Mt/ha, 2.4 Mt/ha, and 15.3 Mt/ha respectively, as against the estimated potential yield of 6.0Mt/ha, 2.5Mt/ha, 6.5 Mt/ha, and 49Mt/ha respectively (MoFA, 2016). Following this report, it can be noted that output of groundnut per hectare for the past years had been on the declining rate despite the abundant resources that are needed for its production in Ghana (refer to section 2.2.2 for output trends in Ghana). The yield gap as identified partly led to declining contribution of agriculture to the development of economies, example of which is the case of the Ghanaian economy, that is, the decline of agricultural contribution to GDP.

Determining the productivity level of farmers and their technical efficiency levels as well as the determinants of technical inefficiency will enable farmers to improve upon their productivity when appropriate recommendations are made. This, therefore, led to a lot of research work in technical efficiency. Classical methods (for example, Maximum Likelihood Estimation (MLE)) of estimation have been adopted by past studies for technical efficiency analysis. Meanwhile, it is argued that the classical methods of estimation have some limitations, for example, inability to make probability statements, inability to incorporate non-sample information into analysis, problem of obtaining exact

finite-sample results and its asymptotic property nature (Coelli et al., 2005 and Kurkalova & Carriquiry, 2003). However, the Bayesian estimation approach had been found as appropriate to overcome the limitations of the classical method of estimation. It is in this light that this study adopts the Bayesian approach for its analysis.

1.2 Problem Statement

According to Shamsudeen et al. (2011), combating food insecurity and nutrition in most parts of the developing world has become greater concern following the increasing population growth rate. They asserted that achieving targets of increasing food availability and incomes, depend on the improvement of farmers' efficiency, which could be tackled by improving the existing resource base given the available technology.

Groundnut is noted to be the most important legume in terms of volume of production and export in Ghana. Meanwhile, productivity levels of groundnut farmers continue to decline despite the available resources that are suitable for its production in Ghana (MoFA, 2016). There have been fluctuations in the output of groundnut over the past years and any increase in output was mostly due to extensification (increased land area) of production rather than intensification, that is, increased productivity (Martey et al., 2015). In order to increase groundnut output in Ghana, there is the need to increase productivity levels of the producers. For example, the land area allocated to groundnut production in the Viet Nam is relatively smaller (0.195 million hectares on average of 2016-2017 production season) than land area allocated to same in Ghana (0.4 million hectares), but Ghana comes after Viet Nam in terms of the ranking of world groundnut producing countries. This is mainly due to the fact that yield per hectare in Viet Nam is higher, that is 2.31mt/ha compared to the yield of 1.1mt/ha in Ghana as noted by USDA (2018).

Under the International Institute of Tropical Agriculture (IITA) program – N₂ Africa, efforts have been made to increase the productivity levels of groundnut farmers by the introduction of new technologies (certify seeds, inoculant, fertilizer and changing agronomic practices). Despite these efforts, productivity levels of groundnut producers in Ghana have not seen the light of growth since reports indicate declining output levels instead. The problem of introduction of new technology to increase productivity levels of farmers is not only limited to its failure, but also the cost involved. As noted by Onumah *et al.* (2010), efforts to improve efficiency of producers is more cost-effective to achieving higher agricultural output than introducing new technologies for same if the prevailing ones are not being optimized by farmers. The problem, therefore, is to conduct the technical efficiency study of groundnut producers in Ghana to identify their technical efficiency level given the prevailing technology. It had been argued that efficiency of the farmer is dependent on the type of management decisions, available technology as well as the prevailing climatic conditions (Rockstrom *et al.*, 2003). Therefore, conducting technical efficiency study and taking farm level management decisions based on result obtained could improve upon groundnut farmer's productivity levels.

Previous studies on technical efficiency of groundnut considered a section of the groundnut farmers in Ghana (Danson-Abbeam *et al.*, 2015 and Shamsudeen *et al.*, 2011). These studies used the classical methods (MLEs) of estimation which certainly come with some limitations. For example, Coelli *et al.* (2005) outlined the shortfalls of the classical methods of estimation and noted that researchers seldom collect their sample data multiple times but the estimators are chosen based on its long-run performance, hence, they are not able

to judge the accuracy of the numerical estimates by testing different estimates from the individual samples. Also making probability statements concerning the unknown parameters, models and hypothesis in the classical methods is not possible. Consequently, incorporation of non-sample information into the estimation process is not convenient in the classical methods and obtaining exact finite-sample results in some estimation problems becomes cumbersome. On the contrary, they argued that the Bayesian estimation approach to inference serves as an alternative that has features to be able to overcome these shortfalls. In the first place, estimators are chosen on their ability to minimize losses resulting from estimation unlike the classical methods where estimators are chosen on their long run performance. Again, results from Bayesian analysis are presented as probability density functions and probability statements can be made to that effect. The ability to obtain exact finite sample results as well as convenient approach to incorporating non-sample information in the form of priors also serves as strength of Bayesian estimation. If by virtue of conducting technical efficiency study, we are able to give policy recommendations that improves technical efficiency of farmer's production, it is therefore essential to use methodology that is more technically viable for same purpose. It is against this background that this study considers the Bayesian approach to technical efficiency analysis of groundnut production in Ghana. From the aforementioned the below research questions arise;

1. What are the productivity levels of groundnut farmers in Ghana?
2. What are the technical efficiency levels of groundnut farmers in Ghana?
3. What are the determinants of technical efficiency of groundnut farmers in Ghana?

1.3 Objectives

The general objective of the research is to analyse the technical efficiency of groundnut farmers in Ghana.

In order to achieve this broad objective, these specific objectives need to be accomplished;

1. Estimate the productivity levels of groundnut farmers in Ghana.
2. Estimate technical efficiency levels of groundnut farmers in Ghana.
3. Analyse the determinants of technical efficiency of groundnut farmers in Ghana.

1.4 Justification

Efficiency studies are conducted with the goal of improving upon the productivity of the decision maker (farmer). The quest to ensure efficiency of production in order to enhance food security and nutrition had led to many studies in this field. Groundnut as ranked the 13th most important food crop in the world is not left out in this quest to achieving efficiency of production.

Improving farmers' productivity levels could be tackled in a number of ways including improving the technical efficiency of farmers and introduction of new technologies. This study seeks to enable farmers to improve on their technical efficiency levels so as to increase their productivity levels. Considering the objectives of the study, estimating the productivity levels of the farmers would enable farmers to know their scale of production, and individual elasticities of the input variables. This would be useful to farmers at farm management decision level. The estimate of the scale of production will inform farmers the stage of their production and therefore, a decision to either increase, maintain or decrease their scale of production. More so, the individual inputs elasticities will inform

farmers the level of combination of various inputs. These management decisions would go along to improve farmers' level of productivity.

Additionally, predicting technical efficiency scores of the farmers will give the level of technical efficiency of the farmers. This estimates will guide decision as to how much gap in output needs to be closed. Hence, efforts would be made to close the gap in output in order to increase the level of output of the producers.

Finally, analysing the determinants of technical inefficiencies among the farmers would guide policy decision. For example, farmers' level of education is an institutional factor which could influence farmers' capacity to understand information delivered to them by stakeholders in agriculture. When this factor is found to explain inefficiencies among the farmers, a policy could be made at the farm management level by responsible institutions to enable the farmers who did not attain education to undergo intensive training to improve their capacity of understanding farm level information.

A few studies in Ghana considered technical efficiency of groundnut producers in selected district(s) using the classical methods of estimation. No substantive study has looked at the efficiency of groundnut farmers in Ghana at large or even considering more than a district. As noted in the earlier sections the classical methods of estimation which was adopted by these previous studies come with some shortfalls. In addition, no substantive work had been conducted using the Bayesian estimation method in Ghana either in efficiency study of groundnut and/or other crops as well as in different fields of efficiency study. In the light of these, the study seeks to use the Bayesian estimation framework to analyse technical efficiency of groundnut farmers in Ghana. From the foregoing, the study;

‘Technical Efficiency Analysis of Groundnut Production in Ghana: A Bayesian Approach’ is very relevant.

1.5 Organization of the Thesis

The study is organized in five chapters. Chapter One is the introduction which include; background of the study, problem statement, research questions, research objectives, justification of the study and this very write up. Each of the four presiding chapters begins with an introduction. Chapter Two is literature review, which is made up of the following sub-sections; production of groundnut, review of methodology, review of Bayesian econometrics and review of empirical related work. Following is Chapter Three which explains the methodology of the study to include, conceptual framework, theoretical framework, empirical model specification, data type, sampling and data collection method and the study area. The Fourth chapter presents the results and discussions of the study. The fifth chapter summarises the study and draws conclusions with policy recommendations. It is worth noting that some of the sections under the various chapters are further divided into subsections.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter reviews past studies undertaken by other researchers and other publications that are relevant to the current study. It is organized in various subsections to cover groundnut production; land area and output trends both globally and locally, review of related methodology, Bayesian econometrics and empirical review of related work.

2.2 Groundnut Production

2.2.1 Global production of groundnut

Groundnut is produced in a lot of countries and/or regions throughout the world. The report of the United States Department of Agriculture (USDA) indicates that groundnut is largely produced in China, United States, Africa, South Asia, Southeast Asia, South America and Mexico (USDA, 2018). The report noted that China is the leading producer of groundnut worldwide. Nigeria is ranked as the third world producer of groundnut after India and also noted to be the leading producer in Africa.

The USDA report also indicated that about 24.76 million hectares of land was devoted to groundnut production in the 2015/2016 production season and preliminary estimates also indicated that about 25.34 million hectares was devoted to production in the 2016/2017 production season. Global average yield of groundnut was also reported to be 1.63mt/ha in the 2015/2016 production season and the preliminary estimate of about 1.68mt/ha in 2016/2017 production season (USDA, 2018).

Table 2.1 shows the rankings of world leading producing countries of groundnut. Even though China leads in the production of groundnut in the world, India recorded the largest area (4.925 million hectares) devoted to groundnut production. In terms of the yield per unit area, United States and Sudan recorded the maximum and minimum output of 4.19mt/ha and 0.82mt/ha respectively.

Table 2.1: Area, Yield and Production of Groundnut in Selected Countries

Rank	Country	Average Area (Million Hectares)	Average Production (millions of mt)	Average Yield (mt/ha)
1	China	4.69	16.72	3.57
2	India	4.93	5.59	1.12
3	Nigeria	2.50	3.00	1.20
4	United States	0.63	2.63	4.19
5	Sudan	1.99	1.64	0.82
6	Myanmar	0.89	1.38	1.55
7	Indonesia	0.61	1.13	1.86
8	Argentina	0.32	1.05	3.26
9	Senegal	1.15	1.00	0.88
10	Cameroon	0.40	0.55	1.38
11	Viet Nam	0.20	0.45	2.31
12	Ghana	0.40	0.44	1.10

Source: USDA (2018)

Due to the high yield of groundnut obtained in US, it is ranked as the fourth leading producer worldwide after Nigeria despite the relatively small area of land devoted to groundnut production. In Africa, Nigeria is noted to be the largest producer of groundnut both in terms of the area allocated to groundnut production and the output of groundnut.

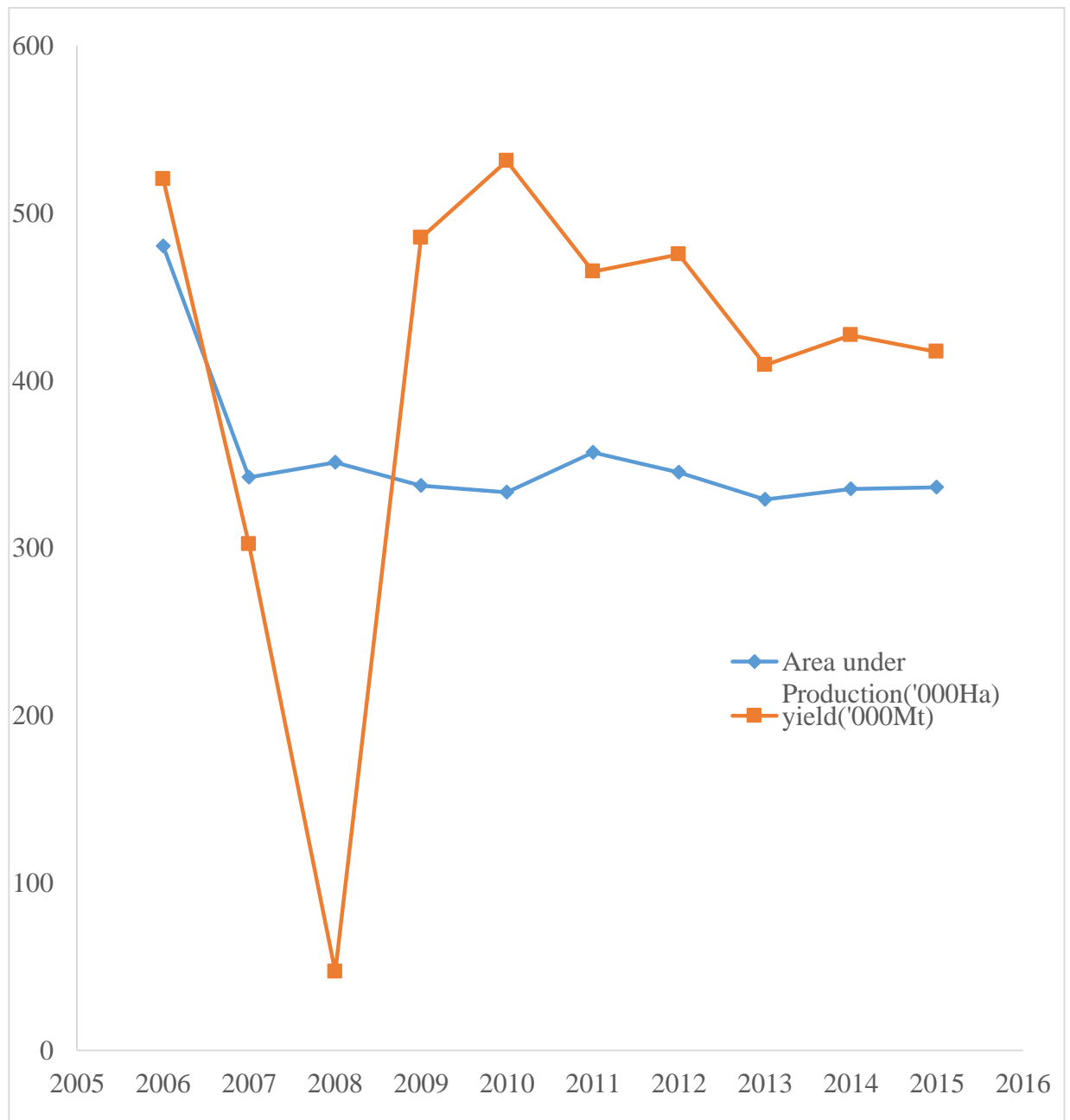
From Table 2.1, countries including, US, China, Argentina, Indonesia and Viet Nam, are producing above the estimated global output of groundnut per hectare. The remaining countries listed in the table are producing below the estimated world average of 1.68mt/ha. The yield per hectare of groundnut obtainable, in other words, the productivity level of a country is largely accountable for the production level (total output) of that country. For example, from Table 2.1, the land area under production in Ghana is 0.40 million hectares and this is about two times the land area allocated to production in Viet Nam. In contrary, yield level recorded in Viet Nam is about double the yield level obtained in Ghana, thus, yield levels of 2.31mt/ha and 1.1mt/ha for the former and later respectively. Viet Nam is therefore placed ahead of Ghana in terms of the total production level as shown in the Table 2.1. Similarly, the land area allocated to groundnut production in Sudan as shown from Table 2.1 is 1.99 million hectares and this land area is also about three times that of the US land area of 0.63 million hectares. Due to high yield of groundnut in US, that is, 4.19mt/ha compared to 0.82mt/ha achieved in Sudan, the former is noted as the fourth leading producer of groundnut with an estimated total output of 2.63 million metric tonnes. The latter is placed as the fifth leading producing country with an estimated total output of 1.64 million metric tonnes. It is also worth noting that all the African countries noted in the Table 2.1 to be among the leading producing countries worldwide, recorded yield levels below the estimated world average of groundnut output per hectare. There is therefore the need for African countries to intensify their groundnut production so as to increase yield per area cultivated.

2.2.2 Groundnut output trends in Ghana

Groundnut is considered as the most important leguminous crop both in terms of volume of production and value (consumption and export) in Ghana (MoFA, 2016). Ghana was ranked as the 10th leading producer of groundnut in the world following the report of FAOSTATS, (2010). Recent publication by the USDA revealed that Ghana lost the position to Cameroon (USDA, 2018). From the Table 2.1, the two countries had equal area of land (0.40) under groundnut production, meanwhile, Cameroon achieved higher yield of 1.38Mt/ha compared to yield level of 1.1mt/ha obtained in Ghana. These estimates demonstrate how productivity levels influence production levels. MoFA (2016), noted that even though there was an increased in land area under groundnut cultivation in the 2016 production season, by about 1000ha from the 2015 production season, yield of groundnut rather decreased from about 427000Mt in 2015 to about 417000Mt in 2016. A careful study of the report of MoFA (2016), shows fluctuations in both the output and land area under cultivation of groundnut which is not coherent of each other. That is, an increased in land area under cultivation in a particular year might not commensurate the output as there might rather be a decreased in output in the same production season. Figure 2.1 shows a plot of land area under cultivation and the corresponding output of groundnut between 2005 and 2016.

From Figure 2.1, the lowest groundnut output of 47,000mt was obtained from land area of about 351,000ha in 2008 production season. Meanwhile, the 2013 production season recorded the lowest land area of 329,000ha devoted to production and a total output of 409,000mt was achieved. The highest land area under production was recorded in the 2006 production season, where about 480,000ha of land was devoted to production and about

Figure 2.1 : Trends of Groundnut Production in Ghana



Source: Author's own plot with data from MoFA (2016)

520, 000mt of groundnut output was obtained. In the 2010 production season, the highest output of about 531,000mt was obtained from a corresponding land area of about 333, 000ha.

The report also noted that on farm yield of 1.65Mt/ha was achieved as against the estimated potential yield of 3.5Mt/ha achievable in Ghana. The yield obtained constitute 47.14% of the achievable yield. The implication is that there is still more gap to be filled in terms of the productivity levels of the groundnut farmers in Ghana. The report also indicates that 336,000ha of land area was devoted to groundnut production in 2016 production season with a corresponding output of about 417000Mt. Out of the total output that was reported in 2016, 375,479Mt was available for human consumption. The report also noted that total export of groundnut in 2016 was 529Mt (MoFA, 2016).

2.2.3 Production areas in Ghana

Ibrahim et al. (2012) opined that groundnut is largely produced in the northern savanna zone of Ghana. Tsigbey & Clottey (2003) also noted that even though groundnut is produced in almost all parts of Ghana, most of the output comes from northern Ghana. MoFA (2016) reported the top ten (10) groundnut producing districts in Ghana. According to the report, all the districts are in the northern region, with the exception of Sissala West District (ranked as the 8th Largest producing district) in the Upper West Region. Among the 10 regions in Ghana, Northern, Upper West, Upper East, Volta (northern part of the region) and Brong Ahafo regions are known to produce groundnut in significant quantities (Tsigbey & Clottey, 2003).

2.2.4 Groundnut production practices in Ghana

Groundnut in Ghana is produced mainly under rain fed condition and also characterized by small scale production by the small holder farmer. The crop is normally produced in one season within a calendar year which starts from around April when the first rains is expected. While the relatively large scale producers of groundnut use tractor plough for

land preparation, the small holder farmer uses either the animal plough or manual hoeing for same (Martey et al., 2015). Before tillage of the land, the field is either sprayed with the herbicides or cleared with cutlasses to get rid of the weeds.

After ploughing of land, the next activity is sowing of groundnut. Sowing of groundnut is done manually using a dibber, that is, the dibber is used to create a hole and the groundnut is then dropped into the hole. The hole with the groundnut seed is then closed with soil by the help of the leg in most cases. Groundnut is either sown in rows or staggered. In circumstances where ridges are made using the hoe, then, groundnut is automatically sown in rows following the ridges. But when the land is ploughed with tractor, the farmer chooses to either sow in rows or staggered. Ibrahim et al. (2012) noted that the production of groundnut is characterized by intercropping with other cereal crops including maize, millet and sorghum.

Since no fertilizer application is done in Ghana by small scale groundnut producer, the next activity on the farm after the groundnut is sown is weed control. Weed control in groundnut production is done by hoeing or the use of a selective herbicides. Manual control of weeds is done once or twice in rear cases. Once the weeds on the groundnut farm is successfully controlled the farmer waits until the groundnut is matured for harvesting. Harvesting of groundnut is done manually by hand pulling, that is, the vegetative part (fodder) of the crop is held with the hands and pulled upwards to get the nuts out of the soil. The nuts still on the fodder are left on the field for some period in order to reduce the moisture content of the groundnut before hand-plucking. This is mostly done if the groundnut is to be dried after harvesting before usage. The unshelled groundnut is then dried and stored in sacks and other locally made silos. The groundnut is further shelled by the use of hand or simple

machines before consumption or sale. On the other hand, if the groundnut is to be used freshly as it is in the case of freshly boiled groundnut, then, it is hand-pluck right after hand pulling and subsequently used for consumption and/or sale.

2.2.5 Export and import of groundnut.

Groundnut products that are exported come in different forms, that is, groundnut is exported either as, shelled, unshelled (in-shell) and processed form. The processing of groundnut comes in different forms as manufacturing food ingredients (peanuts butter and chocolate) and crushing for oil. Exported shelled groundnut may also be slightly processed into different forms (for example roasting) readily for use as snacks before exporting (Koekoek, 2017).

According to Koekoek (2017), the European market is said to be the largest importer of groundnut products globally. In Europe, the Netherlands is said to be the largest importer as it accounts for about 40% of total European imports in 2015. The volume and value of groundnut imports in the Netherlands experienced annual increase of 1.4% and 6.1% respectively, since the year 2011. Other significant importing markets in Europe are Germany, the United Kingdom, Spain, Poland and Italy.

The main suppliers (exporters) of groundnut to European markets from the developing countries includes, Argentina, China and Brazil. Nicaragua and Egypt are also noted to significantly export groundnut to the European markets. Argentina is the largest exporter of groundnuts to the European market, accounting for a share of 42% (volume) of the 338,000 tonnes of groundnut that was imported in Europe by 2015. The other exporting countries were noted to have supplied groundnuts to Europe in proportions of the 2015

total supply as; China (8.1%), Brazil (4.8%), Nicaragua (3.2%) and Egypt (1.7%). The developing countries are noted to be the main sources of export of groundnut as it accounts for over 60% of the world total export. United States of America is the leading supplier of groundnut among the developed countries and also noted as the second largest supplier globally, accounting for about 16% of the 2015 total export to Europe. Other developing countries that are been noted for tremendous increase of export of groundnut in the past six (6) years with their corresponding annual growth rate in export are; Vietnam (27%), Chile (104%) and Ghana (148%). It must however be noted that the supply of groundnut by these countries to European markets were relatively small volumes and ranges between 30 and 300 tonnes.

In the past, China doubles as both world leading producer and exporter of groundnut. But due to current development in industrial usage of groundnut in China, exports of groundnut had reduced. Reports indicate that exports of groundnut have almost halved to 500,000 tonnes over the past decade, while imports have risen almost 50% in China.

Among the developing countries whose export of groundnut to the European market is considered insignificant, Ghana is noted to be the fastest growing in terms of its rate of groundnut supply to the European market as its supply rate has increased for about 148% for the past five years (Koekoek, 2017). The position of China in the import and export of groundnut gives an advantage to small exporting countries like Ghana.

Ghana has the conducive environment and resources for the production of groundnut. This gives her a comparative and competitive advantage in groundnut exports, and, hence, is well positioned to take advantage of the international market opportunities to develop the

sector. From the article (“EU to ban Ghana” 2015), Ghana is said to have made US\$2.4 billion from non-traditional exports, of which groundnuts accounted for US\$6.4million in 2013. Government of Ghana has set a target to raise US\$5 billion as some foreign exchange earnings from the non-traditional export by 2019 of which groundnut is targeted to be the major contributor.

Despite these advantages noted above which could boost the supply of groundnut to the European market by Ghana, it has been noted that Ghana faces a possible rejection of her groundnut product supply to EU following incidence of the product contamination of aflatoxin. This was revealed after a thorough examination conducted on groundnuts produced in Ghana by the European Commission. The examination revealed that most of the produce were infested with high level of aflatoxin, rendering them unfit for the international market (“EU to ban Ghana” 2015). The article noted that as part of efforts to reduce the level of aflatoxin infestation in groundnuts to avoid possible ban from its export, the Ghana Export Promotion Authority (GEPA) in concert with Trade Relate Assistance and Quality Enabling Programme (TRAQUE) – European Union Agency, has initiated a capacity building project to sensitise actors in various value-chain of groundnut in Ghana.

2.2.6 Other economic benefits of groundnut production

Apart from the foreign exchange earnings that a country derives from the production of groundnut, there are numerous other economic benefits and/or uses of groundnut. For example, it has been documented that whiles groundnut serves as a cash crop, it as well doubles as a source of nutrition in northern Ghana just as it is in other countries of the Sub-

Saharan Africa (Ibrahim et al., 2012). The economic benefits and uses of groundnut can be grouped under the categories below.

Income generation: As noted, groundnut serves as a cash crop to the producers in Ghana, especially, Northern Ghana, where it is mostly produced in large quantities (Ibrahim et al., 2012; Martey et al., 2015 and MoFA, 2016). The income generated by the producers is mainly derived from the sale of the groundnut products in the form of shelled or unshelled (in few cases) nuts. Other actors in the value-chain get income from groundnut in the form of profits generated by value addition or activities carried out. A greater share of the groundnuts produced in Ghana by farmers are sold out.

Employment: Groundnut production provides employment to a lot of actors in its value-chain. The value-chain of groundnut just as any other crop starts from its production and continues with other activities that get the product to the final consumer. Actors in all stages of these value-chain are therefore employed. The production of groundnut serves as a major occupation among the females in Northern Ghana and as a minor activity to the male producers. Distribution of groundnut is another stage of the groundnut value-chain that provides employment to the individuals in the chain. As asserted by Owusu-Adjei et al. (2017), distributors in the value chain includes; assemblers, wholesalers and retailers. They noted that processors of groundnut are mostly women who are also engaged in the activity as their occupation.

Nutrition: Groundnut serves as nutrition in different perspective. For example, it can be eaten raw by boiling or roasted as noted by Taphe et al. (2015). In Ghana, roasted groundnut are sometimes eaten with banana or roasted plantain. It is always not uncommon

to always see freshly harvested boiled groundnut arranged in pans and/or packaged in rubbers and sold in the markets. Groundnut could also be processed in different forms and eaten alone or together with other meals. It could be ground into paste and used in diverse ways including; soup preparation, butter for eating bread; local extraction of oil, further processed into cake and powder – locally refer to as kulikuli and kulikuli zim, respectively (Ibrahim *et al.*, 2012). Groundnut is said to aid in combatting food and nutrition insecurity as it provides most food nutrients in proportions as; 20% carbohydrates; 25% digestible protein and 50% high quality edible oil. It also contains minerals such as phosphorus (P), Calcium (Ca), Magnesium (Mg) and Potassium (K) in addition to vitamins; E, K and B (Girei *et al.*, 2013). Globally, groundnut is reported to be fourth oil seed crop, third most significant source of vegetable protein after soybean, followed by cotton seed and it is the thirteenth most important food crop (Taphe *et al.*, 2015).

By-products: Groundnut by-products exist in the form of the haulms left after plucking of nuts on the farm; shells after shelling of harvested dried groundnut and remains in the form of cake after extraction of oil (Tsigbey & Clottey, 2003 and Ibrahim *et al.*, 2012). They noted that these products (haulms and cake) serves as important ingredients in livestock feed. According to the former author, farmers may use the haulms (fodder) regarded as hay to feed their ruminants or they are sometimes sold in urban markets to give extra income to the producer. The cake is used as an important ingredient in poultry feed to serve as a source of protein and other minerals and vitamins mentioned above.

Manufacturing food ingredients for industries: Groundnut serves as an important ingredient for the manufacture of many food products and oil (Koekoek, 2017). Importation of groundnuts into the European market is driven by the industrial manufacture

of food products and its consumption. Apart from industrial extraction of oil, numerous other food products are manufactured from groundnuts in Europe including; peanuts butter, chocolate. Other new products have also been identified in the European markets, such as; ‘drinkable groundnut powder’, ‘plus Bami Goreng with Satay Ayam’, Magnum Double Peanut Butter Ice Cream and Peanut Milk products. Flavoured peanuts with additional coating texture is said to becoming common in the European markets as a peanut snack. Such peanut snack is not uncommon in Ghana, for example ‘Nkatie Burger’ produced by Fabricade Pelo: Burger Food Industries in Taifa-Accra.

Agronomic importance: Groundnut is a leguminous crop and just like any other leguminous crop, it fixes atmospheric nitrogen to the soil (Tsigbey & Clottey, 2003). This improves the nutrient level of the soil, thereby making the crop suitable in a crop rotation practice in a piece of land. The vegetative cover also tends to prevent the direct effect of wind and rain water, which could cause soil erosion.

2.3 Review of Methodology

2.3.1 Productivity measurement

Productivity is a measure of the output obtained relative to the input(s) used in production. Coelli et al. (2005) noted that productivity can be measured in a number of ways. It can be measured as either Marginal Productivity (*MP*) or Average Productivity (*AP*). When productivity is measured in terms of the rate at which output changes per unit change in the input used, it is referred to as *MP*, expressed as;

$$MP = \partial y_i / \partial x_i \tag{2.1}$$

Where;

MP denotes Marginal Productivity,

∂y_i represents the change in the i th output and

∂x_i is the change in the i th input (x).

On the other hand, AP is measured as the output (y) produced per unit of a variable input (x) used, while holding other input variables constant. Since it is measured with respect to one of the variable inputs, it is also known as Partial Factor Productivity, such that, we can have output expressed in terms of each of the inputs used in production of an output. For example, it could be expressed as, output per land, output per labour and output per fertilizer. Mathematically, it can be specified as;

$$AP = y_i / x_i \tag{2.2}$$

Where;

AP denotes Average productivity,

y_i denotes Output of the i th producer and

x_i denotes the i th input.

Productivity can be measured in a variety of ways depending upon the purpose of measurement or the type of approach used. Schreyer (2001) noted that productivity can be measured as output per unit of input, and it could also be measured in terms of gross output or value added of output. Another way to express productivity is to look at it in terms of either Single (partial) Factor productivity (SFP) or Multiple Factor Productivity (MFP). Single (Partial) Factor Productivity (SFP) is said to be the traditional way of measuring productivity as the computation is relatively easy to carry out. It considers the contribution of one input to total output achieved. The computation is made easy because no aggregation of inputs is required, unlike in the TFP approach where input aggregation is a requirement. It is expressed as;

$$PFP = Y / X_i \quad 2.3$$

Where;

Y is the total output produced,

X_i represents the level of input i , used during the production process.

MFP measures productivity of combined inputs relative to total output. It requires that all inputs are specified in the same unit of measurement for its computation and this made the computation cumbersome. It is expressed as equation 2.4;

$$MFP = Y / \sum_{i=1}^n X_i \quad 2.4$$

Where;

Y denotes total output,

X_i represents the sum of all inputs used in the production process

Total Factor Productivity (TFP) is the ratio of total output produced with respect to all inputs used in the production. This measurement is known to provide a wide basis for improving specific input used, because, it does not show interaction between each input and output. The TFP is also expressed as shown in equation 2.5

$$TFP = \sum_{i=1}^n Y_{it} / \sum_{i=1}^n X_{it} \quad 2.5$$

Where;

Y_{it} represents the sum total of output of the i th producer produced in period t ,

X_{it} denotes the sum total of all inputs used in period t .

Kiani et al. (2008) noted that in the stochastic and deterministic models of frontier parametric approach, the level of productivity of a production technology is determined using elasticity of production and return to scale (RTS). Elasticity of production is the percentage change in output relative to the percentage change in input, as the level of input used is altered (Debertin, 2012). He noted that the advantage of this approach in measuring productivity is that it does not require the convention of inputs and outputs into specific unit since elasticity is a ratio of two percentages. RTS is a value that is derived by the summation of the individual input elasticities. Studies including; Bezemer et al. (2005); Binam et al. (2008); Tonini (2011) and Onumah et al. (2013), adopted the TFP approach in their study to measure productivity in agriculture production.

2.3.2 Measurement of efficiency

Efficiency of the *i*th producer is calculated relative to a fully efficient producer (Coelli et al., 2005). Since the work of Farrel (1957), efficiency measurement had been classified into Technical Efficiency (TE), Allocative Efficiency (AE) and Economic Efficiency (EE). TE relates to producing on the production frontier, that is, the ability to obtain maximum amount of output from a given set of inputs and the available technology. While AE relates to using inputs in cost-minimizing proportions to produce a given level of output, the measure of EE results from multiplicative interaction of TE and AE. Economic efficiency is thus defined as the capacity of a firm to produce maximum level of output from cost minimizing input proportions, given the level of technology (Farrel, 1957 and Bravo-Ureta & Pinheiro, 1997).

Various approaches are used for estimation of efficiency which can broadly be classified into frontier approach and non-frontier approach. The frontier approach is also classified

into parametric frontier approach and the non-parametric frontier approach. The parametric frontier approach could further be categorised into deterministic frontier approach and stochastic frontier approach. Whiles the frontier approach requires the construction of a fully efficient frontier against which the individual measurements are estimated, the non-frontier approach makes use of a production or profit function for its estimations.

2.3.2.1 Non-frontier approach

The production function and the profit functions are noted to be the commonly used non-frontier approaches. Authors including, Al-hassan *et al.* (2004) and Dittoh (1991) employed this approach in their study. Quisumbing (1994) noted that the production function approach suffers from simultaneity bias since input variables are endogenously determined. The profit function has also been noted to fail in providing numerical measure of firm-specific efficiency (Aigner *et al.*, 1997) Due to these short falls, the frontier approach was developed.

2.3.2.2 Frontier approach

Aigner *et al.* (1977) and Meeusun & van den Broeck (1997) simultaneously proposed the measure of efficiency using frontier analysis. This involves construction of fully efficient frontier against which individual firms' efficiency are estimated or calculated. Basically, it is the technique of the frontier construction that brings the distinction between the parametric frontier approach (parametric programming) and the non-parametric frontier approach (non-parametric programming).

2.3.2.3 Non-parametric frontier approach

The non-parametric frontier approach can be associated to Data Envelopment Analysis (DEA). DEA makes use of linear programming methods to construct non-parametric frontier which forms the basis for efficiency estimation. From the work of Coelli (1995), mathematical computation of this approach is found to be easy to carry out and does not demand any functional form as well. Another advantage of the non-parametric approach over the parametric approach is that it is suitably used in organizations or industries (banking, telecommunications and health sector) where there are multiple outputs. In spite of these advantages, the approach fails to account for measurement errors and other noise associated with the data (Murillo-Zamorano, 2004). Due to this disadvantage of the approach, the Parametric Frontier Approach was developed to take care of measurement errors and other noise effect in the data.

2.3.2.4 Parametric frontier approach

The parametric frontier approach is sub-divided into Deterministic Frontier Approach and Stochastic Frontier Approach. Deterministic frontier functions are estimated either by econometrics technique or mathematical programming approach, whereas only econometric techniques are applicable in the case of the stochastic frontier functions. Generally, for a cross-sectional data, the parametric frontier is defined as:

$$Y_i = f(x_i; \beta).TE_i \tag{2.6}$$

Where;

Y_i is a scalar output of i th producer;

X_i denotes N vector of inputs;

β represents unknown parameters to be estimated and

TE_i is output-oriented technical efficiency.

A distinction between the deterministic frontier approach and the stochastic frontier approach lies in the manner in which the technical inefficiency is captured.

2.3.2.5 Deterministic frontier approach

The deterministic frontier approach assumes that the technical inefficiency is embedded in one error term ($-u_i$). This is defined as

$$Y_i = f(x_i; \beta) \cdot \exp(-u_i), u_i \geq 0 \quad 2.7$$

Where;

Y_i , X_i and β has similar interpretation as those of the equation 2.6,

u_i denotes the non-negative error term.

The non-negativity condition of the error term u_i , satisfies the condition that $Y_i \leq f(x_i; \beta)$,

which is consistent with $Y_i \leq f(x_i; \beta) \cdot TE_i$. Hence technical efficiency of the deterministic

frontier can be expressed:

$$TE_i = \frac{f(x_i; \beta) \cdot \exp(-u_i)}{f(x_i; \beta)} = \exp(-u_i) \quad 2.8$$

Note that all variables in this equation (2.8) had the same explanations as defined in the earlier equations above.

Whiles this approach is simple in terms of its implementation, it comes with some short falls. That is, there is only one error term, implying that any deviation from the fully efficient producer (frontier) are under the influence of the farmer or agent. In other words, it means that factors including, unfavourable weather conditions, uncertainties, socio

economic and demographic factors and specification errors (measurement errors, approximation errors etc.) are all regarded as inefficiencies on the part of the producer. The SFA was developed to overcome the short fall identified.

2.3.2.6 Stochastic frontier approach

The stochastic frontier approach was simultaneously proposed by Aigner *et al.* (1977) and Meeusen & Van den Broeck (1997), to capture the effects of the factors that are not under the control of the farmer. Hence, a second symmetric random error term v_i was introduced in addition to u_i to account for statistical noise and other factors that are not under the control of the farmer or producer. The frontier of the producer is therefore expressed as:

$$Y_i = f(x_i; \beta). \exp(v_i). \exp(-u_i) \quad 2.9$$

Where;

v_i = random error term,

All other variables in Equation 2.9, have the same definitions as those of Equation 2.7.

In which case, the frontier for the maximum potential output is defined as Equation 2.10.

$$Y_i = f(x_i; \beta). \exp(v_i) \quad 2.10$$

From Equations 2.9 and 2.10, the technical efficiency of an agent relative to a fully efficient agent can be expressed as:

$$TE_i = \frac{Y_i}{Y_i^*} = \frac{f(x_i; \beta). \exp(v_i - u_i)}{f(x_i; \beta). \exp(v_i)} = \exp(-u_i) \quad 2.11$$

The distinction between the fully efficient frontier and the production frontier is therefore attributable to the u_i . The $\exp(-u)$ in equation 2.8 and 2.11 can be differentiated by the fact that in the latter equation, it is attributable to both noise effect (this could be positive or

negative) and inefficiency effect, while in the former equation it is attributable to only inefficiency effect. Battese (1991) asserts that the predicted TE_i scores relative to a deterministic frontier (Equation 2.8) is smaller than those obtained relative to a stochastic frontier (Equation 2.11) for a given data. He noted that this is due to the fact that the deterministic frontier is estimated so that no output value exceeds it.

2. 4 Distributional Assumptions Underlying the SFA

Under the stochastic frontier analysis, Coelli *et al.* (2005) noted the following distributional assumptions underlying ML estimator as; Half-Normal Distribution, Truncated distribution, Exponential distribution and Gamma distribution. They noted that the distributional assumptions are normally conditioned on the error terms. For example, Aigner *et al.* (1977), obtained maximum likelihood estimates under the following half-normal distributional assumptions for each of the random variables in the Stochastic Frontier Model (SFM); $v_i \sim \text{iidN}(0, \sigma_v^2)$, thus the error term v_i s are independently and identically distributed normal random variables with zero means and variance σ_v^2 and, $u_i \sim \text{iidN}^+(0, \sigma_u^2)$, thus, the u_i s are independently and identically distributed half-normal random variable with zero means and variance σ_u^2 .

Using the truncated distribution - $u_i \sim \text{iidN}^+(\delta, \sigma_u^2)$, Stevenson (1980) assumed that the u_i is independently identically distributed as a truncation of the normal distribution with a constant mean and constant variance. The work of Stevenson preceded the work of Battese & Coelli (1995), who assumed a truncation of the normal distribution with a mean u_i and a constant variance where the mean is parameterized as a function of farm

specific factors to explain variations in efficiency. Thus $u_i \sim \text{iid}N^+(\mu_i, \sigma_u^2)$, $\mu_i = z_i \delta$.

2.5 Functional Forms Used in Estimating Production Frontier

A functional form specifies the estimation of relationship between outputs otherwise known as the dependent variable(s) and input factors also referred to as the independent variable(s). Some common functional forms as noted by Coelli et al. (2005) include; linear functional form, Cobb-Douglas functional form, Quadratic functional form, Normalized Quadratic functional form, Translog functional form, Generalized Leontief functional form and Constant Elasticity of Substitution (CES).

The most commonly used functional forms in the production frontiers in literature are the Cobb-Douglas and the transcendental logarithmic (translog) functional forms (Ehlers, 2011). He noted that the choice of either of them for a particular analysis is based on the advantages it provides over the other given the data at hand.

The Cobb-Douglas functional form is a double-logarithmic production function, such that both the output and input variables are expressed in logarithms. This functional form restricts return to scale to take the same value across all firms and assumes elasticity of substitution to be one. Parameters (β s) of the input variables (X_i) are interpreted as the direct partial elasticities of the output with respect to the inputs in the Cobb-Douglas form. This form has been adopted by many researchers in both classical methods of estimation and the Bayesian estimation approach. See example, Onumah et al. (2010) and Taphe et al. (2015), for classical application of the form and Kurkalova & Carriquiry (2002) and Kurkalova & Carriquiry (2003) for Bayesian approach.

The translog form, unlike the Cobb-Douglas form, imposes no a priori restriction on the return to scale. Translog is said to allow for more general specification of the model since it can denote any underlying arbitrary structure of production technology. It has been used by many researchers for empirical analysis due to its flexibility. It must be noted that this form comes with the problem of multicollinearity emanating from the increased in the number of parameters to be estimated. In this functional form, the estimated β s, thus, the coefficients cannot be interpreted directly as elasticities. However, the first-order coefficient of the model can be interpreted as the elasticities when the variables are scaled by their unit means and taking the derivative of the output variable with respect to each of the input variables. The cross effect between variables are easily estimated using the translog form which accounts for one of its advantages over the Cobb-Douglas form. Cross effect between variables cannot be estimated using Cobb-Douglas. The translog form also allows for varying return to scale rather than assuming constant return to scale. The translog form have also been used for many empirical analyses by researchers. In the work of Baten et al. (2009) and Onumah & Acquah (2010), both translog and Cobb-Douglas forms were used and tested for consistency in their estimates and the translog estimates proved to be more efficient compared to estimates of the Cobb-Douglas form. The functional form has also been applied by some literatures that employed Bayesian stochastic frontier analysis including, Bezemer et al., (2005) and Tonini, (2011), just to mention a few.

2.6 Determinants of Inefficiency

The exogenous variables of the inefficiency model constitute the socio-economic characteristics of the producer and other factors which are farm or firm specific. Some of the farm specific factors identified by the authors in the study of technical efficiency

including those above includes but not limited to; gender, age, educational level, years of experience, farm size, credit, household size, Farmer Based Organisation (FBO) membership, and extension visits. These factors have been found to differently influence inefficiencies in different studies. In particular, a factor that is found to be statistically significant in a study may be found as not significant in another study. Also a factor in a study may have a negative influence on inefficiency, however, the same factor may have a positive influence on inefficiency in another study. For example, Asekenye (2012) found a positive relationship between output of groundnut and labour among groundnut farmers in Kenya and Uganda in the same study. However, he noted that the positive sign of labour among groundnut farmers in Uganda was not statistically important. On the contrary, Shamsudeen et al. (2011) found a negative relationship between output of groundnut and labour, though the estimate was not statistically significant. The inclusion of variables in this study followed various studies such as, Danson-Abbeam et al. (2015); Taphel et al. (2015); Adzawla et al. (2015); Onumah et al. (2013) and Shamsudeen et al. (2011)

2.7 Methods of Incorporating Exogenous Influence on Inefficiency

From the work of Kumbhakar & Lovell (2000), three approaches have been identified for Incorporation of exogenous variables to measure variation in technical efficiency. The three approaches are; early approaches, two stage approach and single stage approach. The below detailed the three techniques used in the incorporation of the exogenous variables.

2.7.1 Early approaches

This approach assumes that exogenous variables influence production of the output and are therefore incorporated into the frontier model. This implies that the frontier model contains

both the input variables as well as the exogenous variables, in which case, the stochastic frontier model is specified as shown in Equation 2.12.

$$\ln Y_i = \ln f(x_i, z_i; \beta) + v_i - u_i \quad 2.12$$

Whiles;

Y_i = Output variable,

X_i = Input vectors

Z_i = Vectors of exogenous variables

β = input Parameters to be estimated.

In Equation 2.12, Z_i , the vector of exogenous variables, is assumed to influence output directly such that it influences the structure of production frontier relative to which the efficiency of the firms or farmers are estimated and not the efficiency in itself. The major shortfall of this early approach is that it is not able to explain variation in efficiency because the exogenous variables are assumed not to be correlated with each random component of v_i and u_i . In their work of Bayesian stochastic frontier modelling, Koop *et al.* (1997) and Bezemer *et al.* (2005), referred to this type of exogenous variables incorporation as common efficiency distribution (CED).

2.7.2 Two stage approach

This approach seeks to associate variation in the predicted efficiency with variation in exogenous variables which is firm or farmer specific (Kumbhakar & Lovell, 2000). The two-stage approach as the name suggest is carried out in two stages. In the first stage, the approach assumes independence and identical distribution of the inefficiency effect to

estimate parameters of the production frontier by MLE. The estimated inefficiency effects are then regressed on the exogenous variables in the last stage as;

$$E(u_i | v_i - u_i) = g(z_i; \gamma) + \varepsilon_i \quad 2.13$$

Where;

u_i denotes the inefficiency term,

v_i represents random shocks

Z_i denotes exogenous variables and

γ is the parameters of the exogenous variables to be estimated.

Whiles exogenous variables are assumed to directly influence output in the early approach, they indirectly affect output in this approach. What it means is that the exogenous variables do not influence the structure of the production technology but rather influences the efficiency with which firms or farmers approaches the production frontier. The drawback of the approach is that; there is an assumption of a functional relationship between the estimated inefficiencies and exogenous variables in the second stage of the estimation to allow for variation in the technical efficiency. This consequently violates the independence and identical distribution assumption of the u_i in the first stage.

2.7.3 Single stage approach

Improving on the above two approaches, the single stage approach proposes the frontier model and the inefficiency model separately but simultaneously estimates parameters in both models at once (single stage), using MLE expressed as the model 2.14. van de Broack *et al.* (1994), proposed the estimation of Bayesian stochastic frontier model using this same approach and referred to it as the Varying Efficiency Distribution (EVD).

$$\ln y_i = \ln f(x_i; \beta) + v_i - g(z_i; \gamma) \quad 2.14$$

Note that all variables in Equation 2.14 have same interpretation as defined in Equations 2.12 and 2.13. In this approach, the inefficiency effects are expressed as an explicit function of certain factors specific to the farmer (Reifschneider & Stevenson, 1991). This approach does not only overcome the drawbacks by only allowing for variation in the efficiency, it as well overcome the problem of violation of the identical distribution through incorporation of the exogenous variables in a single frontier estimation procedure. Due to the advantages of the single stage approach it has since been used for analysing the determinants of inefficiency effect in the classical methods (Onumah & Acquah, 2010 and Battese & Coelli, 1995). Studies including Koop et al. (1997); Koop and Steel (1998) and Bezemer et al. (2005) adopted this approach of incorporation of exogenous variables in their Bayesian stochastic frontier analysis studies and referred to it as, Varying Efficiency Distribution (VED).

2.8 Bayesian Econometrics

The concept of Bayesian econometrics was first introduced by Bayes & Price (1763) and Stigler (1986). They noted that Bayesian econometrics has essentially three components including; priors (prior knowledge), likelihood function (in the form of observed data) and posterior distribution.

Koop (2003) opined that Bayesian econometrics is based on probability rules and that everything an econometrician would wish to do, for instance, estimate the parameters of a model, compare different models or obtain predictions from a model, involves rules of probability. He noted that the application of probability rules in Bayesian estimation methods, made the approach a universal one, such that it could be used whenever a

researcher needs to use data to learn about a phenomenon.

2.8.1 Prior knowledge (Prior belief)

van de Schoot et al. (2014) noted that scientific research is normally built upon on the basis of past research results. This is normally incorporated into our current research in the form of method design, measurement and inclusion of variables and conceptualization of the current work, thus, in the case of the classical econometrics. In using Bayesian methodology, our previous knowledge about the subject matter otherwise known as prior knowledge, is stated more clearly and also moderated by the data gathered (Kaplan & Depaoli, 2013). Prior represents the information we have about the parameters of the model before collecting the data (van de Schoot et *al.*, 2014). They noted that it is possible that we do not have an existing information about the parameters of the model and in such cases we still need to incorporate our ignorance of the parameters of the model into the analysis of our data, if a Bayesian analysis is to be made possible. In such instances the priors used are referred to as non-informative priors. On the other hand, informative priors are used when we have a certain estimates of the parameters of the model from previous related studies. The priors are incorporated into the model as hyper-parameters for all parameters of the model. Hyper-parameters are the mean of the parameter of the model in question and its variance. The variance of that parameter denotes the certainty we have about the mean of the prior distribution. A high variance of the mean of the parameter implies high level of uncertainty about the mean of the parameter. In other words, when the variance for the parameter is smaller, it implies a high level of certainty about the mean of the prior distribution.

2.8.2 Likelihood function (observed evidence)

The second aspect of the Bayesian methodology to consider is the data at hand, that is, the observed evidence. The likelihood function reflects the most likely values for the unknown parameters given the data. Analysis of the parameters of the data is obtained by using a likelihood function which contains the parameter given the data set. That is, the likelihood function summarizes the given data into sample mean, variance or standard deviation and the likely parameters associated to the data. The classical methods of estimation use this likelihood function for estimating data at hand, example is the maximum likelihood estimation. In the case of the stochastic frontier model, the parameters of the model includes; β, u_i, σ_v^2 and λ . The values of this parameters are therefore generated in the likelihood function. This values are then combined with the priors for the posterior distributions.

2.8.3 Prior and posterior distributions

In the Bayesian stochastic frontier approach, distributional assumptions are not specified for only the random variables but for all the parameters of the model. Koop & Steel (1998) found exponential distribution to be suitable for Bayesian stochastic frontier analysis. They noted that exponential distribution is restricted form of gamma distribution. Ritter & Simar (1997) asserts that using very flexible form of gamma distribution for one sided error term may result in weak identification challenges, such that it is not possible to distinguish between u_i and v_i . van de Broeck et al. (1994) noted that the exponential model is least sensitive to changes in priors, that is, it is least sensitive to changing the prior information that are to be incorporated into the model. Therefore, the exponential model is found to be suitable in the implementation of Bayesian stochastic frontier analysis. In Bayesian

stochastic frontier analysis, the following parameters are modelled as unknown parameters of the model to be estimated; β, u_i, σ_v^2 and λ , with their respective prior distributions as, multivariate normal distribution (truncated), normal distribution, gamma and gamma distribution (Kurkalova & Carriquiry, 2003 and Griffin & Steel, 2007). Some additional assumptions are made about the u_i and v_i to allow for the Bayesian stochastic frontier analysis as noted by Koop & Steel (1998).

The priors that are specified for the parameters are combined with the likelihood function using Bayes theorem to form the posterior distributions. According to Coelli *et al.* (2005), Bayes' Theorem states that "the posterior probability density function (pdf) is proportional to the likelihood function times the prior pdf. In other words, "Bayes' theorem states that our prior knowledge is updated by the current data to yield updated knowledge in the form of the posterior distribution" (van de Schoot *et al.*, 2014). The posterior distributions are then achieved through a simulation process known as Markov Chain Monte Carlo (MCMC) method. For detailed description of the; Priors, Likelihood function and Posterior Distributions with Bayesian SFA see Koop *et al.* (2005).

2.8.4 Markov Chain Monte Carlo sampling

Pericchi & Perez (2015) noted that Markov Chain Monte Carlo denotes method of simulating random sampling. That is, instead of analytically solving for the posterior distributions of the parameters, they are simulated by the method of MCMC. MCMC method is an iterative method in which successive iterates (draws) depend on the previous one. Correlation of the successive draws is a common challenge in the MCMC method since each successive iterate depends on the previous one. One way to mitigate or correct

this problem of autocorrelation is to discard (burn-in) some iterates within certain intervals of the successive chain simulation. That is, not all the chain length would be used, instead, a k th step in the chain would be used where k represents an arbitrary number to be chosen carefully by the researcher (Kruschke et al., 2013). Jackman (2009) and Link & Eaton (2012) asserted that when very large MCMC sample size are generated without thinning of the chain, accurate posterior distributions of the parameters of the model are obtained, hence, thinning may be optional to the researcher since some of the programs are set to default of MCMC sample size but not limited to thinning.

According to Kruschke et al. (2013), the larger the sample size generated of the parameter values, the more it represents the posterior distributions of the model. He opined that there are indeed two different samples when the Bayesian estimation is considered and that the two should not be misinterpreted. First, there is an empirical sample size that is collected for the study and it is fixed regardless of the MCMC sample size generated. The second one is the sample size (chain length) that is generated by the MCMC process for the parameters of the model. According to Koop (2003), the two most popular MCMC algorithms methods are, Metropolis-Hastings and the Gibbs Sampler. He asserts that the Gibbs Sampler is said to be useful for problems that involves latent variables such as tobit models and stochastic frontier models. This study, therefore, adopts the later for simulation of the posterior distribution since this it involves analysis of a stochastic frontier model.

2.8.5 Bayesian econometrics verses the classical econometrics

Bayesian econometrics is noted to have a lot of advantages over the classical econometrics. Some authors describe the characteristics of the Bayesian approach and the frequentist which in effect yields the relevance of the Bayesian approach. According to Coelli et al.

(2005), estimators in the classical methods are chosen on the basis of their long run performance while in the Bayesian Approach estimators are chosen on the basis of their ability to minimize the loss associated with the estimation error. That is, in the classical setting, there is the need to collect data from a population on repeated times. The different sample from the same population are analysed so that at the long run the estimator which perform better is chosen. However, it is clear that data is seldom collected on repeated times implying that the accuracy of the estimator cannot be determined. In Bayesian approach, there is no need for repeated sampling of the same population, because the choice of the estimator depends its ability to efficiently minimize the loss associated with the estimation error using the same data.

Interpretation of Bayesian results is more intuitive as compared to results from the frequentist (van de Schoot et al. 2014). Kruschke (2013) opined that information contained in the Bayesian analysis to inferences is much credible than those provided by the null hypothesis significant testing in the Classical Methods (CM). For instant, in a 95% confidence interval for a parameter say β_k , which extends from 0.5 to 0.85, it is not possible to conclude that β_k lies within this interval with a probability of 95% (Coelli et al., 2005). It only suffices to say that the probability that the parameter lies in the interval is either 1 or 0, since the test can only confirm β_k as either significant or not significant (thus a probability of 1 or 0 respectively). They further explained that a 95% confidence interval ranging from 0.5 to 0.85 means that in a repeated sampling from a population, 95% of the intervals for the various sample sets data from the population would contain β_k . Using the 95% credible interval in the Bayesian approach, we are able to conclude that the probability that β_k is found in the credible interval say 0.5 - 0.85 is 95%.

Incorporation of non-sample information. In Bayesian approach, there is a formal mechanism of incorporating information about the topic in question that are not within the data collected (Koop, 2003). We are not able to incorporate non-sample information into the estimation method in the classical approach.

Sample size requirement for the execution of data analysis. Button et al. (2013) noted that with small sample size our estimates are of less statistical important or are otherwise not meaningful. Coelli et al. (2005) asserts that maximum likelihood estimates have asymptotic desirable properties. That is, as the sample size increases the more the estimates serve as a representative of the population parameters. What it means is that when the sample size is small, it is not appropriate to use the classical methods since the estimates from such an analysis would be of less statistical important. On the other hand, the efficiency of Bayesian estimates depends on the simulations made from the posterior distribution of the parameters of the model. This implies that with a small sample size, we only need to generate the posterior distributions of the model parameters and make inference based on the accuracy of the parameters generated.

2.9 Empirical Results of Previous Related Work

Shamsudeen et al. (2011) estimated the ‘technical efficiency of groundnut production in West Mamprusi district of Northern Ghana’, using the SFA with the Cobb-Douglas functional form. The goal of the study was to estimate the technical efficiency level of the farmers as well as the factors that constitutes the determinants of the technical efficiency. The input variables of the Cobb-Douglas model include, land, labour and seed and the inefficiency variables comprises, farm size, farming system (tractor ploughing or bullock

ploughing), educational level, credit and soil fatigue” (the number of years plot was cultivated consecutively).

From the results of their analysis, the average technical efficiency score was found to be 70%, which ranges from a minimum of 5% to a maximum of 93%. The result indicated that 99% of the variation in output among farmers was due to technical inefficiency on part of the individual farmers, while 1% of the variation was due to errors of measurement and other factors beyond farmers’ control. While land and seed input variables were found to positively affect output levels, the coefficient of labour was not statistically significant with a negative sign. The inefficiency variables; farm size, education, credit and the use of tractor for ploughing were found to have a positive effect on the technical efficiency of the farmer while soil fatigue negatively affect farmer’s efficiency. The study recommended implementation of policies by concerned stakeholders to improve the fertility level since fatigue soils negatively affect efficiency of farmers.

Using the stochastic Frontier Analysis (SFA) and Marginal Value Productivity-Marginal Factor Cost (MVP-MFC), Danso-Abbeam *et al.* (2015) estimated the resource-use efficiency among smallholder groundnut farmers in northern region of Ghana. The overall objective was to investigate the determinants of output and how the various factors of production are allocated. A Cross sectional data collected from 120 groundnut farmers was used for the study. For the SFA, the translog functional form was specified. The variables of the translog model includes, output of groundnut (kg), thus the dependent variable and four input variables; farm size (acres), seed (kg), herbicide (litres) and labour (man-days), which constitute the independent variables. The inefficiency variables that were analysed in the inefficiency model are; gender, age, educational level, marital status, farming

experience, household size, FBO membership and extension visits. The results indicated that 83% of the variation in output is due to farm specific factors, whereas 17% was due to the random factors. The mean technical efficiency score was estimated to be 84%, with the technical efficiency scores ranging from a minimum of 20.04% to maximum of 98.65%. Whiles labour and seed inputs were found to have a positive effect on groundnut output, farm size had a negative effect on same. Educational level, experience, household size and extension visits were also found as determinants of technical inefficiency among groundnut farmers. The study concluded that none of the input variables were efficiently utilized and hence recommend a farm level policy to enhance extension training of farmers on farm management.

Employing a Cobb-Douglas functional form, Taphe *et al.* (2015) also used the SFA to investigate the productivity and efficiency levels of groundnut farmers in Taraba State in Nigeria. This study considered the cost function, profit function in addition to the production function of the farmers. Therefore, the study considered, technical, allocative, as well as economic efficiency of the groundnut farmers. A cross sectional data of 270 sample size was used for the estimation. The mean technical efficiency of groundnut farmers as revealed by the results of the study is 77%, which ranges from a minimum to a maximum technical efficiency scores of 30% to 98% respectively. The mean allocative and economic efficiency scores were estimated to be 70% and 54% respectively. Farm land, seed, family labour and other agrochemicals were found to significantly affect output levels of groundnut farmers. Farming experience, household size, extension contact and education were also found to positively affect the technical efficiency of the respondents. The significant determinants of allocative efficiency include; Farming experience, literacy

level and family size. Finally, whereas cost of seed and transport were also noted to positively influenced groundnut profit, labour cost and storage cost negatively affected groundnut profit. Based on the estimates of the results, they concluded that groundnut farmers were overall not efficient and that efforts must be put in place to improve upon the efficiency of the groundnut farmers in general.

Whiles the studies discussed so far were on rain fed groundnut production, a technical efficiency study in Sudan by Mahgoup *et al.* (2017) focused on irrigated scheme groundnut production. The study also employed the SFA to estimate technical efficiency of groundnut production and analysed the determinants of technical efficiency in the Gezira Scheme of Sudan. The study used secondary data as well as primary (cross sectional) data obtained from 150 respondents. Using the Cobb-Douglass production function, the estimates of the SFM revealed that age, educational level, sowing date, farm income, irrigation numbers and total labour were the main determinant of groundnut yield under the scheme. The study estimated a gamma value of 0.94 implying that 94% of the variation in output is due to the inefficiency factors whereas 6% of same resulted from random shocks. Estimated technical efficiency values ranges from a minimum of 40% to a maximum of 97%, and a mean technical efficiency of 65%. From the analysis of the inefficiency model, farming experience and family size appeared to be the most important determinants of technical efficiency of farmers. The study recommended improving farmer specific factors as well as the management of the scheme to improve efficiency of the farmers.

Using a four-year panel data from the Ukrainian collective farms, Kurkalova & Carriquiry (2003) used the Bayesian framework to estimate a stochastic production frontier model. The main objective of the study was to estimate the posterior distribution of single-input-

oriented technical efficiency at the farm level. They analysed a Cobb-Douglass production function with an exponential distribution using MCMC method by Gibbs sampler for the simulation of draws from the posterior distribution. A relatively non informative priors were used, in particular, the uniform prior distribution was adopted for the β s and truncated below zero to satisfy the monotonicity assumption of the production function. Gamma distributions were chosen for both the variance of the white noise and the inefficiency term. The prior median efficiency (r^*) was chosen to be 0.875. The result of the study indicates that all the input variables (land, labour, fertilizer, chemicals and fuel) satisfies the monotonicity assumption. The mean of the posterior distribution of technical efficiency was found to be 0.942. The input oriented technical efficiency was computed for each of the input variables. They noted that inefficiency variables that have a mean value above one significantly has a positive effect on technical efficiency. To that effect, the number of agricultural workers per hectare, the distance from the farm to an urban centre, and the age of the farm's manager was found to positively influence the efficiency levels of the farms.

Bezemer *et al.* (2005) also used the Bayesian Approach in their study – ‘livelihoods and farm efficiency in rural Georgia’. In broader perspective, the study was conducted to determine the influence of livelihood diversity on the efficiency of farms. A cross-sectional data from 412 households involved in agriculture and non-agriculture activities in 2002 was used for the study. They estimated a translog production function with an exponential distribution using the MCMC method of Gibbs Sampling and imposing the monotonicity assumption and quasi-concavity. In this study, both the early approach (CED) and single stage approach (VED) to incorporating exogenous variables were considered, hence, two

separate translog models were estimated. A prior median efficiency of 0.875 was chosen for the study. The results of the study indicated that in both models the inputs variables which include; land, labour, capital and animals, satisfies the monotonicity assumption. They noted that almost all the exogenous variables were of less statistical important (in both models) such that it lack the explanatory power. That is, none of their exogenous variables had had a parameter value above 1.

Tonini (2011) also employed Bayesian stochastic frontier approach to analyse the TFP change, using a 14 years' panel data from 406 observations. The data was collected from 29 countries, which was drawn from the data base of FAOSTAT (2010). The objective of the study was to estimate and investigate cross-country differences in agricultural productivity growth rates among the former EU-15 countries. The translog model was used to analyse the production function with five input variables including; land, fertilizer, machinery, labour and livestock. The likelihood function adopted for the study assumed that the inefficiency components that is, u_i and v_i was independent and u_i was treated as unknown parameters. The dependent variable was assumed to have a normal distribution with constant mean and variance $\sim N(\mu, \sigma^2)$. The following prior distributions were chosen for the parameters of the model; u_i and $\beta_s \sim$ truncated normal distribution; lambda (λ) \sim Gamma distribution with a prior median efficiency value of 0.8; and $\sigma_v^2 \sim$ gamma distribution. Whiles lambda had an informative prior that is a value of 0.8, a relatively non-informative priors were chosen for the other parameters of the model. The monotonicity assumption was imposed on the production function. One chain Simulation was generated for various parameters using Gibbs sampler, with burn-in of 5,000 iterations and 195,000 retained draws. In order to decrease the autocorrelation of the chain, a thinning to every

15th draw was adopted. The results of the study indicated that all first order parameters (input elasticities) were found to be positive, implying that the monotonicity assumption was satisfied. Mean technical efficiency score by country were found in the range of 0.24 to 0.91 and the average technical efficiency score to that effect was found to be 0.43.

Kim and Schmidt (2000) also used the Bayesian Approach in their work of a review and empirical comparison of Bayesian and classical approaches to inference on efficiency levels in stochastic frontier models used a panel data of six years from 117 rice farms. They estimated a Cobb-Dougllass production function with an exponential distribution using the MCMC method of Gibbs Sampling and imposing the monotonicity assumption and quasi-concavity. A prior median efficiency of 0.80 was chosen for the study. The input variables for the model includes; land labour seed and two typys of fertilizer. The results of the study indicated that all inputs variables satisfy the monotonicity assumption.

Conclusion

Groundnut is found to be an important legume and its production comes with several economic benefits. Literature suggest that the loss of groundnut output is not uncommon among African producers. Bayesian stochastic frontier model have been identified to suitably fit any form of data at hand and provides additional information that is not otherwise provided by the 'classical stochastic frontier model'. The translog model in literature was also found to prove efficiency and consistency in its estimates over the Cobb-Douglas form. Empirical review on efficiency studies suggest that generally, farmers were found not to be efficient in their production. Most output loss were due to inefficiency on the part of the farmers. Farmers' socio-economic characteristics and other institutional factors were found to be the determinants of inefficiencies among the farmers.

CHAPTER THREE

METHODOLOGY

3.1 Introduction

This chapter presents the conceptual framework and the theoretical framework upon which this study is built. Empirical model specifications and model variables are also discussed by the chapter. The chapter also describes the choice of variables of the models, the study area, data collection procedure and sampling techniques.

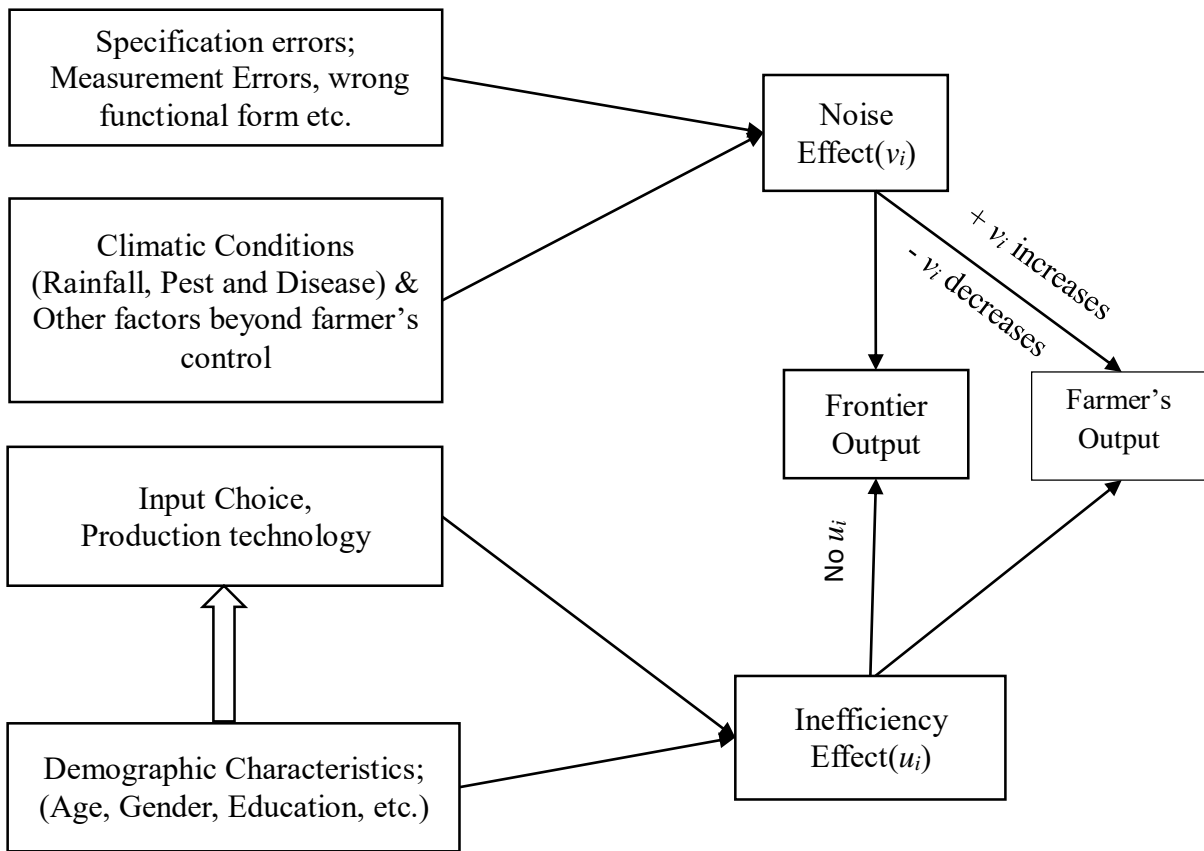
3.2 Conceptual Framework

Using the parametric approach, the stochastic frontier model as independently proposed by Aigner *et al.* (1997) and Meeusem & van den Broeck (1997), was employed for this study. The concept behind this model is the fact that the factors that determine the output of a producer can be grouped into two categories, that is, the noise effect and the inefficiency effect.

The inefficiency effect consists of the demographic factors and management decisions of the farmer. From Figure 3.1, it can be realized that the demographic factors of the farmer have influence on farmer's choice of input and technology adopted. These factors are assumed to be under the control of the producer and any deviation from the potential frontier (frontier output) resulting from these factors form the inefficiency on the part of the farmer. The productivity differences of farmers producing under the same noise effect would result from these factors. The noise effect on the other hand, is also due to the specification errors, (ie errors of measurement, wrong functional forms) and climatic conditions, (rainfall, pest and diseases). These factors are noted to be beyond the control of the farmer (Battese, 1992). He noted that a positive noise effect (v_i) (otherwise known

as the random effect) would lead to an increase in the quantity of the output of the deterministic production function, on the other hand, if the effect is such that it is negative, then, there is a reduction in the output of same.

Figure 3.1: Conceptual Framework



Source: Adapted from Coelli et al. (2005)

3.3 Theoretical Framework

The theory of production as it relates to efficiency can be traced as far back as Farrel (1957). He defined efficiency as the capacity to produce a given level of output at the minimum cost. In addition, Farrel proposed three measurement categories of efficiency that is, technical, allocative and economic efficiency. This study basically considers the measure of technical efficiency. Farrel (1957) asserted that using the stochastic frontier approach, it

is possible to estimate individual firms' performances and compare to the optimal performance such that we are able to differentiate firms that are efficient from non-efficient ones, as well as explain the differences in their performance. This approach to analysing technical efficiency have been applied by many researchers in the field of agricultural economics to determine efficiency of farmers (Shamsudeen et al. 2011; Onumah et al. 2013 and Adzawla et al. 2015). The general form of the stochastic frontier model as proposed by Aigner et al. (1977) and Meeusen & van den Broeck (1977) is specified as Equation 3.1;

$$Y_i = f(x; \beta) \cdot (v_i - u_i) \quad 3.1$$

Where;

Y_i = the mean output of farmer i ,

$f(\cdot)$ is a known function of the firm's inputs, $X = 1, \dots, N$ and a vector of parameters, β , to be estimated,

v_i is the random component representing errors of measurement and other unforeseen occurrences such as unfavourable weather conditions, diseases and pest infestations;

Finally, the u_i is a non-negative error term that represent the technical inefficiency, that is, the amount by which the firms output falls short in terms of the potential output achievable given the inputs and the technology available. Battese and Coelli (1995) made the following assumptions about the random variable v_i and the error term u_i which was adopted for this study. $v_i \sim N(0, \sigma_v^2)$ - v_i is assumed to be independently, identically and normally distributed with mean 0 and a constant variance σ_v^2 . The error term u_i is also assumed to be distributed as a truncation of the normal distribution with mean μ_i and a constant variance σ_u^2 ; $u_i \sim N(\mu_i, \sigma_u^2)$. In this case, the inefficiency error term is explained by

some exogenous variables which could be expressed as;

$$\mu_i = z_i \delta \quad 3.2$$

Where;

μ_i represents inefficiency effects

Z_i denotes a $1 \times n$ vector of exogenous variables which represent factors that explains inefficiency,

δ is an $n \times 1$ set of unknown parameters of the inefficiency factors to be estimated.

Equation 3.2 was adopted for the analysis of the technical inefficiency model.

Battese (1991) noted that technical efficiency is expressed as the ratio of the observed output relative to the output of the frontier production function, in other words, the output of the fully efficient agent. He noted that the output for the frontier production function can be specified as Equation 3.3.

$$Y_i^* = f(x_i; \beta) \cdot \exp(v_i) \quad 3.3$$

From Equation 3.2, observed output for the i th farmer is denoted Y_i . Therefore, taking the ratio of the observed output (Y_i) relative to the frontier output (Y^*) as denoted in Equation 3.3, gives the TE of the i th farmer as shown in Equation 3.4. All other variables in Equation 3.3 have the same interpretation as defined in equation 3.1 above.

$$TE_i = \frac{Y_i}{Y^*} = \exp(-u) \quad 3.4$$

In other words, Y_i is the output obtained by the i th farmer and Y^* is the potential output obtainable given the inputs and the available technology. Y^* can be obtained from the Equation 3.1 by replacing it with Y_i and setting u_i to zero (0), implying that, there is no inefficiency effect. That is to say that the deviation of the output of the producer is due to

only statistical noise and unforeseen circumstances that are beyond the control of the farmer.

Bayesian stochastic frontier model was proposed and used by authors including, van den Broeck et al. (1994); Koop et al. (1995) and Oseiwalski and Steel (1998). According to Coelli et al. (2005), Bayes' Theorem states that "the posterior probability density function (pdf) is proportional to the likelihood function times the prior pdf. The theory can be specified mathematically as the Equation 3.5;

$$p(\theta|y) \propto L(y|\theta)p(\theta) \tag{3.5}$$

Where;

$P(\theta|y)$ = the posterior pdf;

\propto = is proportional to;

$L(y | \theta)$ = the likelihood function and

$P(\theta)$ = the prior Pdf.

θ in Equation 3.5 denotes the parameters of the model and this includes; u_i , β , σ_v^2 and λ .

Following van den Broeck et al. (1994) and Battese (1998), the exponential model is adopted for this study. They noted that the exponential model is least sensitive to changes in priors, that is, it is least sensitive to changing the prior information that are to be incorporated into the model. Koop & Steel (1999) noted that in Bayesian inference, the following assumptions are made about v_i and u_i , in addition to those that were stated in section 2.3 for the MLE.

1. $p(v_i|\sigma^2) = f_N^1(v_i|0, \sigma^2)$ that is the independent assumption of the v_i with mean zero and a constant variance.
2. u_i and v_i are independent of each other for all farmers.

3. $p(u_i|\lambda) = f_G(u_i|1, \lambda)$, such that the u_i s are independent of each other. That is, the assumption that the u_i has an exponential distribution.

Through the modelling of the Bayesian stochastic frontier model, it is referred to as a three level hierarchical model (Kurkalova & Carriquiry, 2003 and Koop *et al.*, 1997). In the first level, the logarithms of the output of the farmers in kilograms is modelled as normally distributed random variable with mean equal to a linear combination of logarithms of the production inputs minus the amount of inefficiency u_i and with variance σ_v^2 as specified in Equation 3.6;

$$\ln(y_i) = \beta_0 + \beta_1 \ln x_1 + \dots + \beta_N \ln x_N + v_i - u_i \quad 3.6$$

In the second level, the technical inefficiency (u_i) is modelled as the exponential random variables to explain technical inefficiencies among the farmers, specified as Equation 3.7;

$$u_i | \delta_i z_i \sim \text{Gamma}(1, \prod_{j=1}^m \delta_j^{z_{ji}}) \quad 3.7$$

Finally, in the Level three of the hierarchical model, priors for the parameters of the model are specified. Following the work of; Osiewalski & Steel, (1998); Koop *et al.* (1997); Griffin & Steel (2007) and Tonini (2011), the below distributions were specified for the various parameters of the model. $Bs \sim N(0, \infty)$ – the intercept and parameters of the production frontier variables has a multivariate truncated normal distribution with zero (0) mean and an infinite variance to depict a non-informative prior. The parameters are truncated below zero to restrict the parameters to be non-negative in order to make the monotonicity assumption. $u_i \sim N(\mu, \lambda^{-1})$; that is, the inefficiency error term u_i has a truncated normal distribution with constant mean and constant variance. $\sigma_v^2 \sim Ga(0.1, 0.1)$; the white noise variance also follows a gamma distribution with flat priors giving non-

informative prior for the white noise variance. $\lambda \sim Ga(\phi, \phi (\ln r^*))$; that is λ has a Gamma distribution, where r^* denotes a prior median efficiency which take the value of 0.8 as adopted from literature (Kim & Schmidt, 2000).

Having specified the priors, we proceed by deriving the conditional posterior distributions for each of the parameters of the model, which serve as a basis upon which the simulations of draws for each of the parameters of the models is made. Combining the likelihood function with the prior distributions of the model parameters gives the joint posterior distributions. It is the joint posterior distribution that the full conditional posterior distribution for each of the parameters of the model are derived. For derivation of these functions see Jondrow et al. (1982) and van de Broeck et al. (1994). The conditional posterior distribution for each of the parameters that are derived from the joint posterior distribution are specified as the following equations;

$$p(u_i | y, \beta, h, \lambda) = f_N(u_i | x; \beta - y_i - (h\lambda)^{-1}, h^{-1}) \times I(u_i) \quad 3.8$$

u_i is a truncated normal distribution, $u_i \geq 0$.

$$p(\beta | y, h, u, \lambda) = f_N(\beta | \hat{\beta}, h^{-1}(X'X)^{-1}) \times I(\beta) \quad 3.9$$

β is a multivariate normal distribution, $\beta \geq 0$

$$p(h | y, \beta, u, \lambda) = f_G(h | I / (y + u - X' \beta)'(y + u - X' \beta), I) \quad 3.10$$

h has a gamma distribution, $h \geq 0$

$$p(\lambda^{-1} | y, \beta, u, \lambda) = f_G(\lambda^{-1} | (I+1) / (u' j, -\ln(r^*)), 2(I+1)) \quad 3.11$$

λ^{-1} also have a gamma distribution, $\lambda^{-1} \geq 0$

Note: h in the equations represents the variance of the white noise which is specified in this study as, σ_v^2 . The Gibbs sampler was then adopted by the MCMC method to simulate draws for each of the parameters of the model. With the draws, the posterior distributions of the parameters of the model were then approximated and summarized using posterior density functions into descriptive statistics such as the mean, variances and percentiles.

3.4 Empirical Model Specification

This study employed the transcendental logarithmic (translog) functional form for the analysis of the data due to its advantages in the estimation of production functions. For example, Onumah et al. (2010) noted that the translog functional form is flexible as it has a lot of parameters to allow for second order approximations. Onumah and Acquah (2010) also tested the efficiency of the translog and Cobb-Douglas forms and confirmed that the estimate of the translog form were more efficient and consistent than those of the Cobb-Douglas form.

Two models were considered in this work, that is, the Cobb-Douglas and translog functional form. Ehlers (2011) asserts that the Deviance Information Criterion (DIC) values is used to measure the fitness of a model in the Bayesian approach. The model that have a smaller DIC value relative to the number of parameters of the model is judged the best fit model for the data. It is widely used for Bayesian model selection since it is easily computed during the simulation of the Markov chains. He noted that robustness of the model is one key factor to note when making judgment about which model best fit a data. Following the work of Ehlers (2011), the translog model was chosen over the Cobb-Douglas. Considering the output and input variables of this study, the empirical model for the analysis was specified as Equation 3.12.

$$\ln y = \ln \beta_0 + \sum_{i=1}^4 \beta_i \ln x_i + \frac{1}{2} \sum_{i=1}^4 \sum_{j=1}^4 \beta_{ij} \ln x_i \ln x_j + (v_i - u_i) \quad 3.12$$

Where;

Y = Output of groundnut (kg/acre),

X_1 = Labour (man-days/acre),

X_2 = Seed (kg/acre),

X_3 = Herbicides (litres/acre),

X_4 = intermediate inputs (GHC/acre).

Note that all variables of the Equation 3.12 are normalized by their corresponding farm size so that there will be no land size effect on the analysis. All farms are judge on the basis of a unit and for that matter same size. This is also important as it reduces the number of variables included in the translog model. Because the translog model has been noted to give challenges, that is, the problem of multicollinearity, given rise to bias estimates as the number of variables in the model increases. Following the work of, Kurkalova and Carriquiry (2003); Onumah et al. (2010); Bezemer et al. (2005) and Tonini (2011) it can be realized that not more than five input variables have been considered in the translog model.

3.4.1 Estimating productivity

The productivity levels of the farmers were estimated by calculating the elasticities and return to scale of the farmers. Since this study employed translog functional form, all variables of Equation 3.12 were normalised with their respective means to have unit means so that the first order parameter estimates were interpreted as the elasticities. The elasticities are then obtained by taking the derivatives of output variable with respect to the

input variables in Equation 3.12 as shown in the Equation 3.13. From Equation 3.13, the coefficients of the squared terms and the cross-product terms are equated to zero so that the first term β_j s are interpreted as direct elasticities.

$$\varepsilon_{y_i} = \frac{\partial \ln E(Y_i)}{\partial \ln X_{ji}} = \left\{ \beta_j + \beta_{jj} \ln X_{ji} + \sum_{i=1}^4 \beta_{jk} \ln X_{ki} \right\} = \beta_j \quad 3.13$$

Return to scale (RTS) value of the farmers was computed by the summation of the individual elasticities as shown in the Equation 3.14;

$$RTS = \sum \varepsilon_{y_i} \quad 3.14$$

The value of RTS gives a decision as to the scale of production of the farmers, such that a value of $RTS > 1$; $RTS < 1$ and $RTS = 1$ implies increasing return to scale, decreasing return to scale and constant return to scale respectively.

3.4.2 Estimation of technical efficiency

Given the output of the farmer to be Y_i and the output of the fully efficient frontier to be Y_i^* as specified in the Equations 3.1 and 3.3 respectively. The technical efficiency of the i th farmer is obtained by taking the ratio of the output obtained by the i th farmer (Y_i) relative to the fully efficient output (Y_i^*). The technical efficiency scores of the farmer do not make use of any model specification. It is simply predicted by dividing the two outputs as shown earlier in Equation 2.11.

3.5 Description and Measurement of Variables Used in the Frontier Model

Output: This was measured as the total quantity of groundnut harvested, dried and shelled and weighed in kilograms (kg) during the 2017 groundnut production season. All output of groundnut that was used for family consumption and given out as gift were all measured and added to the total output. The measurement was done with reference to a scale used by

the ministry of food and agriculture where a bowl of groundnut is measured to be 2.5kg. Total number of bowls of shelled groundnut obtained by the farmer was simply multiplied by 2.5 to get the total output in kilograms.

Land Size: the basic input for any agricultural production activity is land. In this study, land size is referred to the portion of land under groundnut production for each individual farmer and it was measured in acres. It must be noted here that land size is used to scale all other variables of the translog model, such that, it did not appear as a variable in the model but the variables are rather measured per acre basis. It should be noted that acre was used as the unit of measurement of farm size instead of hectares, because, farmers originally measured their farms in acres. Most farmers had their farm size to be an acre and converting it to hectares makes the figures very small. A hectare is equivalent to 2.5 acres.

Labour: This is an input variable that performs almost all activities including planting, weeding, harvesting, shelling and transportation; during the production of groundnut. It was measured in terms of man-days that is the number of person(s), per day, who work on the groundnut farm throughout the production season. Family labour have been observed by Taphe et al. (2015) to have a positive influence on the output of groundnut in Nigeria. Studies including Tonini (2011) and Karkulova & Carriquiry (2003) also noted that labour satisfies the monotonicity assumption in agriculture productivity, implying a positive relationship between labour and agriculture output.

Seed: seed is the input that was used for sowing (planting) to reproduce new set of fruits, thus, the nuts, in which case the output. The measure of seed quantity sown also followed the applied measurement for output of groundnut described earlier. Seed considered in this

study includes certify seed and saved seed. Certify seed is the seed that is produced by a seed grower from the foundation seed. On the other hands, groundnut seeds that are stored by farmers from their previous season production and used for sowing is referred to as saved seed. Other things constant, the quantity of seed used per acre determines plant population per acre. In the same way, seed quantity increases as the number of acres cultivated increases. Asenkenye (2012) measured groundnut seeds sown in kilograms in his study and observed that quantity of groundnut seed sown has a direct relationship with the level of output of groundnut.

Herbicide: these are agrochemicals that are used for the control of weeds. Both selective and non-selective herbicides were considered in this study. The non-selective herbicides are used on the groundnut field during land preparation and the selective herbicides are used for controlling weeds in the groundnut farm during the vegetative growth stage of the crops. It was measured in litres, that is, the total litres of both non-selective and selective herbicides used on the farm. From the work of Kurkalova & Carriquirry (2003), agrochemical was found to satisfies the monotonicity assumption, that is, increasing agrochemical lead to increasing output.

Intermediate inputs: this input is measured as expenditure spent on assets that are in the form of fixed assets (capital) that may not be used up during the production season. Other services used in the production process are also classified as intermediate inputs. These input variables and services includes; hoe, cutlass, suck, knapsack, pan and/or basket, and tractor services. This type of measure of fixed assets for agriculture production has been used by Onumah et al. (2013). It must be noted that aggregating these inputs into one unit also help reduce the number of variables to be included in the translog model. These items

were measured in different units, therefore, in order to get them in the same unit, they were valued in Ghana cedi (GH¢). Since some of the items were not used up in one production season, the value of such items (hoe, cutlass and pan) were depreciated using the straight line method. In the work of Bezemer et al. (2005), it has been noted that increased in capital level leads to increase in the level of agriculture output. Table 3.1 shows the input variables of the model and their a priori expectation.

Table 3.1: A Priori Expectation of the Input Variables

Variable	Measurement	A priori sign
Labour	Man-days	+
Seed	Kilograms	+
Herbicides	Litres	+
Intermediate inputs	GH¢	+

Source: Field Survey, 2017

3.6 Explaining technical inefficiency

Following Equation 3.2, an empirical model was specified as Equation 3.15 to explain technical inefficiency among groundnut farmers.

$$\mu_i = \delta_0 + \sum_{i=1}^5 \delta_i z_i + \omega_i \quad 3.15$$

Where;

δ_0 = constant

δ_i = parameters of inefficiency variables to be estimated

Z_i = inefficiency variables

ω_i = error term to capture the effect of inefficiency variables that are not captured in the model.

The error term μ_i is used to explain inefficiency among groundnut producers.

The variables in Equation 3.15 are the socio-economic characteristics of the farmers as well as some exogenous factors. Table 3.2 gives the description, measurement, a priori expected signs and literature that support the choice of the a priori expected signs.

Other things constant, all variables are expected to positively affect efficiency of the farmer with the exception of age and gender of the farmer, which certainty cannot be given to their influence on efficiency. Because the latter two variables have been found by different studies to have opposite effects on technical efficiency. In other words, age and gender have been found by different studies to either positively or negatively affect efficiency and in most cases not statistically important. The inclusion of the variables in the efficiency model follow other previous related studies.

Table 3.2: Summary of Inefficiency Variables and a Priori Expectations

Variable	Description	Measurement	A priori Sign	Literature Support
Z ₁	Age of farmer	Number of years	+/-	
Z ₂	Gender of farmer	Dummy (male = 0 & female = 1)	+/-	
Z ₃	Educational level	Number of years spent in school.	+	Danso–Abbeam et al. (2015)
Z ₄	Household Size	Number of persons	+	Taphe et al. (2015)
Z ₅	Extension visits	Frequency of times	+	Mahgoub et al. (2017)

Source: Field Survey, 2017

3.7 Description of technical inefficiency variables

Age: this variable was measured as the number of years of the farmer. The a priori expectation of this variable is not certain, because, as a person increases in age, they might be gaining experience which is expected to increase their efficiency levels. On the other hand, younger people easily accept new methods of production and are energetic to go about their activities which could also increase their efficiency level of production. Hence, the variable has been found in different literature to either positively or negatively affect technical inefficiency of the producer. Bezemer *et al.* (2005) noted a negative sign of this variable, but not statistically important. Age was also found to be statistical important and implied reduction in inefficiency among male farmers in the work of Onumah *et al.* (2013).

Gender: female farmers are less privileged to access to land in the northern part of Ghana, such that, they could be limited in their scale of production. The scale of production may affect efficiency of the producer. On the other hand, their male counterparts may have other farms in addition to the groundnut farms. This, therefore, implies that the male groundnut farmer may not in the first instance, utilized the available land resource for groundnut production only. In addition, they may also not commit other resources and their time on their groundnut farms as much as their female counterparts may will to do. In effect, there is no very clear stand to conclude on the nature of a priori sign for gender in this study. Different studies found different influence of gender on efficiencies and in some cases the variable is not able to explain efficiency. For example, Adzwala *et al.* (2015) and Taphe *et al.* (2015) found a negative sign for male farmers but it was not statistical significant. Gender is measured as a dummy variable in this study and take the value of 1 if farmer is a female and 0 otherwise.

Educational Level: Onumah et al. (2010) asserts that educational level is expected to have a positive effect on the efficiency and productivity of a farmer. They noted that as the level of education of the farmer increases, it is expected that their ability to understand and apply new and improve methods of farming also enhances. Educated farmers would also be able to read the manuals of herbicides and other inputs thereby ensuring the efficient utilization of those inputs to improve upon their efficiency level. Hence, this study expected a positive sign for educational level. Educational level of the farmer is measured in this study as the number of years a farmer spent in formal educational.

Household Size: this is measured as the number of persons in a particular household size. This variable is expected to positively affect efficiency. Because as the number of the persons in the family increases, it is assumed that the labour they provide also increases (Mahgoub et al., 2017). In addition, family labour had been found by related studies to be cheap and readily available. Implying that there would be timely performance of farm activities among farmers who have larger household size (Al-hassan, 2008). Timely performance of farm activity may positively influence productivity of the farmer and therefore improves their technical efficiency levels.

Extension Visit: this variable describes the number of times the farmer had contacts with the extension agents. Agriculture extension Agents (AEAs) pay visits to farmers to disseminate agriculture information to them. This information is normally in the form of improved agricultural practices and new technologies that have been developed. The aim of the visits is to guide and encourage farmers to adopt improve agricultural practices and new technologies to improve upon their productivity levels. Taphe et al. (2015) noted a

positive relationship between extension contact and technical efficiency levels and concluded on same reasons explained above. It measured as the frequency of visit.

3.8 Analytical Software

The data was analysed using Stata 15 and OpenBUGS (Bayesian inference Using Gibbs Sampler). Specifically, Stata 15 was used for analyses of descriptive statistics and the OpenBUGS was used for the estimation of productivity levels, technical efficiency levels of the farmers and the analysis of the determinants of technical inefficiencies among groundnut farmers. These three objectives were analysed in the OpenBUGS in a single stage.

3.9 Data Type, Sampling and Data Collection Method

Data for execution of the research was sourced mainly from survey conducted by administering structured questionnaires on groundnut farmers (2017 production season) in the study area which constitutes primary data. Both quantitative and qualitative data was collected for the study. Quantitative data includes all observations that can be measured numerically. All other variables that are non-numerical and thus cannot be measured on a scale but can only be put into categories were classified as qualitative data. However, it should be noted that numbers were assigned to some of the non-numerical categories in which case they become dummy variables, such variables were then described and analysed as quantitative variables. Quantitative data used in this study include; demographic characteristics of the farmers (age in years, experience of farming, household size, educational level, gender (dummy), farm size (acres),) groundnut output and inputs (land size, seed, herbicides, intermediate inputs, labour).

The sampling procedure in this study followed a multi-stage sampling technique. In the first stage, three (3) regions including; Northern, Volta and Upper West, were purposively selected for the study. The choice of the regions was based on the fact that groundnut is produced in large quantities in those regions and they best serve as a representative. Northern region alone is said to produce over 70% of the groundnut output in Ghana. In the second stage, two (2) districts each, were purposively selected from each of the regions on the basis of their records in groundnut production. In the third stage, two communities from each district, were randomly selected from the six district which made up a total of 12 communities. Finally, in the fourth stage, twenty-five (25) farmers were randomly selected from each of the communities adding up to a total of 300 respondents (see appendix 3.2).

The main data collection method used for the study was personal interviews with the farmer using structured questionnaire. However, observations and further interactions with the farmers gave additional information that was useful to this study. A pre-test of the survey was made and the questionnaire corrected to suit the field conditions and inconsistencies. For example, both family labour and hired labour were initially considered but after pre-test it was realised that the groundnut farmers relied mainly on family labour and hired labour was insignificant.

3.10 Study Area

The study was conducted in three administrative regions of Ghana. They include, Volta region, Northern region and Upper West region. Two districts were chosen from each of the three regions that is; Krachi Nchumuru and Krachi West from Volta region, Nankumbi South and Yendi Municipality from the Northern region and Sissala West and Sissala East

from the Upper West Region. Two communities each were chosen from each of the districts above, (see appendix 3.2 for the communities). The three regions were chosen because they are part of the five main regions that produced groundnut in large quantities in Ghana.

Northern Region and Upper West Regions are two of the three northern regions of Ghana. The three regions share borders with Republic of Togo to the east, Ivory Coast to the west and Burkina Faso to the north. Within the country, the northern Ghana is bordered by Volta Region to south east and Brong-Ahafo Region to the south west (Martey et al., 2015). It must be noted that Northern Region share border with both Upper East Region and Upper West Region to the north and Upper West Region share border with Upper East Region to the east. Volta Region share boundaries with Northern Region to the north and to the west with Greater Accra, Eastern and Brong Ahafo Regions and to the south is Gulf of Guinea and Togo to the east (GSS, 2013).

Geographically, Northern Region and Upper West Region (in addition to the Upper East Region) is located between longitude $8^{\circ} 46'01.88''\text{N}$ and $10^{\circ}58'34''\text{N}$ and latitude $2^{\circ}45'45.40''\text{W}$ and $0^{\circ}32'59.95''\text{W}$ (Martey et al. 2015). Volta region is located between latitudes $50 45''\text{N}$ and $80 45''\text{N}$ along the southern half of the eastern border of Ghana. The total land area of Ghana is estimated to be 238,530 square kilometres, out of which, Northern region, Upper West region and Volta region occupy land area of 70,380, 18,480 and 20,570 square kilometres respectively (MoFA, 2016).

The two northern regions in this study are found in the guinea savannah agro-ecological zones, characterized by one rainy season with annual average rainfall of about 1100 mm.

Temperatures in the Northern regions ranges between 20⁰C (during harmattan periods in December) and 40⁰C (in March, just before the onset of the rainy season in the next month). Volta region is unique in terms of its ecological zones and also has two rainy season. It has different agro-ecological zones found in Ghana within it. The area that was selected for the study within the region falls under the northern part of the region, characterized by the Sahel-Savannah zone where average annual rainfall (Annual mean rainfall ranges between 1,168mm and 2,103) is said to be on the minimum within the region. Temperatures in the region ranges from (21–32)⁰ C (GSS, 2013). Common trees that are found in the study area includes; shea nut (*Vitellaria paradoxa*), acacia, (*Acacia longifolia*), baobab (*Adansonia digitata* Linn), mango (*Mangifera indica*), dawadawa, and neem (*Azadirachta indica*).

Ghana's population as at 2010 was 24,658,823, out of which the population of Northern Region, Upper West Region and Volta Region were found to be 2,479,461, 702,110, and 2,118,252 respectively. Majority of the people in this area lives in the rural area, that is, out of these figures above, 69.70%, 83.70% and 66.30% lives in the rural area. The major occupation of this rural dwellers is agriculture. The report of MoFA (2016) indicates that 90%, 88.60% and 73.20% of rural households in the Northern, Upper West and Volta regions respectively are engaged in agriculture. Martey et al. (2015) noted that more than 80% of the people in northern Ghana are engaged in agriculture production. They noted that these regions are well known for the production of grains including; groundnut, Bambara groundnut, cowpea, soybean and cereals such as rice, maize, sorghum and millet.

CHAPTER FOUR

RESULTS AND DISCUSSIONS

4.1 Introduction

This chapter presents the results and discussions from the analyses of data. It covers the socio-demographic characteristics of groundnut farmers interviewed. The productivity and technical efficiency levels of the farmers, as well as the factors that influences farmers' technical efficiency levels are also discussed under this chapter.

4.2 Socio-Demographic Characteristics of Farmers

The socio-demographic characteristics of the groundnut farmers interviewed are summarized in Table 4.1. Each characteristics is further discussed in the below headings.

4.2.1 Age distribution of groundnut farmers

The result of the age distribution indicated that 94.33% of the farmers are in the working age bracket (age 15 - 64) and only 5.67% of them fell within the aged bracket (65+). The mean age of farmers was found to be 41years with the minimum and maximum age of 18 and 87 years respectively. The implication of this age bracket of the farmers is that farmers themselves are relatively energetic to provide labour for their farm operations. It also means farmers have reach experience to enable them carry out their production efficiently. This finding is similar to the work of Anang *et al.* (2015), who found the mean age of small scale rice farmers in northern Ghana to be 41 years. The implication of farmer's age on groundnut output is discussed in a later sub-section.

Table 4.1: Socio Demographic Characteristics of the Respondents

Socio variable	Respondents	Percent
Age of Farmer		
15 – 24	40	13.33
25 – 34	69	23.00
35 – 44	77	25.67
45 – 54	61	20.33
55 - 64	36	12.00
65+	17	5.67
Total	300	100.00
Gender of Farmer		
Male	111	37.00
Female	189	63.00
Total	300	100
Level of Education		
None	199	66.33
Primary	28	9.33
JHS/JSS/MSCL	38	12.67
SHS/SSS/Vocational/Technical	23	7.67
Tertiary	12	4.00
Total	300	100
Farm size(acres)		
1 – 3	251	83.67
4 – 6	43	14.33
7 – 9	2	0.67
10+	4	1.33
Total	300	100
FBO Membership		
Members	86	28.63
Non-members	214	71.27
Total	300	100
Farming Experience		
1 – 3	49	16.33
4 – 6	16	5.33
7 – 9	75	25.00
10+	160	53.33
Total	300	100
Household Size		
1 – 3	17	5.67
4 – 6	89	29.67
7 – 9	82	27.33
10+	122	40.67
Total	300	100

Source: Field Survey, 2017

4.2.2 Gender of farmers and groundnut production in Ghana

Out of the 300 groundnut producers that were interviewed, 111 of them are males and 189 of them made up the females, representing 37% and 63% respectively. The result indicates that groundnut production in the study area is dominated by females. Martey et al. (2015) found similar result with the female groundnut farmers in northern Ghana to be 70.60%. This result is contrary to the work of Anang et al. (2016) who found males to be the dominance (78%) in small scale rice production in northern Ghana.

The dominance of females in groundnut production is partly due to the fact that the crop serves as a major crop that is produced by the female farmers as opposed to their male counterparts who produces it as one of their minor crops. An interaction with the farmers revealed that in the Volta and Northern regions, male farmers who are mostly yam farmers cultivate groundnut on a piece of land in which they harvested their yam. In the Upper West region, the main crop produced by the male farmers is cotton. Most of the activities (including sowing, plugging, drying, winnowing) of groundnut production are mostly regarded as female's activities. The women therefore perform such activities even if the farm is owned by their male counterparts. The performance of these activities by female can be viewed as a motivating factor for high number involvement of them in the production of groundnut.

Both male and female farmers give each other labour support. Whiles the male farmer may support the female counterpart with activities such as, weeding, uprooting, and spraying of herbicide, it is not uncommon to find the females supporting their male counterpart with activities including, sowing, plugging and winnowing.

4.2.3 Educational level of groundnut farmers interviewed

A total of 101, representing 33.67% of the respondents attained formal education whereas 199 of the respondents representing 66.33% did not attain any form of formal education as shown in Table 4.1. Out of those who attained formal education, 66 of them representing 22% of the total respondents had basic education while 23 of them had secondary education representing 7.67% of the total respondents and the remaining 12 respondents representing 4% had tertiary education. Many studies in the northern part of the country observed low levels of education and absence of education among farmers (Wiredu *et al.*, 2010 and Adzawla *et al.*, 2015). The result of the inefficiency model further explains the influence of education on the technical efficiency of the farmers interviewed.

4.2.4. Household size of respondent

From Table 4.1, mean household size of the respondents was found to be about nine (9) persons, with the minimum and maximum household size of one (1) person and thirty-two (32) persons respectively. The result is different from the earlier work of Danso-Abbeam *et al.* (2015) who found the mean household size to be 12 persons. The mean male adult persons and female adult persons were found to be about two (2) persons and three (3) persons respectively. Similarly, the mean male children persons and female children persons were also found to be about two (2) persons and three (3) persons respectively.

Households in the study area are mostly headed by the males and this is in conformity with work of Martey *et al.* (2015), who noted the dominance of household heads by males in the northern Ghana. From this study, 101 of the farmers representing 33.67% of the respondents were family heads. Out of the 111 males that are among the respondents, 78 of them are family heads representing 78.22% of the respondents who are family heads and

the rest 23 household heads are females. Farmer's relationship to the household head shows that 144 of the females interviewed are wives to their male counterparts who are the family heads. While 39 of the respondents are children to the household head, nine (9) of the respondents are brothers of the household heads. The last category non-household heads are aged females (9 of the respondents) who are parents to the household heads.

4.2.5 Farmer Based Organization (FBO) membership

Farmer Based Organizations are established with the goal of facilitating the activities of the small scale farmer. Notwithstanding that farmers in this groups could benefit from mutual labour support, they could also receive benefits such as credit facility, training on improved agronomic practices, marketing of their surplus output and access to agricultural inputs (Uaiene et al., 2009). From Table 4.1, 86 (28.63%) of the farmers were members of FBO and the remaining 214 (71.27%) were not members of any FBO. This result is similar to the result of Martey et al. (2015) who found majority (82%) of the farmers in northern Ghana to be non-members of FBO.

4.2.6 Land holding of farmers in the study area

Table 4.2 shows gender and land holding distributions of the farmers in the study area. It must be noted that in the study area, land holdings of the females are most often than not dependent on the holdings of their male counterparts and in which case their spouse. Generally, the land available to the female in the study area is usually small since it is dependent on the holdings of their husbands who may then give a portion of the land to them for their yearly production. Land in this study was measured as land size (acres) available to the farmer for their groundnut production in the 2017 production season.

Table 4.2: Gender and Landholdings of Farmers

Land holdings(acres)	Respondents		Total(%)
	Males(%)	Females(%)	
1 – 5	47(15.67)	143(47.67)	190(63.34)
6 – 10	47(15.67)	37(12.33)	84(28.00)
≥ 11	17(5.67)	9(3.00)	26(8.67)
Total	111(37.01)	189(62.99)	300(100)

Source: Field Survey, 2017

The minimum and maximum land holdings were found to be an acre and sixty (60) acres respectively. The mean land size available to the female farmer was found to be 1.10 acres. The estimates from Table 4.2 also indicate that about 75% of the female population falls under the land holdings of 1 to 5 acres as opposed to about 43% of their male counterparts in that category of land holdings. A total of 286 farmers got their land through inheritance and 2 farmers obtained theirs through sharecropping. The rest of the farmers numbering 12, got their land through gift from friends and other family members.

4.2.7 Extension visit to farmers

Farmer-extension agent contact serves as a means by which information is delivered to farmers. The contact is supposed to enhance exchange of innovative farming ideas between farmers and extension agents in order to improve the productivity levels of the farmers. From Table 4.3, majority of the respondents – 215 (71.67%) did not get access to extension service. Out of the 85 (28.33%) respondents that had the extension contact, 33, 39 and 13 of them were visited by agents from MoFA, NGOs and both agencies respectively.

Table 4.3: Marital Status, Extension Service, Access to Credit of Farmers

Socio Variables	Respondent	Percent
Marital Status		
Single	35	11.67
Married	237	79.00
Divorced	5	1.67
Widowed	23	7.67
Total	300	100
Extension Service		
Access	85	28.33
No access	215	71.67
Total	300	100
Access to Credit		
Access	48	16
No access	252	84
Total	300	100

Source: Field Survey, 2017

4.2.8 Marital status of farmers in the study area

Table 4.3 depicts the proportions of marital status of the farmers in the study area. Out of the 300 farmers that were interviewed, a total of 63, representing 21% of the respondent are not married. From the unmarried category, 35 of the farmers are single, thus, they have never married. The rest were made up of the divorced and the widowed which numbered 5 and 23 persons respectively. On the other hand, 237 farmers representing 79% of the respondents were married.

4.2.9 Credit access by farmers

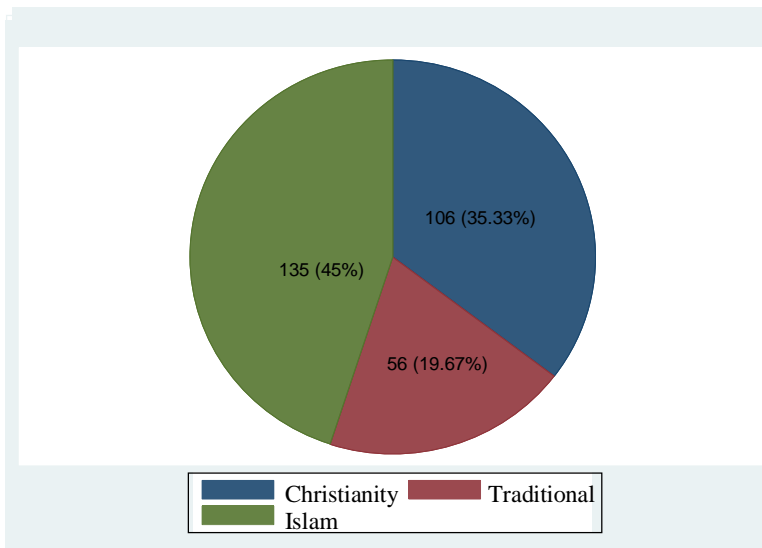
Credit facility enhances inputs purchasing power of the farmer and also facilitate timely operations of the farming activities. This in turn is expected to boost output obtained by farmers. Access to credit in the study area and for that matter Ghana, is a major challenge to the rural farmer. Table 4.3 shows that while 48 (16%) of the respondents had access to credit, 252 (84%) of them did not obtain any form of credit in the 2017 production season.

The sources of the credit obtained by the farmers includes, bank institutions, NGOs, and other sources (Village Savings and Loans Association (VSLAs) and MoFA), in proportions of 10, 13 and 17 of the respondents respectively. The remaining sources of farmer's access to credit are, family and friends, money lenders and FBO and number of respondent(s) that had the credit were; 3, 3, and 1, respectively.

4.2.10 Religious denomination of farmers in the study area

Ghana is dominated by three main religions, that is, Christianity, Islam and traditional religion. Figure 4.1, depicts the distribution of farmers interviewed in their respective religions. From Figure 4.1, majority of the respondents (135) representing 45% were found to be Muslims, that is, they belong to Islamic religion. Those farmers who practice Christianity were 106 denoting 35.33% of the farmers interviewed and the remaining 56 respondents constitute the traditional religion.

Figure 4.1: Religion of Farmers in the Study Area



Source: Field Survey, 2017

4.3 Groundnut Production System

The use of herbicide by groundnut farmers for weed control during land preparation is not uncommon. Danso-Abbeam *et al.* (2015) noted the usage of herbicide by all groundnut farmers. Herbicide can be used in two stages during the production of groundnut, that is, during land preparation and also for weed control during the growth stage of the groundnut. Out of the 300 respondents interviewed, 173 (57.67%) of them used the herbicide during land preparation stage only. The remaining 108 (36.00%) of the respondents used the herbicide in both stages. Only 19 (6.33%) of the farmers used the herbicide for weed control during plant growth only (see appendix 4.4). An interaction with the farmers revealed that non-selective post emergence herbicide was used after the land had been ploughed before sowing of groundnut or just a day after sowing of the groundnut. This would then be followed by the use of selective herbicide for weed control during plant growth stage by the farmers who applied herbicide in both stages.

Two ploughing systems were used by the farmers for groundnut production during the 2017 production season, that is, tractor ploughing system and hoeing system. A total of 248 (82.67%) respondents used the tractor ploughing system and the remaining 52 (17.33%) of the respondents resorted to the hoeing system (see appendix 4.4). Tsigbey & Clotey (2003) identified three ploughing system, that is, the two listed above and animal traction. An interaction with the farmers in the Upper West who mostly made use of the animal plough in the past revealed that due to mechanization the animal traction is not gaining it grounds. The farmers noted that the animals were always used by children for the ploughing but these children now find themselves in school and are not available for same job.

Based on the reasons of choice of ploughing system, a total of 127 (see appendix 4.4) of the respondents chose the tractor plough because of its availability. An interaction with the farmers in Upper West region where all the respondents used the tractor plough revealed that the animal traction is better as compared to the tractor ploughing. They opined that the tractor tillage is deep, given rise to heavy amount of soil. The farmers noted that this practice may turn the top soil containing most of the nutrients deep the grounds where groundnut plants could not utilize the nutrients. They assert that the animal plough gives shallow plough leaving the top soil on the surface of the land. Only ten (10) of the respondents from this region claimed the tractor system was better due to its efficiency.

Out of 148 farmers in the Volta and Northern region that used tractor ploughing system, 109 of them made the choice with the opinion that it is better than the hoeing system. According to the farmers with the tractor plough, they are able to increase seed quantity sown per acre of groundnut farm cultivated. Other things constant, they expect an increase in output due to increased quantity of seed sown. Seed quantity sown in relation to output obtained is discussed later in the preceding sub-sections. In addition to the above, 32 of these respondents also made the choice because its availability. The last eight (8) respondents in this category of ploughing also made the choice due to its cost-effectiveness compared to the hoeing system.

The hoe system was used by farmers in Volta and Northern regions who were mostly the farmers that cultivated groundnut in a crop rotation after yam. The majority of respondents (28) in the hoeing system category also opined that the system is better compared to tractor system when the crop rotation system is considered. They further explained that the tractor is not able to plough better in the old yam months and in other cases destroy other crops

(for example cassava) that has been intercropped with the yam and yet to be harvested. The rest of the respondents (6) also made the choice on the motive of availability of the system. According to those farmers, they did not get the tractor service as at when they wanted to plough their plots and had to resort to the hoeing system. On the other hand, 19 of the farmers who used the hoeing system also made the choice based on the cost of tractor ploughing. That is, they do not have the money to pay for the cost of ploughing, instead, they resorted to using their own labour for the hoeing system.

4.4 Certify Seed and Fertilizer Application Awareness

Most farmers in Ghana resort to sowing their saved seeds from their previous year's production output. The case of groundnut farmers is not exceptional and even seem to be on the alarming rate. Investigating certify seeds awareness among the groundnut farmers interviewed revealed that 107 of farmers representing 35.67% of the respondents are aware of groundnut certify seeds. This implies that majority of the respondents – 193 (64.33%) are not aware of the existence of groundnut certify seeds (see appendix VI). It is worth noting that while only 11 (10.28%) of the respondents who are aware of the certify seeds did sow it, 96 (89.72%) of respondents in this category sown their saved seeds from their previous year's production output. Out of the 107 respondents that are aware of the certify seeds, 80 (74.77%) of farmers in this category opined that they resorted to their saved seeds due to unavailability of the certify seeds and the remaining 16 (14.95%) of the respondents did sown their saved seeds due to the high cost of the certify seeds. The result is similar to the work of Martey *et al.* (2015) who observed that majority of groundnut farmers in northern Ghana relied on saved seeds from previous production, market and neighbouring farmers.

Due to continuous decline of soil fertility, conscious effort had been made to the development of fertilizer that is suitable for application in leguminous crops. To that effect, the Triple Super Phosphate (TSP) had been introduced by IITA to farmers in its operational areas in Ghana. The study revealed that only 98 (32.67%) of the farmers interviewed are aware of fertilizer application in groundnut production. Neither the farmers that are aware nor those that are not aware (202) of the fertilizer application did applied it.

4.5 Summary Statistics of Variables of the Stochastic Frontier Model

Table 4.4 presents the summary statistics of the output and input variables of the Bayesian stochastic frontier model. The summary statistics are then discussed under the individual sub-headings for each input.

Output. In this study, output of groundnut is the dependent variable. From Table 4.4, the minimum and maximum output of groundnut obtained per acre cultivated was found to be 9.33kg and 595kg respectively. Mean output per acre was estimated to be 134.74kg with a standard deviation of 95.32. The output of groundnut per acre as revealed by this work is far less the achievable and potential yield of 1.65mt/ha and 3.5mt/ha respectively as reported by MoFA (2016).

Table 4.4: Summary Statistics of the Variables of the Model

Variable	Units	Minimum	Mean	Maximum	Std. Dev.
Output/Acre	Kg/acre	9.32	134.73	595.00	95.33
Labour/Acre	Man-days/acre	7.20	34.19	135.00	14.86
Seed/Acre	Kg/acre	7.50	21.74	37.50	6.00
Herbicides/Acre	Litres/acre	0.25	1.58	4.00	0.84
Intermediate input/Acre	GH¢	3.22	83.82	191.67	36.66

Source: Field Survey, 2017

The implication of this result is that there is a wide gap in productivity of groundnut that need to be bridged.

Labour: labour is an input variable that is used in all kinds of agricultural activities. It cannot be completely replaced by mechanization of any form. Mean labour in terms of man-days used for groundnut production in the study area was found to be about 74 man-days with a standard deviation of 43 man-days. The minimum and maximum man-days used per acre of groundnut cultivated was found to be about 7 man-days and 135 man-days respectively. The average man-days as found in this study is different from average man-days of 132 found by Danso-Abbeam *et al.* (2015). This may be due to the level of herbicide usage which is increasing year after year. Thus, the use of selective herbicide to control weeds in growing groundnuts is being adopted by farmers to replace labour needed for manual weeding. Groundnut producers in the study area depends almost entirely on family labour for their operations. The plough which was done manually had been replaced by the use of tractor which otherwise could have demanded the use of hired labour. An interaction with some farmers who use the hoe plough revealed that due to lack of money to pay for the tractor services, they resorted to family labour support to manually plough their lands.

Seed: From Table 4.4, the minimum and maximum seed sown per acre were estimated to be 7.5kg to 37.5kg respectively. The mean seed sown per acre was also found to be 21.74kg. Generally, mean seed used for groundnut production among the respondents was found to be 53.17kg, which ranges from a minimum of 9.00kg to a maximum of 382.50kg. Asekenye (2012) observed an average of 45.4kg and 31kg of groundnut seed sown respectively in Uganda and Kenya. Section 4.6 and 4.7 discusses the contribution of seed

to the output levels of groundnut.

Herbicide: Table 4.4 shows that the mean litres of herbicide used per acre of groundnut cultivated was 1.58 litres. While the minimum litres of herbicide used per acre was found to be 0.25, the maximum litres of herbicide was found to be 4 litres. This result is not in line with the work of Adzawla *et al.* (2015) who found litres of herbicide used per acre by farmers to be 0.82 litres. This difference may be due to the fact that farmers in this recent study resort to both selective and non-selective herbicides for weed control during plant growth and in land preparation stage respectively.

Intermediate Inputs: intermediate inputs were used in diverse ways by the farmers interviewed. In some cases, it was replaced by labour. For example, valuing the cost of tractor ploughing as an intermediate input was replaced by labour when the hoe plough is used in which case the hoe becomes the intermediate input instead of the cost of ploughing. The mean expenditure on intermediate input per acre was found to be GHC83.82. The minimum and maximum expenditures on intermediate inputs were estimated as GHC3.223 and 191.67 respectively.

4.6 Productivity Levels of Groundnut Producers

The result of the study indicated average output of groundnut to be 326.33kg. This output ranges from a minimum of 20kg to a maximum output of 2,722.50kg. Meanwhile, in terms of per acre basis, the minimum and maximum output of groundnut was found to be 9.33kg and 595kg respectively as indicated in Table 4.4. Mean output per acre was also found to be 134.74kg. Comparatively, this output value (converting 134.74kg/ha to Mt/ha gives a value of 0.34mt/ha) is far less than that of the national output (1.65mt/ha) MoFA (2016).

Table 4.5 shows the productivity responses of groundnut output with respect to the individual inputs, that is, labour, seed, herbicide and intermediate inputs. The estimates from the translog model shows that a percentage increase in any of these inputs lead to an increase in the productivity level. This implies that the production function is well behaved and satisfies the monotonicity assumption as noted by Tonini et al. (2011). That is, an increase in any of the inputs levels lead to increase in output level of groundnut. Since increase in input levels corresponds to increase in the level of output, farmers could continue to increase their input levels to the point that any increase in the input level would yield no additional output (constant return to scale).

Table 4.5 Productivity Estimates and Return to Scale of Production

Input variables	Units	Mean
Labour	man-days	0.2687
Seed	kilograms	0.5468
Herbicides	litres	0.2146
Intermediate inputs	GH¢	0.0708
RTS		1.1009

Source: Field Survey with Authors Own Calculations

From Table 4.5, the value of RTS of 1.10 means that the production function of the groundnut farmers demonstrates an increasing return to scale. This means that groundnut farmers are producing at the stage one of the production function, such that, an increase in all the inputs levels result in a more than proportionate increase in the level of output. In particular, a RTS value of 1.10 implies that when all inputs are increased by 1%, it will lead to 1.10 percentage increase in the level of groundnut output (greater than proportionate

change). The economic implication of this result is that there is the need for groundnut producers to expand their scale of production so as to increase productivity levels at the long run. The return to scale value is different from that obtained by Shamsudeen *et al.* (2011), who found groundnut producers in West Manprusi district of northern Ghana to be producing at a constant return to scale – RTS value of 1.03. They noted that the RTS value was consistent with the expected RTS value of the Cobb-Douglass form considered in their study which restricts return to scale to be essentially 1. Following the work of Danso-Abbeam *et al.* (2015), who employed the translog functional form, the estimates of the first order coefficient showed that farmers were producing at an increasing return to scale.

4.7 Posterior Distributions of the Parameters of the Stochastic Frontier Model

Table 4.6 presents the posterior distributions of the parameter estimates. The Gibbs sampler was run for one chain, with burn-in of 20000 iterations, 80002 retained draws and a thinning to every 20th draw in order to reduce the level of autocorrelation of the chain. One way to check the accuracy of the estimates in Table 4.6, is by comparing the Monte Carlo (MC) error (which measures the variability of each estimate due to the simulation) with the corresponding posterior standard deviation (Tonini, 2011). He noted that convergence is normally achieved when the MC errors are lower than the standard deviation. From Table 4.6, it can be realized that the MC errors values are lesser than their corresponding standard deviation values, indicating the convergence of the estimated model and accuracy of the estimates.

Sigma square value (σ_v^2), that is, the variance of the white noise in the Table 4.6 explains the variation of total output due to random factors (Kurkalova & Carriquiry, 2003). The

value of the variance (of the white-noise error term) – sigma square was found to be 0.223. This means that 22.3% of the variation in total output is due to random shocks which includes; pest and diseases infestation, unfavourable weather conditions and statistical errors. In other words, it can be deduced that 77.7% of the variation in total output is associated to farmer specific factors. This estimate implies that variation in total output of groundnut is largely accounted for by farmer specific factors.

Table 4.6: Bayesian Parameter Estimates of the Stochastic Frontier Model

Variable	Para – meters	Mean	SD	MC_err	2.5%	Median	97.5%
Constant	β_0	0.326	0.124	0.006	-0.020	0.348	0.507
Labour	β_1	0.269	0.112	0.002	0.054	0.264	0.498
Seed	β_2	0.547	0.131	0.002	0.290	0.547	0.806
Herbicides	β_3	0.215	0.084	0.009	0.048	0.215	0.379
Intermediate Input	β_4	0.071	0.126	0.002	-0.183	0.072	0.317
Labour Square	β_5	-0.566	0.339	0.004	-1.208	-0.573	0.097
Seed Square	β_6	-0.658	0.273	0.003	-1.190	-0.660	-0.118
Herbicide Square	β_7	-0.166	0.185	0.002	-0.529	-0.165	0.198
Intermediate Input Square	β_8	-0.167	0.151	0.002	-0.461	-0.168	0.131
Labour * Seed	β_9	1.000	0.221	0.003	0.565	1.001	1.426
Labour * Herbicides	β_{10}	-0.804	0.165	0.002	-1.132	-0.802	-0.481
Labour * Intermediate Inputs	β_{11}	-0.082	0.170	0.002	-0.408	-0.083	0.255
Seed * Herbicides	β_{12}	0.472	0.184	0.003	0.113	0.475	0.826
Seed * intermediate Inputs	β_{13}	0.084	0.169	0.002	-0.247	0.083	0.421
Herbicide*Intermediate inputs	β_{14}	0.044	0.087	0.001	-0.121	0.043	0.212
White-noise variance	σ_v^2	0.223	0.066	0.003	0.141	0.043	0.405
Lambda	λ	0.295	0.098	0.004	0.007	0.298	0.567
DIC		521.50					

Source: Field survey with Authors Own Calculations

SD = Standard Deviation; MC_err. = Monte Carlo error; DIC: Deviance Information Criterion; % = Percentile

The value of lambda – λ , gives information about the inefficiency level of the farmers. In other words, it shows by how much the producer has fallen short of the total output (Kleit & Tecrell, 2001). Specifically, the value of λ thus 0.295 in Table 4.6 implies that the groundnut farmers are 29.5% technically inefficient. That is to say that the groundnut farmers are producing at 70.5% of the total groundnut output that can be obtained given the input resources and the technology at hand.

The estimates of the production elasticities (at the sample mean) for labour, seed, herbicide, and intermediate inputs are; 0.269, 0.547, 0.2145 and 0.071 respectively. All the input variables met their a priori expectation. The results of the parameter estimates imply that a percentage increase in labour, seed, herbicides and expenditure on intermediate inputs will lead to a corresponding increase of 0.27%, 0.55%, 0.21% and 0.07% into total output of groundnut respectively.

From the result of the inputs elasticities, it has been demonstrated that seed contributes largely to increase in output level compared to the other input variables in the model. This result commensurate the work of Taphe et al. (2015) who found groundnut seed as the most important input factor among the other input variables that increases output of groundnut in Taraba State in Nigeria. The study of Shamsudeen et al. (2011) also noted a positive relationship between output of groundnut and seed sown. Increase in quantity of seed sown increases groundnut plant population per acre. Plant population determines output level, such that, as plant population increases, extra nuts are harvested from the added groundnut plants which increases total output level, other things constant.

The positive relationship between labour and groundnut output is also in agreement with

the work of Danso-Abbean et al. (2015). Asekenye (2012) also found a positive relationship between output of groundnut and labour among groundnut farmers in Kenya. However, he noted a positive statistically insignificant effect for this variable among the groundnut farmers in Uganda in same study. On the contrary, Shamsudeen et al. (2011) found a negatively insignificant relationship between output of groundnut and labour. The possible implication of this relationship between output of groundnut and labour in this study is that family labour was readily available to facilitate timely performance of farm activities. Also, when labour used per acre increases, it implies that operations performed are done with accuracy. For example, using 20kg of seed on an acre of land would require less labour as compared to 35kg per acre. Following the effect of seed on output, it has been demonstrated that increased in quantity of seed has a positive effect on output. From Table 4.6, the cross effect between labour and seed leads to a significant increase in output. Specifically, increasing both labour and seed by 1% leads to an increase in output by 1%.

Herbicide usage was found to have a positive effect on groundnut output, thus, increase in the quantity of herbicides lead to increase groundnut output. This finding commensurate the work of Taphe et al. (2015) who found a positive relationship between output of groundnut and agrochemicals among small scale farmers in Taraba State of Nigeria. Farmers who used herbicide during land preparation stage noted that as the weeds are controlled with the herbicide before sowing of the groundnuts, the growth of weeds in the field is suppressed and the groundnut turn to grow faster. The implication of the effect of herbicide as noted by the respondents is that the young growing groundnut plant is not being competed by weeds for nutrients, water and space. This enable the plant to grow faster with the available soil nutrients, water and space.

The positive relationship between output of groundnut and intermediate inputs implies that as the amount of money spent on intermediate inputs increases, output level of groundnut increases. This could be explained in diverse ways, for example, increased output would mean increased in the quantity of sacks needed to store groundnut and for that matter increased expenditure on sacks.

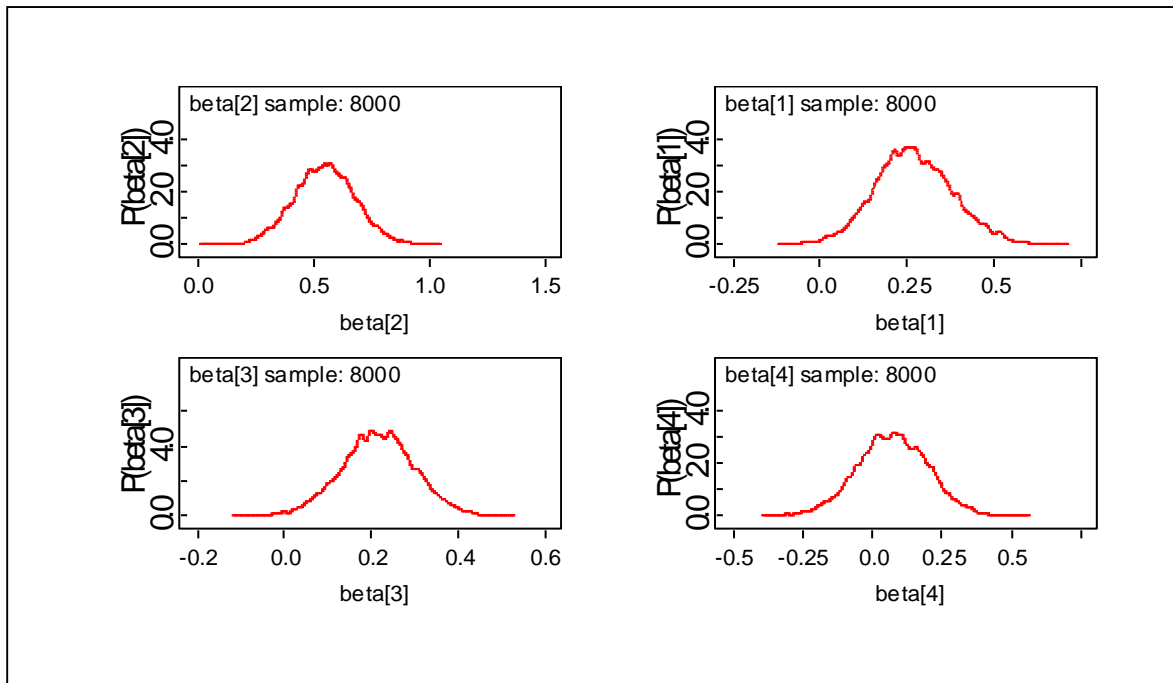
From Table 4.6, all the squared terms of the input variables have a negative sign as opposed to the positive sign observed for the first order parameters of the input variables. The implication is that output will increase initially when input levels are increased, but as more and more of the inputs are added, output level eventually reduces at the long run.

The result of the interaction effect (cross product terms) of labour and seed, seed and herbicide, seed and intermediate inputs and herbicide and intermediate inputs shows a positive effect on output. That is, increasing any two of the inputs simultaneously leads to increase in the level of groundnut output. Such inputs are known to be complementary of each other. On the other hand, the cross product of, labour and herbicide and labour and intermediate inputs have a negative sign. Thus, increasing any two of the inputs simultaneously lead to decreased level of output. These pair of inputs can be thought of as substitutes that is, increasing the level of one of the inputs demand decreasing the level of the other. For example, using herbicide to control weeds in groundnut production means reduction in the level of labour for same. Again, using tractor ploughing which is valued as intermediate input in this study, also requires in the level of labour for same activity.

The Bayesian approach, unlike the frequentist approach, allows the posterior kernel density to be recovered for all parameter estimates instead of for a single point estimate. This gives

more information about the underlying parameter certainty (Tonini, 2011). Figure 4.2 shows the posterior kernel density for the first order parameters of the model

Figure 4.2: Posterior Kernel Density Plots of Input Variables Parameter Estimates



Source: Field Survey, 2017

(See Appendix 4.1 for posterior kernel density for all the parameters of the translog model).

4.8 Technical Efficiency Levels of Groundnut Farmers

In terms of technical efficiency scores, Bayesian econometrics provides additional information about farmers' technical efficiency scores that are not provided in the classical methods (Griffin & Steel, 2007). It is possible to generate the posterior distributions of the technical efficiency scores (see Appendix 4.2 for the posterior distribution of the first 38 groundnut producers) just like the posterior distributions that are generated for the parameters of the input variables and the other variables of the Bayesian model as shown

in Table 4.6. Table 4.7 shows the posterior distributions of the minimum and maximum technical efficiency scores.

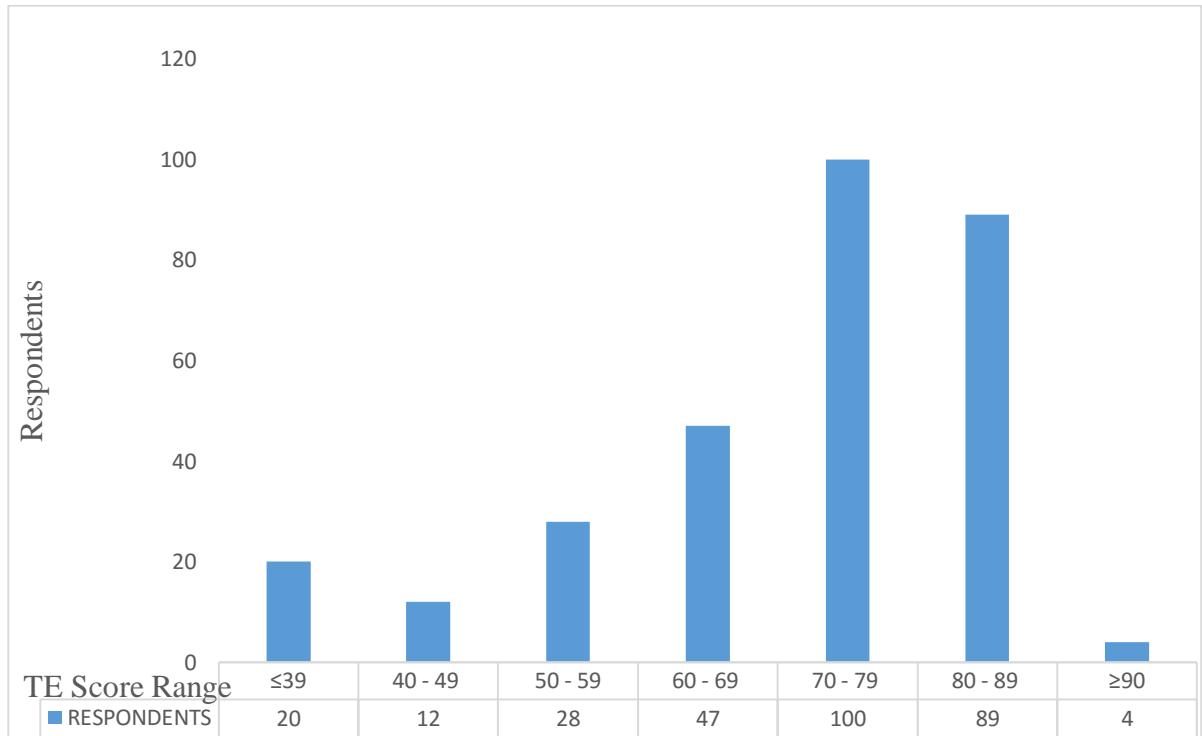
Table 4.7: Posterior Distributions of Minimum and Maximum Technical Efficiency Scores

Farmer	Mean	SD	MC_error	2.5 Percentile	Median	97.5 percentiles
49	0.130	0.141	0.007	0.036	0.090	0.609
139	0.951	0.093	0.001	0.645	0.989	1.000

Source: Field Survey with Author's Own Calculations

From Table 4.7, the minimum and maximum technical efficiency score was found to be 13% and 95.13% respectively. Minimum and maximum efficiency scores were obtained by farmers with codes 49 and 139 respectively. The technical efficiency scores implies that the least efficient farmer was producing at 13% of the achievable output of groundnut, given the inputs and the technology adopted by the farmers. On the other hand, the most efficient groundnut farmer among the respondents was producing at 95.13% of the total output obtainable with respect to the inputs used, given the technology. It can be deduced from the result that none of the groundnut farmers is producing on the fully efficient frontier, that is, no farmer is fully technically efficient. The average technical efficiency score was found to be 70.5%. This implies that on the average, groundnut farmers in Ghana are producing at 70.5% of the total output of groundnut achievable, given the inputs and the technology at hand. Figure 4.4 shows the technical efficiency scores across the respondents.

Figure 4.3: Distribution of Technical Efficiency Scores of Farmers



Source: Field Survey with Author’s Own Plot

From Figure 4.4, it can be shown that majority of the respondents (100) are producing at technical efficiency range of 70% - 79%. The mean technical efficiency score of about 70.5% is similar to the result of Shamsudeen *et al.* (2011), who found the mean technical efficiency value of groundnut farmers to be 70%. On the other hand, the result is different from the work of Taphe *et al.* (2015) who found the mean technical efficiency score of groundnut farmers to be 77%. The higher technical efficiency score level of groundnut farmers in Nigeria compared to Ghana as identified above could be responsible for the corresponding average yield of 1.2mt/ha and 1.1mt/ha respectively identified by USDA (2018) as shown in Table 2.1.

The implication of the technical efficiency value of 70.5% is that there is an output loss of 29.5% resulting from inefficiency. From the estimate of σ_v^2 , it implies that 22.3% of the

29.5% output loss is due to factors that are beyond the control of the farmer. Therefore, controlling for about 77.7% of the 29.5% loss of output would reduce output loss to about 9.5%. From the result of the input elasticities, given the climatic conditions and the technology adopted, groundnut farmers in Ghana still need guidance at the farm level management decisions to produce at fully efficient frontier.

4.9 Determinants of Inefficiency of Groundnut Farmers

In technical efficiency study, it is important to analyse the determinants of technical efficiency of the producers in order to derive policy recommendations based on the result of the analysis. It would not suffice to make policy recommendation on the fact that farmers were identified to be technically inefficient. The σ_v^2 value of 22.3% implies that 22.3% of the inefficiency of the farmers is due to white-noise, while 77.7% is due to some exogenous factors. Hence, analysing the inefficiency model to reveal those factors that determine inefficiency among the farmers will aid in policy recommendations that would curb the situation. From the analysis of the inefficiency model, the exogenous factors that were found to explain technical efficiency include, gender of farmer, educational level of the farmer, and extension visit.

Table 4.8 presents the posterior distribution of the inefficiency variables. Kurkalova & Carriquiry (2003) noted that the value of parameters (δ s) of the inefficiency variables that are different from one indicates the ability of the corresponding exogenous factor to explain technical efficiency. Specifically, values of parameters greater than one implies that the corresponding factor has a negative effect on technical inefficiency. From Table 4.8, the parameter values of variables including, gender of farmers, educational level of farmers and

number of extension visit are essentially greater than 1 indicating their explanatory power on technical efficiency.

Table 4.8: Posterior Distributions of Determinants of Inefficiency

Variables	Param	Mean	SD	MC_error	2.5%	Median	97.5%
	-eters						
Constant	δ_0	1.504	0.466	0.997	0.654	1.460	2.819
Age of famer	δ_1	0.899	0.771	0.001	0.045	0.201	2.483
Gender of farmer	δ_2	1.743	1.079	0.002	0.078	0.185	5.929
Education level	δ_3	2.309	1.599	0.030	0.115	0.294	7.991
Household size	δ_4	0.872	0.617	0.002	0.044	0.128	2.877
Extension contact	δ_5	1.413	1.046	0.011	0.053	0.367	5.100

Source: Field Survey with Author's Own Calculations

The parameter estimate of the variable gender implies that female groundnut farmers are more technically efficient than their male counterparts. In other words, the female groundnut farmers produced at a higher technical efficiency levels than the male groundnut farmers. This higher efficiency levels of female groundnut farmers may be due to the fact that they are committed to their groundnut farms and perform their cultural practices on timely basis. Martey et al. (2015) noted that groundnut production is a female dominated economic activity in northern Ghana.

Most males who engaged in groundnut production do it as an extra farm activity and do not regard it as a major economic activity. What this means is that the male farmer may not be committed to timely performance of activities including, sowing (because the males mostly relies on their female counterparts to sowing their groundnut) and controlling weeds (since they may have to pay attention to other crop farms at the same time) in their groundnut farms. In the same way, because the production is a minor activity for them,

they may not be willing to commit other resources efficiently to the production of groundnut. For example, a male farmer who owns a yam farm, may be constrained to using herbicide to controlling weeds for groundnut land preparation since the same farmer will need the herbicide to control weeds in his yam farm. In effect, the male farmer may not be efficient in the production of groundnut as compared to their female counterparts.

The parameter for educational level also had a value of 2.3 which is significantly above 1 and implied a positive effect on technical efficiency. The positive effect of education on technical efficiency means that as the educational level of the farmer increases, their efficiency level also increases. This also implies that farmers that are educated are more technical efficient than those that did not attain education. The positive effect of education on technical efficiency met the a priori expectation of the variable. The result of this study on education is in agreement with the work of Mahgoub *et al.* (2017), who found a positive relationship between technical efficiency and years of education in Sudan. They argued that this positive relationship between technical efficiency and years of education may be due to the potentials of groundnut farmers who attained education to easily adopt new agricultural technologies, efficiently allocate their resources to enhance their productivity levels. Education also enhances farmers' level of understanding of agricultural extension recommendations which may have the potential to greatly improve their efficiency levels.

Extension visit's parameter also had a value of 1.4 which is above 1, indicating a positive relationship between extension visit the farmer had within the production season and their technical efficiency levels. In other words, farmers who were visited frequently by agricultural extension agents were found to be more technical efficient than their counterpart farmers who received less or no visit. The parameter also met the a priori

expectation. The result is in conformity with the work of Taphe *et al.* (2015) who found a positive relationship between technical efficiency and extension visit. This relationship is suggested to be due to the fact that farmers who had access to extension contact are likely to become aware and could adopt new agricultural technology and improve upon their cultural practices in the farm. Recommendations made by extension workers are expected to enhance farm management level decisions of the farmer. Farm management level decisions has a great impact on farmers' level of efficiency. Through ideal farm management decisions, farmers can efficiently allocate inputs in their right proportions which subsequently improves upon their productivity levels.

The other inefficiency variables had parameter values below 1 and implied lack of statistical explanatory power. The parameter estimate for household size did not meet the a priori expectation. This variable was expected to increase the level of efficiency. Because, other things constant, a larger household size is expected to provide labour as and when it is needed. The parameter value obtained for age in this study is not uncommon, since age had been found by different researches to have different effect and in most cases not statistically significant. The lack of explanatory power by these variables is not uncommon in Bayesian technical efficiency analysis as documented by Bezemer *et al.* (2005) and Coelli *et al.* (2003).

CHAPTER FIVE

SUMMARY, CONCLUSIONS AND POLICY RECOMMENDATIONS

5.1. Introduction

This chapter presents the summary of the thesis and draws conclusions from the major findings of the thesis. Based on the major findings of this thesis, policy recommendations are made for future interventions.

5.2 Summary and Major Findings

Groundnut has been identified as the most important leguminous crop in Ghana, both in terms of volume of production and exports. Its production has faced numerous challenges over the past decades in Ghana as the output of groundnut continues to decline despite the abundant resources that support its growth. Ghana was ranked as the 10th producing country in the world in the year 2010 by FOASTAT, but currently, reports indicate that Ghana loss this position. Reports also indicate that any increase in output of groundnut was realized from increase in land area under groundnut production rather than increased productivity levels of farmers. The question is, what then is responsible for the declining productivity of the groundnut farmers in Ghana? This study was therefore carried out to estimate the productivity levels and technical efficiency levels of groundnut farmers in Ghana as well as analyse the factors that are responsible for inefficiencies among the farmers. The Bayesian stochastic frontier approach was used to analyse the objectives of the study. Two model specifications were considered in this study and the translog was found to be more efficient than the Cobb-Douglass by the DIC value estimates. Bayesian estimation approach employed in this study provided information about the parameter estimates which otherwise could have not been achieved using the classical method of estimation. The

translog model together with the inefficiency model were estimated in a single stage using the OpenBUGS software. A cross-sectional data of three-hundred (300) groundnut farmers sampled across three administrative regions in Ghana was used for the study.

From the Bayesian stochastic frontier model analysis, two important parameters are estimated – lambda and variance of the random error term. The value of variance of the random error term, σ_v^2 implies that 22.3% of the variation in output is due to factors beyond the control of the farmers and the remaining 77.7% of the variation is due to farm-specific factors. The parameter estimate for Lambda – 29.5% implies that farmers are 29.5% technically inefficient. Therefore, there is the potential for further increase in output to meet the optimal output given the inputs and available technology.

The result of input parameters indicates that an increase in any of the input variables corresponds to increase in total output of groundnut, that is, the production function is well behaved and thus satisfies the monotonicity assumption. In particular, the estimates of the Bayesian stochastic frontier model demonstrated that when input levels are increased by 1%, it leads to a corresponding increase of (0.27, 0.55, 0.21 and 0.07) % of output for labour, seed, herbicide, and intermediate inputs, respectively. The sum of input elasticities gave a RTS value of 1.10 indicating that farmers are producing at an increasing return to scale. The RTS value implied that when all the inputs are increased by 1%, there is a more than proportionate increase in the level of groundnut output of 1.10%.

The result of the predicted technical efficiency scores show that farmers were producing at an average TE score of 70.5%. The TE scores ranges from a minimum of 13% to a maximum of 95.13%. From estimated inefficiency model, farm-specific factors including

extension visit, educational level and gender of farmers had parameter values above 1 and implied statistical explanatory power of the variables to explain inefficiencies among the farmers.

5.3 Conclusions

The production function of the groundnut farmers demonstrates an increasing return to scale. It can be concluded that groundnut farmers are producing at the stage one of the production function. Producing at the stage one is not economically viable, since increasing inputs leads to increasing output, and the implied need for improvement at the stage. The implication is that the groundnut farmers could increase their scale of production to achieve optimal level of production at the long run. From the value of variance of the random error term (σ_v^2), it can be concluded that there is the potential for further increase in output to meet the optimal output given the inputs and available technology, since the variation in output levels is largely due to farm specific factors.

The predicted technical efficiency scores imply that on the average groundnut producers in Ghana are producing at a technical efficiency level of 70.5%. None of the producers were found to produce at the fully efficient frontier given the available inputs and the production technology.

From the Inefficiency model analysis, it can be concluded that factors including; gender of the farmers, extension visit to farmers and educational levels of the farmers, significantly explain inefficiencies among the farmers. In particular, female groundnut farmers were found to be more technically efficient than their male counterpart producers. As extension visit also increases among the farmers, they become more technically efficient. Farmers

who are educated were also found to be more technically efficient than those that did not have any formal education, in other words, as farmers' level of education increases they become less inefficient.

5.4 Policy Recommendations

The result of the study exhibits that increase in factor inputs lead to a more than proportionate increase in the level of output. The study therefore recommends increase scale of production with effective management decisions by groundnut farmers so as to take advantage of scale of production economy. Effective management entails the judicious combination of individual inputs. For example, the parameter estimate for seed input shows that output increases for about 0.55% when there is a percentage increase in quantity of seed sown. This output increase resulting from seed increment is comparatively higher than the increase in output resulting from the other inputs. Hence, there is a higher potential to increase seed quantity per unit area than the other inputs.

The study also recommends that groundnut farmers should be given the necessary support by the district assemblies through the department of agriculture to enable them fill the gap in output so as to increase the level of technical efficiency as they only produce at efficiency score of 70.5%.

The study also strongly recommends that government through MoFA should extend the scope of extension delivery and increase the number of extension agents since frequency of extension visit has a positive effect on technical efficiency. Increase in the scope of extension delivery because most areas were found not to be part of the catchment areas of the extension agents and farmers in those areas did not receive any extension visit. On the other hand, when the number of extension agents are increased, it would improve upon

farmer/AEA ratio and subsequently increase the number of visit. District assemblies through department of agriculture should facilitate access to information to farmers who did not have access to formal education. These farmers should also be given intensive training to boost their level of understanding of recommendations and new technologies introduced to them.

REFERENCES

- Adzawla, W. Donkoh, S.A., Nyarko, G., O'reilly, P. Olayide, O.E., & Awai, P.E. (2015). Technical efficiency of bambara groundnut production in Northern Ghana. *UDS International Journal of Development [UDSIJD]*.
- Africa Agriculture Status Report (2016): Progress towards Agricultural Transformation in Africa
- Aigner, D. J., Lovell C. A. K., & Schmidt, P. (1977). Formulation and Estimation of Stochastic Frontier Production Function Models. *Journal of Econometrics*.
- Al-Hassan, S. (2008): Technical Efficiency of Rice Farmers in Northern Ghana. African Economic Research Consortium, Nairobi. Research Paper p. 178
- Al-hassan S., Sarpong, D.B. and Al-Hassan R. (2004): Allocative Efficiency, Employment and Rice Production Risk: An Analysis of Smallholder Paddy Farms in the Upper East Region of Ghana. *Ghana Journal of Development Studies*, Vol. 1 No. 2
- Anang T.B., Bäckman S., & Sipiläinen T., (2016): Technical efficiency and its determinants in smallholder rice production in northern Ghana. *The Journal of Developing Areas*. 50(2)311-328 Tennessee State University College of Business. DOI: <https://doi.org/10.1353/jda.2016.0072>
- Asekenye C, (2012): An Analysis of Productivity Gaps among Smallholder Groundnut Farmers in Uganda and Kenya. Master's Thesis. Available: http://digitalcommons.uconn.edu/gs_theses/323
- Badiane O., Makombe T. (2015): Beyond a Middle Income Africa: Transforming African Economies for Sustained Growth with Rising Employment and Incomes.
- Baten, M.A., Kamil, A.A. and Haque, M.A. (2009): Modelling Technical Inefficiencies Effects in a Stochastic Frontier Production Function for Panel Data. *Africa Journal of Agricultural Research* 4(12): 1374-1382.
- Battese E. G. (1991): Frontier production functions and technical efficiency: A survey of Empirical Applications in Agricultural Economics. *Agricultural Economics*. 7:185-208.
- Battese G.E. & Coelli T.J. (1995): A Model for Technical Inefficiency Effects in a stochastic frontier production function for panel data. *Empirical Economics*. 20:325-32.
- Bayes, T., & Price, R. (1763). An essay towards solving a problem in the doctrine of chance. By the late Rev. Mr. Bayes, communicated by Mr. Price, in a letter to John Canton, M. A. and F. R. S. *Philosophical Transactions of the Royal Society of London*, 53, 370–418. doi:10.1098/rstl.1763.0053

- Bezemer D., Balcombe K., Davis J. and Frazer I. (2005): Livelihood and Farm Efficiency in Rural Georgia. *Applied Economics*, University of Groningen. DOI: 10.1080/00036840500215253.
- Binam, J.N., Gockowski, J. and Nkamleu, G.B. (2008): Technical Efficiency and Productivity Potential of Cocoa Farmers in West Africa Countries. *The Developing Economics*, XLVI- 3: 242-63.
- Bravo-Ureta E.B. & Pinheiro E.A. (1997): Technical, Economic and Allocative Efficiency in peasant farming: Evidence from the Dominican Republic. *The Developing Economics*, Chichester.
- Coelli, T.J. (1995): Recent Development in Frontier Modelling and Efficiency Measurement. *Australian Journal of Agricultural Economics* 39, 3: 219–45.
- Coelli T., Rao D.S.P, O'Donnell C.J., & Battese GE. (2005): An Introduction to Efficiency and Productivity Analysis. *Springer Publication. New York, USA*.
- Danso-Abbeam G., Dahamani A. M., & Bawa G. A-S. (2015). Resource-use-efficiency among smallholder groundnut farmers in Northern Region, Ghana. *American Journal of Experimental Agriculture*. 6:290 - 304.
- Debertin L. D. (2012): Agricultural production economics. 2nd edition. *Macmillan Publishing Company, a division of Macmillan Inc.* University of Kentucky, US.
- Dittoh J.S. (1991): Efficiency of Agricultural Production in Small and Medium Scale Irrigation in Nigeria. *Africa Rural Social Science Series*, Research report No. 20.
- Ehlers S. R. (2011): Comparison of Bayesian models for production efficiency. *Journal of Applied Statistics*, Taylor & Francis Group, London – UK. 38(11): 2433-2443, DOI: [10.1080/02664763.2011.559203](https://doi.org/10.1080/02664763.2011.559203)
- EU to ban Ghana from exporting peanut (20 May 2015), B&FT news.
<https://www.ghanaweb.com/GhanaHomePage/business/EU-to-ban-Ghana-from-exporting-peanut-358856>
- FAOSTAT (Food and Agriculture Organization of the United Nations), 2010. FAOSTAT Database. <http://faostat.fao.org>.
- Farrel M.J. (1957): The measurement of productive efficiency. *Journal of Royal Statistical Society*. 3:253-290.
- Ghana Statistical Service (2015): Annual Gross Domestic Product. Statistics for Development and Progress. Accra, Ghana.
- Ghana Statistical Service (2013): 2010 Population and Housing Census, Volta Region, Analysis of District Data and Implications for Planning.

- Girei AA, Duana Y, Dire B. (2013): An Economic Analysis of Groundnut (*Arachis hypogea*) Production in Hong Local Government Area of Adamawa State, Nigeria. *Journal of Agricultural and Crop Research*. 1(6): 84-89.
- Griffin E. J. & Steel J. F. M. (2007): Bayesian stochastic frontier analysis using WinBUGS. *Journal of Productivity Analysis*. 27(3):163-176. Springer. URL:<http://www.jstor.org/stable/41770273>
- Ibrahim M., Florkowski J. W. & Kolavalli S. (2012): The determinants of farmer adoption of improved peanut varieties and their impact on farm income: Evidence from northern Ghana. Agricultural and Applied Economics Association Annual Meeting, Seattle, WA.
- Tsigbey, F.K., Brandenburg, R.I., and Clotey, V.A. (2003): Peanut Production Methods in Northern Ghana and some Disease Perspectives. *Online Journal of Agronomy* 34:36-47.
- Jackman, S. (2009): Bayesian analysis for the social sciences. New York, NY: Wiley.
- Jondrow J., Lovell, V. A. K., Materov I.S. & Schmidt P. (1982): On the estimation of technical efficiency in the stochastic frontier production function model. *Journal of econometrics*. 19: 233 – 238
- Kaplan, D., & Depaoli, S. (2013): Bayesian statistical methods. In T. D. Little (Ed.), *Oxford handbook of quantitative methods* (pp. 407–437). Oxford, UK: *Oxford University Press*.
- Kleit N. A. & Tecrell D. (2001): Measuring Potential Efficiency Gains from Deregulation of Electricity Generation: A Bayesian Approach. *The Review of Economics and Statistics*, 83:3; 523-530. Harvard College and the Massachusetts Institute of Technology
- Kim, Y. and P. Schmidt (2000). A Review and Empirical Comparison of Bayesian and Classical Approaches to Inference on Efficiency Levels in Stochastic Frontier Models with Panel Data. *Journal of Productivity Analysis*.
- Koop G. (2003): 'Bayesian Econometrics' *John Wiley & Sons Ltd*. The Atrium, Southern Gate
- Koekoek J.F. (2017): CBI Sector Expert Food Ingredients. Exporting groundnuts (peanuts) to Europe. <https://www.cbi.eu/market-information/processed-fruit-vegetables-edible-nuts/groundnuts-peanuts-europe/>
- Koop, G., J. Osiewalski & Steel M. F. J. (1997): Bayesian efficiency analysis effects: Hospital cost frontiers. *Journal of Econometrics*.

- Koop, & Steel M. F. J. (1998). Bayesian analysis of Stochastic frontier models. University of Edinbergh, Edinbergh EH8 9JY, U.K.
- Kruschke K. J. (2013): Bayesian Estimation Supersedes the *t* Test. *Journal of Experimental Psychology*. 142:2, 573–603. DOI: 10.1037/a0029146
- Kumbhakar, S.C. and Lovell, C.A.K. (2000): Stochastic Frontier Analysis. A Cambridge University Press Publication.
- Kurkalova L. A. and Carriquiry A., (2003): Input- and Output-Oriented Technical Efficiency of Ukrainian Collective Farms, 1989-1992: Bayesian Analysis of a Stochastic Production Frontier Model. *Journal of Productivity Analysis*, 20(2):191-211.Springer
- Link, W. A., & Eaton, M. J. (2012): On thinning of chains in MCMC. *Methods in Ecology and Evolution*, 3, 112–115. doi:10.1111/j.2041-210X.2011.00131.xLi
- Lipton M. (2005): Crop science, poverty, and the family farm in a globalizing world (2020 Discussion Paper 40). Washington, DC: International Food Policy Research Institute.
- Mahgoup O.B., Ali A.E.S. & Mirghani A. O., (2017): Technical efficiency analysis of groundnut production in the Gezira Scheme, Sudan. *International Journal of Scientific and Research Publications*.
- Martey E, Wiredu N. A. & Oteng-Frimpong R. (2015): Base line study of groundnut in northern Ghana. *Lambert Academic Publishing*.
- Meeusen, W., & Van den Broeck, J. (1977): Efficiency estimation from Cobb-Douglas production functions with composed errors. *International Economic Review*.
- Ministry of Food and Agriculture (MOFA) (2016): *Agriculture in Ghana: Facts and Figures (2015)*. Statistics, Research and Information Directorate (SRID), Ministry of Food and Agriculture, Ghana.
- Murillo-Zamorano, L. R. (2004): Economic Efficiency and Frontier Techniques. *Journal of Economic Survey* 18 (1).
- Norton R. D. (2004): Agricultural development policy: concepts and experiences. *John Wiley & sons, Ltd*, The Atrium, Southern Gate, Chichester, West Sussex, England.
- Onumah E.E., Brummer M., Horstgen-Schwark G. (2010): Elements which delimitate technical efficiency of fish farms in Ghana. *Journal of the World Aquaculture Society*, 41(4).
- Onumah, E.E. and Acquah, H.D. (2010): Frontier Analysis of Aquaculture Farms in the Southern Sector of Ghana. *World Applied Sciences Journal* 9(7):826-835

- Onumah J.A., Al-Hassan R.M., Onumah E.E. (2013): Meta-frontier analysis of organic and conventional cocoa production in Ghana. *Journal of Economics and Sustainable Development*. 4(4):106 – 118.
- Owusu-Adjei E., Baah-Mintah R. and Salifu B. (2017): Analysis of the Groundnut Value Chain in Ghana. *World Journal of Agricultural Research*, 5(3) 177-188. doi: 10.12691/wjar-5-3-8.1.
- Osiewalski, J. & Steel, M. F. J. (1998): Numerical tools for the Bayesian analysis of stochastic frontier models. *Journal of Productivity Analysis*.
- Pericchi R. L. & Perez E.M., (2015): Hypothesis Testing and Estimation under a Bayesian Approach. Statistics Day in Puerto Rico. Be part of ASA-PR!
- Quisumbing, A.R. (1994): Gender Differences in Agricultural Productivity: A survey of Empirical Evidence. Education and Social Policy Discussion Paper No. 36, World Bank, Washington D.C.
- Reifschneider, D. & Stevenson, R. (1991): Systematic Departures from the Frontier: A Framework for the Analysis of Firm Inefficiency. *International Economics Review* 32:715-23.
- Ritter D. Simar L., (1997): Pitfalls of normal – Gamma stochastic frontier models. *Journal of productivity analysis*. 8: 167 – 182.
- Schreyer P. (2001): Measuring Productivity: Measurement of Aggregate and Industry-level Productivity growth. An OECD manual.
- Shamsudeen A., Donkoh S.A., & Sienso G. (2011): Technical efficiency of groundnut production in West Mamprusi District of Northern Ghana. *Journal of Agriculture and Biological Sciences*.
- Stevenson, E.R. (1980): Likelihood functions for generalized stochastic frontier estimation. *Journal of Econometrics*. 13(1): 57-66.
- Stigler, S. M. (1986): Laplace's 1774 memoir on inverse probability. *Statistical Science*, 1, 359 –363.
- Taphe B.G., Agbo F.U. & Okorji E.C. (2015): Resource productivity and technical efficiency of small scale groundnut farmers in Taraba State, Nigeria. *Journal of Biology, Agriculture and Healthcare*. 17:2224-3208
- Tonini A. (2012): Bayesian stochastic frontier: an application to agricultural productivity growth in European countries. *Economic Change and Restructuring*, 45:247–269. Springer, US.
- United States Department of Agriculture, Foreign Agricultural Service, (2018): World Agricultural Production. Circular Series WAP 4-18

- Uaeieni, R.N., Arndt, C. and Masters, W.A. (2009): Determinants of Agricultural Technology Adoption in Mozambique; Discussion Papers No. 67E.
- van de Schoot R., Kaplan D., Denissen J., Asendorpf B. J., Neyer J. F. & van Aken G. A. M., (2014): A gentle introduction to Bayesian analysis: applications to developmental research. *Society for Research in Child Development, Inc.* The Netherlands. 85(3): 842–860. DOI:10.1111/cdev.12169
- Van den Broeck, J., G. Koop, J. Osiewalski, and M. F.J. Steel. (1994): “Stochastic Frontier Models: A Bayesian Perspective.” *Journal of Econometrics.* 61: 273-303. XXXV-1:48–67

APPENDICES

Appendix 3.1 : Survey Questionnaire

Questionnaire Code.....

SURVEY QUESTIONNAIRE

**DEPARTMENT OF AGRICULTURAL ECONOMICS AND AGRIBUSINESS,
UNIVERSITY OF GHANA, LEGON**

**RESEARCH TITLE: TECHNICAL EFFICIENCY ANALYSIS OF
GROUNDNUT PRODUCTION IN GHANA: A Bayesian Approach**

This study is a partial fulfilment of the award of Master of Philosophy in Agricultural Economics at the University of Ghana. Any information provided by the respondent would be used purposively for data analysis and will therefore remain confidential.

Name of enumerator.....

Interview date
...../...../2017

SECTION A. Background Information

- 1. Name of farmer..... TEL.....
- 2. Community..... 3. District.
- 4. Region

SECTION B. Socio - Demographic Characteristics of Groundnut Farmers

- 5. Age of farmer.....years.
- 6. Gender of farmer Male [] Female []
- 7. Are you the household head? Yes [] No []
- 8. If no to question 7 above, what is your relationship with the household head?
- 9. What is your religion?
Christianity []
Traditional []
Islamic []
Others, specify.....
- 10. What is your marital status?
Single []
Married []
Divorced []
Widowed []
Others specify
- 11. What is your level of education?

- None []
- Primary []
- JHS/JSS/MSCL []
- SHS /SSS/Vocational/technical []
- Tertiary []

12 What is number of years you spent in school?

13. What is the size of your Household?persons.

14. Table 1: Household Size by Gender and Age Category

Persons age 18 and above(Adults)		Persons below age 18 (children)	
Males	Females	Males	Females

15. Are you a member of any FBO? Yes [] No []

If yes to question 15, answer question 16 below;

16. What form of assistance/support do you receive as a member of the FBO? Tick as many as applicable;

- Credit support []
- Improved Agronomic Practices []
- Marketing of produce []
- Input access []
- Mutual labour support []
- Others, specify.....

17. Did you get access to extension contact in the 2017 production season? Yes [] No []

If yes to 17 then answer question 18 & 19

18. Which agency did you have contact with?

- MoFA []
- NGO(s) []
- Both agencies []

19. How many times were you visited?

20. Did you receive any form of credit in the 2017 farming season? Yes [] No []

21. If yes to 20 above, indicate the source. Tick as many as applicable;

- Bank institutions []
- Family & friends []
- Money lenders []
- NGO []
- FBO []

Others, specify.....

22. How did you acquire your land?

Inherited []

Leased []

Purchased []

Sharecropping []

Others, specify.....

23. How many acres of land was available to you for your groundnut farming in the 2017 farming season?

SECTION C. Groundnut Production System

24. How long have you been engaged in groundnut production?years

25. How many acres of land did you plant to groundnut in the 2017 farming season?

26. How did you clear your land?

Herbicides []

Manual clearing []

Others, specify

27. What ploughing system did you use for the 2017 farming season?

Tractor []

Animal traction []

Hoeing []

28. What informed your choice of ploughing system?

Availability of system []

Better system []

Cost of ploughing []

Others, specify

29. Which month did you plant your groundnut in 2017 farming season?

30. Was the land previously used for any other crop production? Yes [] No []

31. If yes in question 30 above, state the number of years.years

32. How many years have you produce groundnut on the land you used for 2017 production seasonyears.

33. Which method did you use in planting your groundnut seeds?

Using dibber []

Broadcasting []

34. If you used dibber, did you plant in. Rows Staggered
35. How many seeds did you plant per hole?
36. Did you intercrop groundnut with any other crop? Yes No
37. If yes in question 36 above, mention the crop(s).....,,
38. How did you shelled your groundnut? Manual shelling Shelling machine
39. If manual shelling to 38, Indicate reason for your choice.
- Cost effective
 - Unavailability of shelling machine
 - Quality grains
 - Others, specify.....

SECTION D. Input Levels and Output Level Information

40. Are you aware of groundnut certified seeds? Yes NO
- If yes to question 40 above then answer 41 and 42 below.
41. What kind of seed did you plant?
- Certified Seed
 - Saved Seed
 - Both
42. What informed your decision about the choice in 41 above?
- Cost of seed
 - Availability of seed
 - High yielding Seed
 - Others, specify.....
43. What quantity of seed did you plant per acre?Kg.
44. How much was the cost of the seed planted per acre? GHC.....
45. Are you aware of fertilizer application in groundnut production? Yes No
- If yes to question45, answer question 46, 47 and 48
46. Indicate your source of information? Tick as many as applicable;
- MoFA
 - NGOs
 - FBO
 - Colleague farmers
 - Others, specify.....
47. Did you apply fertilizer in the 2017 farming season? Yes No
48. If yes to question 47, what type of fertilizer did you apply?

- NPK []
- Urea []
- TSP []
- Others specify.....

49. What informed your choice in 38 above?

- Specific for legumes []
- Availability []
- Cost of fertilizer []
- Others, specify.....

50. Indicate the type of intermediate input you used in the 2017 farming season

Table 2: Intermediate Inputs

Item	Quantity	Unit cost/per Ha (GHC)	Total Cost (GHC)	Lifespan (years) if purchased
Hoe				
Cutlass				
Sack				
Pan/ Basket				
Knapsack				
Tractor				
Sheller				
Others, specify				

51. Labour Requirement. Indicate in the table below your source(s) of labour

Table 3: Sources Labour of in Terms of Gender and Age

Adults ≥ 18 years		Children < 18 years	
Males	Females	Males	Females

52. Fill the table below to indicate the labour used for each activity

Table 4: Labour by Activity

Activity	Man-days	Unit cost GHC	Total cost GHC
Land clearing			
Hoe plough			
Planting			
Weeding			
Uprooting			
Plugging			
Drying			
Shelling			
Winnowing			
Other activity			

53. Did you apply herbicides at any stage of production? Yes No
 If yes to question 53 above, then answer 54 & 55

54. At what stage did you apply the herbicide?

Weed control during land Preparation

Weed control during plant growth

Both stages

55. How many litres of herbicide did you apply in the 2017 farming season?.....

56. What is the cost of the herbicides per litre GHC...

57. How many sacks of unshelled groundnut did you get for 2017 farming season?

58. What is your total yield of groundnut for 2017 farming season in terms of shelled?....kg

59. What is the selling price of your groundnut?per (bowl) 2.5 kg

60. What amount of the total yield was consumed?kg

61. What quantity of the total yield was given out as a giftkg

62. What proportion of the yield was stored..... kg.

63. What quantity was spoilt? kg

64. How did you transport your produce home after harvesting? Tick as many as applicable;

On head

Personal bicycles

Commercial transport - tricycles or vehicles

Others, specify.....

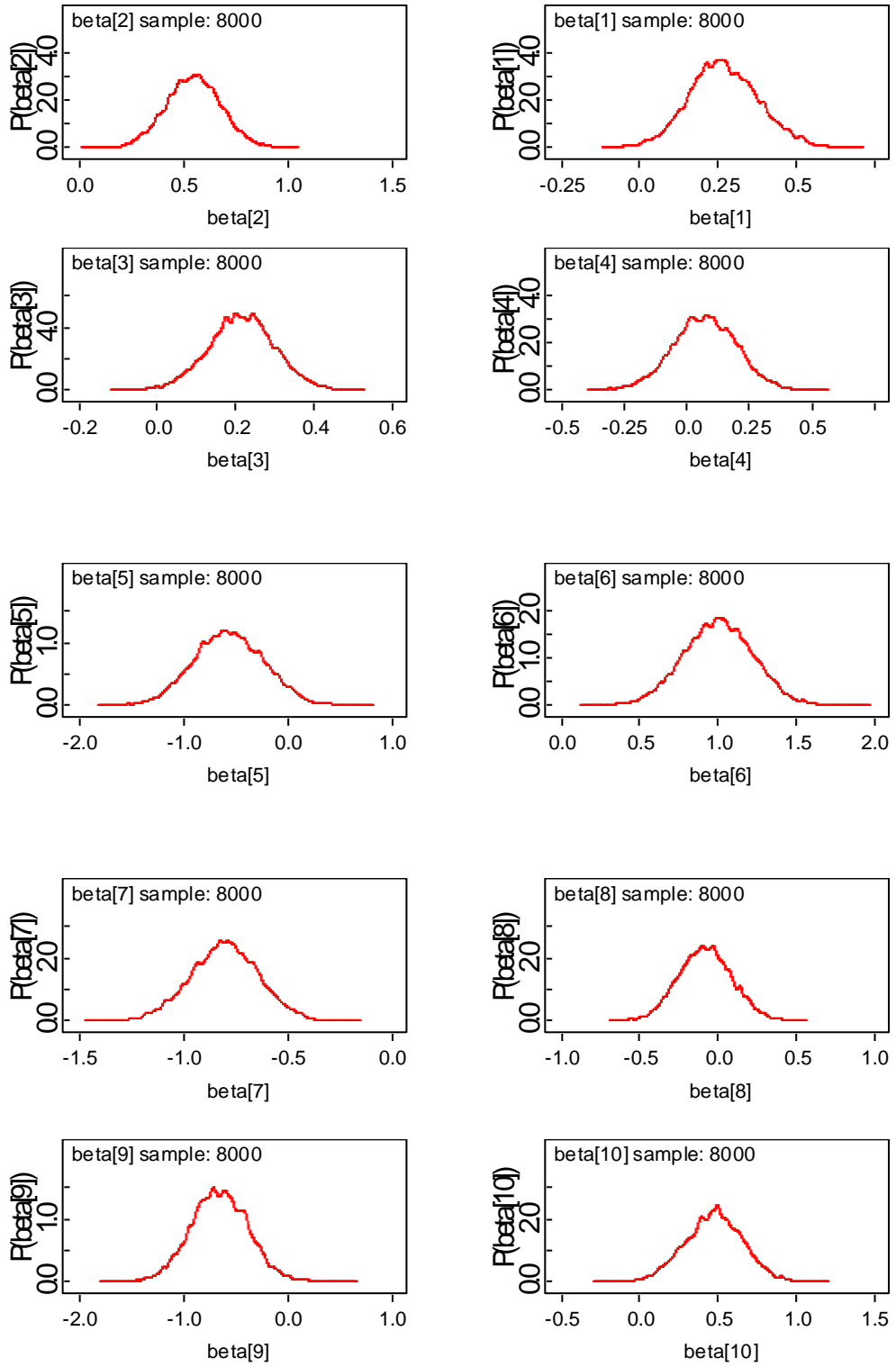
65. What is your average cost of transportation for the 2017 farming season? GHC.....

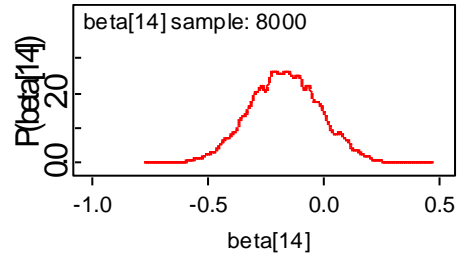
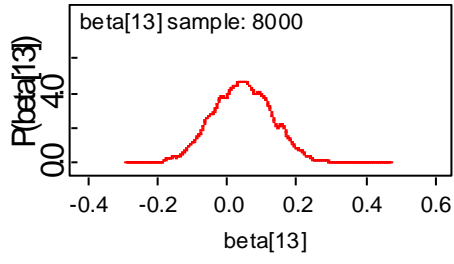
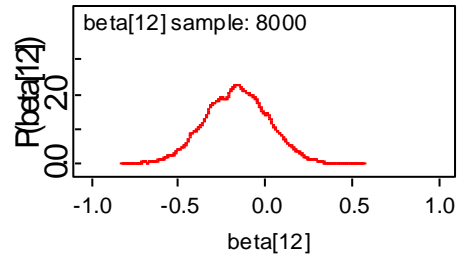
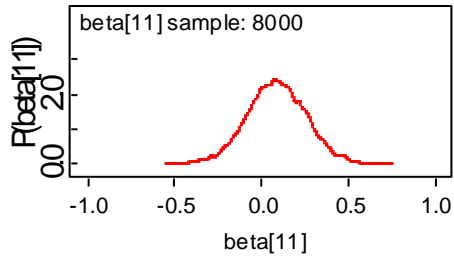
Thank you

Appendix 3.2: List of Regions, Districts and Communities Visited

Region	Districts	Communities	Respondents
Volta	Krachi-Nchumuru	Boafri	25
		Chinderi	25
	Krachi West	Kpolo	25
		Kalnja	25
		Sub-total	100
Northen	Nanumba South	Lungni	25
		Kpansu	25
	Yendi Municipality	Kulkpanga	25
		Dikpang	25
		Sub-total	100
Upper West	Sissala West	Kusali	25
		Nyemati	25
	Sissala East	Tumu	25
		Chinchang	25
		Sub-total	100
		Total	300

Appendix 4.1: Posterior kernel density functions of parameters





Appendix 4.2: Posterior Distribution of Technical Efficiency Scores

Respondents	Mean	SD	MC_error	2.5%	Median	97.5%
eff[1]	0.731	0.175	0.002815	0.3693	0.7481	0.989
eff[2]	0.7607	0.1779	0.004271	0.3833	0.7883	0.9986
eff[3]	0.6923	0.1853	0.003066	0.3301	0.7031	0.9854
eff[4]	0.7866	0.1631	0.003815	0.4276	0.8163	0.9982
eff[5]	0.8194	0.1468	0.003457	0.4826	0.8503	0.999
eff[6]	0.7301	0.1877	0.003739	0.3347	0.758	0.9923
eff[7]	0.7718	0.1611	0.002312	0.4132	0.7975	0.9912
eff[8]	0.8187	0.1385	0.001636	0.4901	0.8473	0.9936
eff[9]	0.5448	0.2127	0.005667	0.2135	0.5149	0.9699
eff[10]	0.6338	0.1983	0.003435	0.2765	0.6317	0.9758
eff[11]	0.7005	0.1861	0.002645	0.3315	0.7133	0.9858
eff[12]	0.7341	0.1743	0.002896	0.3654	0.7552	0.9903
eff[13]	0.4209	0.2068	0.006295	0.1423	0.3736	0.9277
eff[14]	0.8077	0.1511	0.003183	0.4643	0.8392	0.9952
eff[15]	0.7474	0.1713	0.002746	0.3782	0.7729	0.9898
eff[16]	0.7826	0.1596	0.002861	0.4224	0.8115	0.9938
eff[17]	0.7729	0.1604	0.002504	0.4198	0.7954	0.9921
eff[18]	0.5202	0.2069	0.004626	0.1991	0.4873	0.9527
eff[19]	0.6073	0.2071	0.004266	0.2403	0.5944	0.9778
eff[20]	0.7881	0.1566	0.002971	0.4378	0.8178	0.9943
eff[21]	0.7588	0.177	0.004165	0.3753	0.7868	0.9959
eff[22]	0.8046	0.1587	0.003777	0.4387	0.8371	0.9995
eff[23]	0.7196	0.1816	0.003477	0.3527	0.7374	0.991
eff[24]	0.6719	0.1937	0.00374	0.2994	0.6769	0.9857
eff[25]	0.6559	0.1939	0.003179	0.2945	0.6594	0.9812
eff[26]	0.5331	0.2109	0.005044	0.1991	0.5081	0.9626
eff[27]	0.6747	0.1931	0.00292	0.3006	0.6845	0.9821
eff[28]	0.1625	0.128	0.005565	0.05055	0.1268	0.5449
eff[29]	0.512	0.2183	0.006368	0.1836	0.4719	0.9702
eff[30]	0.6164	0.2037	0.004555	0.2546	0.6067	0.9766
eff[31]	0.8059	0.1599	0.003682	0.4402	0.8406	0.9997
eff[32]	0.7531	0.1718	0.002846	0.3882	0.7764	0.9914
eff[33]	0.5055	0.2152	0.00527	0.173	0.4724	0.9577
eff[34]	0.8496	0.1228	0.00157	0.5501	0.8798	0.9952
eff[35]	0.7042	0.1913	0.00326	0.311	0.7221	0.9878
eff[36]	0.5115	0.2134	0.006227	0.1917	0.4755	0.9648
eff[37]	0.3616	0.2003	0.00737	0.1217	0.3063	0.92
eff[38]	0.7361	0.1766	0.00305	0.3627	0.7551	0.9913

Appendix 4.3: Deviance Information Criterion Estimates from Translog and Cobb-Douglas Functional Forms

Translog model estimates				
	Dbar	Dhat	DIC	pD
y	392.4	263.2	521.5	129.1
total	392.4	263.2	521.5	129.1
Cobb-Douglas model estimates				
y	529.7	471.1	588.2	58.54
total	529.7	471.1	588.2	58.54

Appendix 4.4: Herbicide, Ploughing system, Seed and Fertilizer.

Variable	Respondents	Percentage
Herbicides Usage		
Land preparation stage	173	57.70
Plant growth stage	19	6.30
Both stages	108	36.00
Total	300	100
Ploughing System		
Tractor Ploughing	248	82.70
Hoe Ploughing	52	17.30
Total	300	100
Reasons for ploughing system choice		
Availability of system	127	42.30
Better system	146	48.70
Cost of ploughing	27	9.00
Total	300	100
Certify Seed Awareness		
Aware	107	35.67
Not Aware	193	64.33
Total	300	100
Seed Type Planted		
Certify Seed	8	7.48
Saved Seed	96	89.72
Both	3	2.80
Total	107	100
Reasons for Choice of Seed		
Cost of Seed	16	14.95
Availability of Seed	80	74.77
High yielding Seed	11	10.28
Total	109	100
Fertilizer Application Awareness		
Aware	98	32.70
Not Aware	202	67.30
Total	300	100
Fertilizer Application Awareness Source		
MoFA	27	27.55
NGO	44	44.90
FBO	5	5.10
Colleague farmers	17	17.35
School	5	5.10
Total	98	100