ADOPTION OF IMPROVED TECHNOLOGY AND FARM LEVEL TECHNICAL EFFICIENCY OF SMALL-SCALE OIL PALM PRODUCERS IN THE WESTERN REGION OF GHANA

BY

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THIS THESIS IS SUBMITTED TO THE UNIVERSITY OF GHANA, LEGON IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE AWARD OF MASTER OF PHILOSOPHY DEGREE IN AGRICULTURAL ECONOMICS

DEPARTMENT OF AGRICULTURAL ECONOMICS AND AGRIBUSINESS, COLLEGE OF AGRICULTURE AND CONSUMER SCIENCES, UNIVERSITY OF GHANA, LEGON

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DECLARATION

I, Emmanuel Nimbuen Johnson, author of this Thesis, "**ADOPTION OF IMPROVED TECHNOLOGY AND FARM LEVEL TECHNICAL EFFICIENCY OF SMALL-SCALE OIL PALM PRODUCERS IN THE WESTERN REGION OF GHANA**", do hereby declare that except for the references cited, which are appropriately acknowledged, this entire work was done by me in the Department of Agricultural Economics and Agribusiness, University of Ghana, Legon from June 2012 to July 2013. This work has never been presented either in whole or in part for any other degree in this University or elsewhere.

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(Co- Supervisor)

DEDICATION

This thesis is dedicated to the Almighty God, my beloved parents and well-wishers.

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I am grateful and remain humble to God Almighty, who told me it was possible when there was no glimpse of possibility, only He is Great.

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ABSTRACT

Over the last 60 years, a series of interventions geared towards increasing oil palm output have been initiated by the Government. Recent major Government interventions are the expansion of the seednuts production capacity of the Oil Palm Research Institute (OPRI) from 2 million to 5 million seednuts per year, the President's Special Initiative on Oil Palm and the Oil Palm Master Plan. The oil palm sector is dominated by small-scale producers who have low productivity as a result of using traditional technology, having inadequate extension service, and low application of vital inputs. Small-scale producers comprise of smallholder, out-grower and independent smallholders. This study examined the adoption, productivity and technical efficiency level of small-scale oil palm producers in the Western Region of Ghana. Primary data was collected using a set of structured questionnaire from two hundred and fifty (250) small-scale producers. The Poisson regression was used to examine the factors that influence adoption, whilst the stochastic production frontier was used to analyse productivity and technical efficiency. Results reveal that oil palm productivity increases with intensity of improved oil palm technologies adopted. Factors that positively influence adoption were farmers' contact with extension, hired labour, type of small-scale producer and access to credit. The results also show that the smallholder producers, who produce under the management of oil palm companies, are more productive than the independent producers. On average the estimated yield of the independent producers 6.8mt/ha, was almost three times lower than smallholder producers (16.7mt/ha). All explanatory variables for the production function estimation were positively related to output except for age of the tree. Oil palm production exhibited increasing returns to scale in the study area. The mean technical efficiencies for independent and smallholder producers were 0.62 and 0.91, respectively. The study concludes that smallholder producers are more productive and technically efficient compared with independent producers. The study recommends that Government and stakeholders improve labour training and extension services for independent producers. Furthermore, independent producers are encouraged to become smallholders under the supervision of the plantations.

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LIST OF ABBREVIATIONS AND ACRONYMS

ATE	Average Treatment Effect
BOPP	Benson Oil Palm Plantation
CIMMYT	International Maize and Wheat Improvement Centre
DEA	Data Environment Analysis
DF	Dummy for Fertilizer
FAO	Food and Agriculture Organization
FAOSTAT	Food and Agriculture Organization Statistics
FASDEP	Food and Agriculture Sector Development Policy
FFB	Fresh Fruit Bunch
FTC	Flexible Technical Change
GDP	Gross Domestic Product
GIS	Geographic Information System
GOPDA	Ghana Oil Palm Development Association
GSS	Ghana Statistical Service
IPM	Integrated Pest Management
Kg	Kilogram
LR	Likelihood Ratio
MoFA	Ministry of Food and Agriculture
mt	Metric Tonne
NERICA	New Rice for Africa
NORPALM	Norwegian Palm
OLS	Ordinary Least Squares
OPRI	Oil Palm Research Institute
Ox	Object-oriented matrix programming language
PFP	Partial Factor Productivity
PSI	President’s Special Initiative
RS	Residential Status
RSPO	Round Table on Sustainable Palm Oil
RTS	Returns To Scale

SF	Stochastic Frontier
SFAMB	Stochastic Frontier Analysis Method by Bruemmer
SFPF	Stochastic Frontier Production Function
SRID	Statistical Research and Information Directorate
STC	Simple Technical Change
TE	Technical Efficiency
TFP	Total Factor Productivity
TWT	Total Weighted Trees

CHAPTER ONE

INTRODUCTION

1.1 Background

Oil palm cultivation originated from the humid lowland tropics of Africa. The main species of oil palm being cultivated today is *Elaeis guineensis* which is a native of West Africa (Jacquemard, 1998). From its centre of origin, the oil palm has spread to other developing regions with similar climates, including Southeast Asia and the Pacific region. In Southeast Asia the first industrial plantations based on Deli (oil palm) trees were established in Sumatra in 1911 (Jacquemard, 1998). But as indicated by Basiron (2007), growth was initially very slow in Southeast Asia and acceleration of plantation development has only happened during the last 62 years (from 1950 to 2012), through large-scale investments resulting in high productivity for the cultivation of oil palm as one of the designated crops for deliberate diversification of the country's agriculture development.

Among the vegetables oil producing crops, oil palm is one of the world's most rapidly increasing crops and produces more vegetable oil than any oil crop, because it has a high oil yield per unit area per year that far exceeds those of other vegetable oils; besides it has low production costs and is cheaper for the consumer in the market place when compared with other oil crops (Carter et al., 2007). World oil palm production increased by 87.2 percent from 29,858,675mt in 1980 to 233,810,539mt in 2011 (FAOSTAT, 2011), mainly in Southeast Asia. Malaysia and Indonesia account for about 44% and 42% of the world total output respectively and Africa accounts for only about 6% of total world output (Basiron, 2007). The huge increase in output is mainly due to expansion in the area cultivated. The world's total cultivated area stands at 10.92 million hectares for which Malaysia and Indonesia cultivate 3.88 and 4.87 million hectares respectively (Carter et al., 2007).

Oil palm has over the years been used for many different purposes; about 80% of the product is consumed by humans, whilst the remaining goes to animal feeds, energy source and various industries uses. Oil palm is very important for human consumption and it is consumed as red palm oil, margarine, vegetable fat, edible or industrial frying oil and as various special purpose fats. In industries, the derivatives of oil palm are used worldwide as raw materials for a wide range of purposes including the manufacturing of ice cream and confectionery soaps, cosmetics, detergents, inks, epoxy resins and animals feeds. Nutritionally and health wise, oil palm is highly beneficiary, because it is rich in carotenoids, which is needed to protect the eye against certain eye diseases by increasing vitamin A in the blood, moreover oil palm is rich in essential fatty acids and has long been utilized as a source for biofuel (Jacquacmard, 1998).

As posited by Basiron (2007), oil palm production has been used strategically by Malaysia and Indonesia for employment creation, poverty reduction and rural development. For example in Malaysia, the plantation sector is one of the largest employers in the country and has created substantial livelihood improvement for millions of rural small-scale producers (Basiron & Weng, 2004). Moreover the oil palm sector has provided basic infrastructure to oil palm producing rural areas, hence with proven track record the oil palm industry in Malaysia and Indonesia is recognized by other developing nations as a model for poverty eradication, which need to be emulated (Basiron & Weng, 2004). Also as mentioned in (MoFA, 2011), the Kwaebibriem District in the Eastern Region, which is the centre of oil palm development in Ghana, has the second lowest poverty rate in the country as the result of oil palm production.

The economies of most African countries are agriculture oriented, but productivity and output are low due to low levels of industrialization and the fact that production is mainly in the hands of small-scale producers. This has resulted in virtually low output for all major crops produced on the continent, resulting in a demand gap that must be filled by importation at high foreign currency. The oil palm sector in Ghana has undergone tremendous changes over the years as various governments have tried to transform the sector with growth oriented strategies and practices aiming to drastically reduced the demand gap and stimulate growth in the oil palm sector.

In Ghana, like many oil palm producing countries in Africa, the sector is divided into small-scale, medium-scale and large-scale production systems with the small-scale producers dominating (MoFA, 2011). According to GOPDA (2000) the large-scale oil palm production system covers an area of 500 ha and above and these are mainly state and private owned enterprises which were established to meet the local demand of Ghana and provide the surplus for export. The medium-scale production system covers an area of 7.5 to 500 ha. Both production systems use modern agronomic practices and improved materials. Finally the small-scale oil palm production system covers an area up to 7.5 ha.

Oil palm is cultivated in rural villages mainly in the rain forest and deciduous agro-ecological zones of the Eastern, Ashanti, Western and Central Regions.

Productivity in the oil palm sector has continuously been very low in Ghana and the major policy goal of successive governments has been to raising productivity. According to MoFA (2012), yield of fresh fruit bunches (FFB) ranges from 10 to 15mt/ha on large plantation, smallholders and out-growers produce between 7 to 10mt/ha and independent producers produce 3mt/ha. On the average, large plantation produce higher yield than independent small-scale farms due to better planting material and cultural practices on large plantations, but cannot compete with those of Malaysia and Indonesia with average yields ranging from 25 to 30mt/ha. These shortcomings in small-scale production are mainly due to low level of improved technology adoption and investment to increase the productivity of small-scale producers (MoFA, 2011).

As posited by Carrere (2010), oil palm production in Ghana started as far back as the eighteenth century and production was mainly by small-scale producers who harvested palm bunches from natural palm groves and used seedlings from underneath these trees to establish their plantations. Establishment of plantations were not favoured by the then British colonial authority as indicated by Carrere, (2010), because they believed that the small-scale farming system was more resilient economically than the exotic large plantation, and moreover they did not want to disrupt the export flow of palm product by engaging in land issues with the indigenous inhabitants by dispossessing them of their land for the establishment of large plantations.

Ghana's first international commercial trade in oil palm took place in 1820 and was based on a small-scale production system, whereas plantations were established by 1850. As far back as the 1880s palm oil accounted for 75% of the country's export revenue, providing the leading foreign exchange earner for Ghana from about the mid nineteenth century to the beginning of the twentieth century (MoFA, 2012). Malaysia which is currently dominating the market started the establishment of oil palm plantations with planting materials from Ghana. Ghana has a total of 305,758 ha of oil palm and produced an estimated 243,852mt of palm oil in 2011 and has unmet demands of 35,000mt (MoFA, 2012).

1.2 Problem Statement

The performance of oil palm sub-sector has yet to reach its full potential due to constraints that are affecting the sector and agriculture in general. The agriculture sector is predominantly small-scale and is plagued with usage of traditional technology, inadequate extension services, no or insufficient application of vital inputs (e.g. fertilizer and improved planting material), lack of support for credit and inputs provision, poorly organised value chain, extension and research services and poor infrastructural such as roads, market and processing facilities, fragmented nature of small-scale producers and agro-management practices. As a result, small-scale producers produced on average 3mt/ha compared with 15mt/ha on large-scale plantations, where producers or farm managers apply factors such as good management practices in terms of improved seedlings, appropriate planting density, provision of wire collars mesh, cover crops, fertilizer application, regular weeding, timely harvesting and evacuation of fresh fruit bunches (FFB).

1960 which signifies the beginning of serious government effort in the oil palm sector, small-scale production constituted 93% and in 2011 after series of interventions 80% of total production was produced by small-scale producers (MoFA, 2011).

Low adoption of improved technologies by small-scale oil palm producers results in low productivity which is translated into inadequate income and working capital, and therefore, small-scale producers are unable to purchase productive inputs like improved seeds, fertilizers and pesticides and pay for hired labour and land preparation. One way of overcoming the challenges that are hindering small-scale oil palm productivity is to increase the rate of adoption of improved technology.

Empirical evidence strongly suggests that poverty, adoption of improved technology, inefficiency and unemployment are of great concern to development economists especially in developing countries (Feder et al., 1985; Amos, 2007; Antle & Crissman, 1990). This is because encouraging small-scale producers to adopt improved technology to increase productivity and efficiency in the agriculture sector is particularly essential for generating income, creating employment and reducing poverty. As a result understanding of the current factors that affect adoption of improved technology and inefficiency inherent in the sector as well as their determinants are essential.

The success of the proposed Oil Palm Masterplan objectives for the development of 10,000 ha oil palm nucleus plantation associated with 40,000 ha smallholder and 110,000ha village level replanting programme can only be achieved to a greater extent by increasing the productivity of small-scale producers and the level of efficiency in managing their farms (MoFA, 2011).

The basic principle behind this study is that if some producers are not adopting the complete package of the improved technology or are partially adopting them, and are not making efficient use of available technologies, then efforts designed to increase adoption rate, improve efficiency and productivity would be more cost-effective and necessary than introducing new technologies as a means of increasing agriculture output. Therefore it is important to quantify current rate and intensity of adoption, productivity and levels of technical efficiency of small-scale oil palm producers. It is mainly by understanding these factors that we can design appropriate policies and strategies that will increase the intensity of adoption resulting in improve productivity of the sector.

The study therefore seeks to address the following Research Questions:

1. What is the intensity of adoption of improved technologies?
2. What are the factors that influence the adoption of improved technologies?
3. What are the levels of productivity of inputs used in the production of oil palm by small- scale producers?
4. What is the level of technical efficiency of small-scale oil palm production?

5. Does adoption influence productivity and technical efficiency of small-scale oil palm production?

1.3 Objectives

The primary objective of this study is to assess the role of improved technology adoption on technical efficiency of small-scale producers. The specific objectives are as follows:

1. To examine the intensity of adoption of improved technologies;
2. To assess the factors that influence the adoption of improved technologies by small-scale oil palm producers;
3. To estimate the level of productivity of small-scale oil palm producers;
4. To estimate technical efficiency of small-scale oil palm producers; and
5. To determine the factors that influence technical efficiency of small-scale oil palm producers.

1.4 Justification

Ghana is not self-sufficient in oil palm production and therefore relies on importation in order to meet domestic demand. Productivity among independent smallholder is low compared with out-growers and smallholders for the large plantations (MoFA 2011).The need to improve small-scale oil palm producers' capacity to produce efficiently is grounded on the fact that it will increase productivity, provide employment and help reduce poverty and rural-urban migration for rural population. Hence, any research focusing on identifying the determinants of adoption, productivity and efficiency among oil palm producers is commanding.

This study is timely and strategic in that it will provide empirical evidence on the intensity and factors that influence the adoption of improved technologies. Similarly, empirical evident on the level of productivity and factors that influence technical efficiency can be used by government, researchers, policy makers, extension agents, and organizations and other stakeholders to design programmes and projects to implement the Oil Palm Masterplan and subsequent plans and strategies that will help increase productivity and supply raw materials as well as enhance food security and producers' revenue. Moreover, this study will contribute to the body of knowledge in research and served as a springboard for possible interventions and policy formulation in the oil palm sector.

1.5 Organization

This study comprises five chapters. Following chapter one which covers the background of the study, research problem investigated, objectives, justification and organization of the study. Chapter two presents the literature review of various materials relevant to this study. Chapter three highlights the research methodology which describes the theoretical underpinnings and its empirical application; data analysis techniques employed in the analysis of the data; the sampling technique, type of data collected and a brief description of the study area. Chapter four is dedicated to results and a discussion of the study. Chapter five presents the summary, conclusion and policy recommendation of the study and directions for future research.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter reviews the relevant and appropriate literatures related to the study. Section 2.2 discusses the types of small-scale system of production. Section 2.3 defines adoptions, and discusses the methods used to examine the intensity of adoption and the determinants of adoption. The measurement and empirical application of adoption are also described in this section. Section 2.4 defines productivity as it is applied in the context of agriculture and describes the methods of measuring productivity as well as factors that influence productivity as it relates to agriculture and the empirical application of productivity analysis. In Section 2.5, technical efficiency is addressed looking at the various methods used to analyse efficiency, narrowing down to the empirical application of the stochastic frontier production approach.

2.2 Small-scale Systems of Production

Vermeulen and Goad (2006) state that smallholder is common currency use in discussion on sustainable small-scale oil palm production and that several observers used the term to mean a broad scale of local residents involved in the palm oil industry. Which include: peasant producers who have chosen to grow oil palm on their own plots, Settlers and trans-migrants brought in specially to provide labour in areas under large-scale plantation and are given land to cultivate oil palm, also indigenous people whose land have been encroached on by large plantation through government influence and producers in debt to company-established cooperatives. The RSPO defines smallholders more tightly as family-based enterprises producing palm oil on less than 50 ha of land, Vermeulen and Goad (2006). In Ghana, the term smallholding is used to mean producers operating less than 7.5 ha (GOPDA, 2000).

There are three types of small-scale farming system practice in Ghana. They are: smallholder, out-grower and independent smallholder. Based on MoFA (2011) definition, smallholder is a producer who is allocated an area of land owned by the plantation/processing company, thereby obligating him/her to supply the same plantation/processing company with all fruit from the land allocated to him/her. Out-grower on the other hand is a producer who operates on land not owned by the plantation/milling company. However, the out-grower and a particular plantation and milling company sign a contract for the out-grower to supply all his fruits to the mill and the milling company may provide inputs and extension services on credit. Finally the independent smallholder is a producer who cultivates oil palm fruit from land either owned or rented. They have no contract to supply any particular mill and are free to sell his fruit to whomever he sees fit.

2.3 Adoption of Improved Technology

2.3.1 Introduction

Asfaw et al. (2011) posited that the achievement of high agricultural productivity will only be possible with the production and diffusion of high yielding improved technology. According to Feder et al. (1985) adoption of improved technology in agriculture is very important because a majority of the population are poor and derive their livelihood from agricultural production. Since new technology adoption offers hope and opportunity to increase production and income extensively, it is necessary for small-scale producers to adopt improved technologies.

This section seeks to examine literature on how adoption is defined broadly, as well as in the specific context of agriculture. Various methods used to estimate the intensity of adoption, as well as methods used to assess factors that influence adoption are reviewed. Finally the empirical applications of adoption analysis are also reviewed.

2.3.2 Definition of Adoption

Namara et al. (2007) defined adoption as an act of accepting a technology with approval. Adoption process in agriculture is defined as a series of stages that the producers pass through, from first hearing about the technology (an awareness stage), to collecting information about the technology's expected benefits in terms of its profitability and ease of operation (the evaluation stage); if the information is found to be adequate and the evaluation is positive, the producer will experiment with the technology (the trial stage and the final full-scale adoption stage of the technology) (Rogers, 1962; Feder, et al., 1985). Feder et al. (1985) distinguished between farm level and aggregate adoption of a technology according to its coverage. They defined farm level adoption as the degree to which a new improved technology is incorporated into the production process in long-run equilibrium when the producer has complete information concerning the new technology and its potential and applies it on his farm. In the context of aggregate adoption, the definition transcends to the process of diffusion of a new technology within a given geographical area or within a given population. This definition of aggregate adoption also concords with that of Thirtle and Ruttan (1987) which states that aggregate adoption is the spread of a new technology within a population.

Rogers (1983) distinguished between adoption and diffusion. He defined adoption as the process by which producers utilize a new improved technology or otherwise at a given period of time, while diffusion (aggregate adoption) on the other hand is defined as the process by which a technology is communicated through specific channels over time and space among the members of a social structure. Adoption typically refers to the decision to use a new improved technology or practice by producers on a consistent basis and diffusion on the other hand, often refers to a spatial and temporal spread of the new improved technology among different farm units. The definition by Rogers (1983) further identifies four elements essential for comprehending and making adoption and diffusion effective:

(i) The technology that represents the new idea, practice, or object being diffused;

(ii) Communication channels which represent the way information about the new technology flows from change agents (the extension agents, technology suppliers) to the adopters (e.g. producers);

(iii) The time period over which a social structure adopts a new improved technology;

(iv) The component of the social structure.

Nkonya et al. (1997) measured the rate of adoption as the percentage of producers who have adopted the new improved technology, while intensity of adoption on the other hand is defined as the level of adoption of the new improved technology or the number of hectares cultivated with the new improved technology. According to Bonabana-Wabbi (2002), the intensity of adoption is measured from the number of technologies being adopted to the number of producers adopting them and uses percentages to calculate the intensity of adoption of IPM practices input used and yield estimates. Kaguougo et al. (2012) and Nkonya et al. (1997) measured factors affecting the intensity by examining their influence on areas planted with the improved technology, using the Tobit model.

2.3.3 Measurement of Adoption

Measuring adoption involves measuring choices. Bonabana-Wabbi (2002) asserts that measurement of adoption can be done by estimating the intensity and rate of utilization of the improved technology being investigated depending on the nature of the data, i.e. whether they are qualitative or quantitative. For instance in the study to investigate the determinants of adoption and intensity of use of improved maize varieties in Ethiopia, Alene et al. (2000) employed the Tobit model and used both quantitative and qualitative data.

Feder et al. (1985) posit that adoption decision involves choice of how many resources, like land to be allocated to the new improved and old technologies if the technology is not divisible (e.g. mechanization, irrigation). Conversely, if the technology is divisible (e.g., improved seed, fertilizer, agronomic practices and herbicide), the decision process involves area allocations as well as levels of use or rate of application. Therefore, the process of adoption decision includes the simultaneous choice of whether to adopt a technology or not, and the rate and intensity of its use. Besides, before adoption choices are made a producer makes a set of several interdependent decisions (Hassan et al., 1998).

In measuring adoption, distinction has to be made between technologies that are divisible and those that are not divisible with regards to the measurement of intensity of adoption. The intensity of adoption of divisible technologies can be measured at the individual level in a given period of time by the share of farm area utilizing the new technology or quantity of input used per hectare (Feder et al., 1985). Likewise this measure can be applied to the aggregate level of adoption in the same locality. Nevertheless, the intensity of adoption of non-divisible agricultural technologies such as tractors and combine harvesters at the farm level at a given period of time is dichotomous (use or no use), and the aggregate measure becomes continuous. In the latter case, aggregate adoption of a lumpy technology can be measured by calculating the percentage of producers using the new technology within a given area. Aggregate adoption is measured by the aggregate level of use of a specific new technology within a given geographical area or a given population.

2.3.4 Adoption Determinants

The determinants of adoption of new improved technologies can be divided into three major groups, namely: farm and producers' associated attributes; attributes associated with the technology (Adesina and Zinnah 1993) and the farming objective (CIMMYT, 1988). Factors in the first group include a producer's education, age, household size and farm size. The second group depends on the type of technology (e.g., the kind of characteristics a producer likes in an improved oil palm variety). The third group assesses how different strategies used by the producer, such as commercial versus subsistence farming, influence the adoption of technologies. Bonabana-Wabbi (2002) also summarized these factors that influence adoption as: social factors, economics factors and institutional factors.

Rogers (1983) identifies five characteristics of the improved technology that determines the intensity of adoption. Those characteristics of improved technology include: relative advantage, compatibility, complexity, divisibility, and observability. Similarly Fliegel and Kivlin (1962) summarised from adoption literatures and found that features that affect adoption behaviour, some of which are not mutually exclusive, and they include:

(i) Initial costs;

(ii) Operating and maintenance costs;

(iii) Rate of recovering cost – that is speed with which investment in a practice is returned to the farm operator through increased earnings;

(iv) Divisibility – that is the degree to which a practice can be tried out on a small scale before full adoption;

(v) Mechanical attraction – that is the extent to which a new technology possesses mechanical qualities suitable for the producer;

(vi) Complexity – the ease with which a practice can be described, demonstrated, and understood;

(vii) Compatibility – that is the process with which a new technology can be assimilated into the producer system;

(ix) Saving of time;

(x) Saving of physical discomfort cost – that is the extent to which a new practice accomplishes a task more easily or more pleasantly; and

(xi) Relative advantage cost – that is the overall significance of a new technology for the entire farm programme.

Factors affecting the adoption of improved technology are examined using the dichotomous choice models (Tobit, Probit and Logit) and count model (Poisson model). This is used when the dependent variable is qualitative in nature. The choice of the explanatory variables is guided by economic theory and the adoption literature. The explanatory variables can be broadly categorized into producer and farm characteristics, technical factors and producer perceptions of technology characteristics. Moreover attributes that influence adoption of agricultural technologies are inherent in the producer and farm, the technology and the producer's objectives (Adesina & Zinnah, 1993; Adesina & Baidu-Forson, 1995).

2.3.5 Empirical Applications of Adoption Analysis

Babatunde and Qaim (2009) employed the Count Data model (Poisson regression model) to estimate the determinants of income diversification and found that education, productive assets, electricity and pipe-borne water had positive and significant influence on the number of income sources.

Diagne and Demont (2007) examined empirical models of adoption and demonstrated that the sample adoption rate does not consistently estimate the population adoption rate even if the sample is randomly selected. They proved that instead, the sample adoption rate is a consistent estimate of the population's joint exposure and adoption rate, which does not provide information about adoption per se. They used Average Treatment Effect (ATE) as counterfactual outcomes framework to calculate the true population adoption rate. ATE measures the exposure to the technology and was applied to estimate the population adoption rates and determinants of the NERICA rice varieties in Cote d'Ivoire. The ATE approach has significant policy implications with respect to judging the inherent merit of a new technology in terms of its potential demand by the target population independent of issues related to its accessibility and in terms of the decision to invest or not in its wide scale dissemination. They found that the NERICA adoption rate in Cote d'Ivoire could have been up to 18% in 2000 instead of the actually observed 4% joint exposure and adoption rate, if the whole population were exposed to the NERICAs in 2000 or before. This, the authors argued, justifies investing in the dissemination of the NERICA varieties; considering that the 18% is bound to increase significantly in the future as producers learn more about the characteristics of the NERICAs and become comfortable with their performances.

Dontsop et al. (2011), Diagne and Demont (2007) and Diagne (2006) employed and concord with the average treatment effect methodology as posited by Adesina and Baidu-Forson (1995).

Feder et al. (1985) examined economic studies of technology adoption and argued that farm size, risk and uncertainty, human capital, labour availability, credit, land tenure, and complementary input availability were the major factors affecting the adoption of agricultural technologies.

Kaliba et al. (2000) examined factors influencing the adoption of improved technologies (maize seeds and inorganic fertilizer) by producers in Tanzania. The results indicated that availability of extension services, on-farm field trials, variety characteristics and rainfall were the most important factors that influenced the intensity of adopting improved technologies. The Tobit and Probit models were used to identify factors influencing adoption of improved maize varieties.

Nchinda et al. (2010) posits that if the intensity and factors that influence adoption are to be estimated simultaneously, that is the adoption and the intensity decisions are assumed to be taken at the same time, the Tobit model is appropriate compared to the other dichotomous models based on the assumption that there is no selection bias and moreover it provides both the influence of exogenous factors on the probability of adoption and the intensity of adoption in addition to estimating the marginal effects of the factors (Chukwuji & Ogisi, 2006).

2.3.6 Conclusion

Adoption is a process that a producer passes through from first hearing about the technology to the final full stage of adoption. Adoption measurement involves measuring choices. It can be measure by estimating the rate of adoption and intensity of adoption (Bonabana-Wabbi, 2002; Nkonya et al., 1997) and assessing the determinants of adoption. The intensity is expressed as a percentage, which measures the proportion of improved technologies adopted to the total number of improved technologies. Adoption is influenced by various social, technical, economics and institutional factors.

This study seeks to estimate the intensity of adoption and factors that influence the adoption, therefore the adoption intensity is measured as a percentage and the Poisson regression model which is best suited is used to examine the factors that influence the adoption of improved technology, based on the assumption that there is no over-dispersion.

2.4 Productivity

2.4.1 Definition of Productivity in the Context of Agriculture

Iyaniwura and Osoba (1983) and Antle and Capalbo (1988) defined productivity as the quantitative relationship between output and inputs levels in an economy or a sector. Dayal (1984), and Abdullah and Hussein (1993) argued that agricultural productivity is a measure of the efficiency with which inputs are used in agriculture to produce an output. Moreover Krueger et al. (1991) and Stern (1989) improved the productivity concept and posited that agricultural productivity goes beyond production on the farm, to the heart of economic performance which is used as a gauge for planning and development policies by governments and other stakeholders. It is cardinal because as agriculture develops, it releases resources that enhance structural transformation towards industrialization and economic improvement for all including the poor. Increasing agricultural productivity performance is critical to improving the economic well-being of developing countries, especially in meeting the ever increasing need for food and reducing pervasive poverty in rural communities. Since rural poverty reduction is a critical policy concern of many governments and other stakeholders, Ahluwalia (1978) suggests that agricultural performance is inversely related to levels of rural poverty; therefore raising agricultural productivity will reduce poverty and meet the food need of poor rural people. As a result policy makers should endeavour to identify the productivity variables and causal factors that will help improve agricultural production and design development programmes that will focus on removing the constraints adversely affecting productivity in these developing countries.

Hayami and Ruttan (1985) assert that productivity in the context of agriculture performance can be increased particularly in two ways; through increasing use of inputs (land, labour, planting materials, capital etc). Productivity is at its maximum, when inputs used in production yields a maximum output, as such, this measurement of productivity in the context of agriculture can facilitate the comparison of the relative performance of similar production units like farms, in different localities with similar conditions and factors.

2.4.2 Measurement of Productivity

Generally agricultural productivity is measured by dividing output by input(s). According to Kelly et al. (1996), most agricultural productivity measurements empirically fall into two broad categories: average productivity and marginal productivity. Average productivity is a simple ratio: output produced divided by the quantity of inputs used. Marginal productivity is the extra output that can be produced by employing additional units of that input while holding all other inputs constant (Kibaara, 2005). Moreover it is a measure of efficiency which provides valuable information about how to increase output and profits. There are two types of average productivity measurements as stated by Kelly et al. (1996), namely the Total Factor Productivity (TFP) and the Partial Factor Productivity (PFP), which is consistent with that posited by Owuor (1999) and Odhiambo and Nyangito (2003). The reliability of average productivity measurements depends on the quality of the data in both the numerator and the denominator, as well as on the appropriateness of the indexing procedures used to aggregate dissimilar outputs and inputs. Average productivity also measures efficiency and relies on other inputs employed in the production process (Kibaara, 2005). Notwithstanding, that average productivity measurements provide little information on how to improve productivity, that which is necessary for policy enhancement; yet improving productivity is one of the fundamental issues donors and policymakers want to overcome.

Productivity change measurement is essential in agriculture because information gathered during the measurement process can help increase productivity in agriculture which is cardinal to reducing poverty and enhancing national food security. Increased productivity is visible when growth in output surpasses growth in input. Productivity growth with constant or reduced inputs is the best kind of growth to achieve rather than achieving growth of output by increasing inputs, since these inputs are subject to diminishing marginal returns (Palanisami et al., 2011).

2.4.3 Partial Factor Productivity

Owuor (1999) and Odhimbo and Nyangito (2003) defined partial factor productivity as the ratio of physical output to any one of the physical inputs. For example labour productivity is the ratio of output to only labour input and similarly capital productivity is the ratio of output to only capital input. Partial factor measures are advantageous for indicating factor-saving biases in technical change but are probably going to exaggerate the overall improvement in efficiency because they do not account for changes in other inputs use (Fuglie, 2010).

Eatwell and Newman (1991); Alston et al. (1995) and Kelly et al. (1996) posited that partial productivity measures has a weakness in that it does not control for the level of other inputs employed in production. For example, average agricultural yields per labour reported in agricultural national statistics come from farms cultivated with different types of inputs like land, labour, planting materials and capital, but partial factor productivity for labour only account for the labour input utilized, neglecting the other inputs used in production. However, carefully constructed partial factor productivity measures are legitimate measures of the variations in measured output attributable to variations in measured inputs. According to Kelly et al. (1996) Partial productivity measures are reported in either physical units or value terms.

2.4.4 Total Factor Productivity

Kelly et al. (1996) defined total factor productivity as the ratio of an index of aggregate output to an index of aggregate input and attempt to be a control for the full range and intensity of all inputs used in the production process. The indices are based on price and quantity values; therefore good priced data are necessary for good estimates for total factor productivity. Thus TFP measures are difficult to estimate when the value of key inputs can't be tracked from markets that are not well-functioning, as such good priced data is an important element for good estimates of total factor productivity.

Eatwell and Newman (1991) described total factor productivity as a multi-factor productivity measure that controls for all inputs factor in the measurement of productivity. Therefore, total factor productivity is a generalization of single factor productivity measures such as land productivity and labour productivity. Similarly, Dayal (1984) estimated land and labour productivities and aggregated them to measure total factor productivity which was used to quantify and map out productivity in India.

Grosskopf (1993) improved the literature on productivity measurement when he observed that the traditional approaches to productivity measurement usually assumed that observed output is frontier output. The frontier output implies that the observed output is the maximum output, which implies that production is technically efficient, and there is no inefficiency in the production process. He then separated total factor productivity approaches into two: those that ignore inefficiency, that is, approaches in the frontier framework, and those that explicitly allow for inefficiency, that is, non-frontier framework. Furthermore Grosskopf (1993) posited that, total factor productivity measurement can be classified into parametric (econometric approaches) models and nonparametric (index number) models.

According to Coelli (1995); and Kalirajan and Shand (1999), the parametric approach does account for the influence of measurement error and other noise in the data and it includes econometric approach, deterministic and stochastic approaches. While the non-parametric approach as posited by Kumbhakar and Lovell (2000), does not account for possible influence of measurement error and other noise in the data. The most widely used non-parametric approaches for measuring productivity growth are indices like the Malmquist Productivity Index, the Data Enveloping Analysis and the Tornqvist-Theil Index (Evenson et al., 1999).

2.4.5 Marginal Productivity

Marginal productivity is different from average productivity. It is an important indicator because it shows how much output a producer obtains by adding one more unit of an input if the levels of all other inputs remain constant. By equating the marginal value product to the cost of the input, one can evaluate economic efficiency and identify constraints. If the marginal value product is greater than the unit cost of the input, a producer can increase profits and become more efficient by increasing the use of such input. If producers are prevented from using more of the input to produce, then the preventing factors are constraints. These constraints must be targeted through appropriate policies.

2.4.6 Factors that Influence Productivity

Productivity growth in developed economies is influenced by both technological innovation and organizational changes (Brynjolfsson & Hitt, 2003). In a developing country like Ghana, factors that influence agricultural productivity include technology, relative output and input prices, input use, agricultural research and extension, education of producer, market access and availability of credit. In addition other factors such as weather, agricultural policies, land tenure system, inadequate involvement of beneficiaries in decision-making, insecurity and the legal and regulatory environmental issues have a bearing on productivity (Odhiambo & Nyangito, 2003). Brynjolfsson and Hitt (2003) found that the differences in productivity across countries with difference time factors are explained by differences in the levels of factors like land, labour, tractors, livestock, fertilizer and mechanization that influence production in these countries.

2.4.7 Empirical Applications of Productivity Analysis

Owour (1999); and Nyoro and Jayne (1999) employ partial factor productivity to estimate land and labour productivities. Owour (1999) uses cross section data for inputs and output, as well as market and farm-gate output prices. Data used for agricultural labour was only taken from family labour since data for hired labour for all crops were not available, therefore only the productivity of family labour was computed using family members above 10 years involved in agricultural activities. Nyoro and Jayne (1999) on the other hand utilized secondary national data on specific crops like coffee, tea, pyrethrum, sugarcane and rice to calculate productivity of inputs. A practical problem encountered with small scale farming, like the one analyzed by Owour (1999), was the issue of shared resources, that is, many producers practice intercropping and how family labour is shared among many farm activities, therefore obtaining precise measurement of factor inputs like labour used for individual crops becomes difficult, if not impossible. This was resolved by summing up the values of crops produced on the farm in revenue. Nyoro and Jayne's (1999) study shows that labour productivity declined in Kenya between 1970-1974 and 1990-1994, but land productivity on the other hand had increased greatly in the country until around 1990 after which it started declining. The decline in both labour and land productivity was attributed to the decline in use of fertilizers and hybrid seeds and the reduction in credit schemes in the agricultural sector, intermittent policy environment in the country, poor sequencing of liberalization policies, poor management of producers organization (particularly coffee), and increased population pressure that has pushed production into marginal areas. Another problem that arises in aggregating revenue is the price to consider for the output because different households experience different prices. Price differentials are due to inter-temporal and spatial factors. This shortcoming was resolved again by assuming that all households in the same geographical zone faced the same output price.

Dayal (1984) used three indexes to measure productivity which include land productivity (market value of agricultural output per hectare of cropped area), labour productivity (market value of agricultural output per agricultural worker), and a composite index of land and labour productivity or aggregate productivity. Dayal (1984), used a three year average output value of each of the 18 major crops, converting them into money value by using regional farm gate prices. The indexes of land and labour productivity were measured by the market value of output of 18 crops per unit of area occupied by the crops and per unit of labour input. Finally, the composite index of agricultural productivity was obtained by calculating a ranking coefficient of the two indexes and districts ranked according to the value of land productivity and labour productivity. The two ranks were averaged to get the composite index of aggregate productivity. Furthermore, the three indexes were then mapped in order to identify the agricultural productivity patterns in India at the district level.

Dorfman and Foster (1991) examined three methods used to measure productivity in agriculture: total factor productivity (TFP), simple technical change (STC), and flexible technical change (FTC). Both STC and FTC allow for non-constant returns to scale, thereby avoiding one potential source of bias (Morrison 1985), while the TFP allows for constant returns to scale. The production function was specified to have three inputs: labour, capital, and materials. Labour includes both family and hired labour. Capital includes land, structures, inventories, equipment, and breeding stock. Included in materials are the inputs of energy, fertilizer, pesticides, feed, seed, and a miscellaneous category.

Hayami (1969) and Hayami and Ruttan (1970) suggested the meta-production function approach and this was further advanced by Lau and Yotopoulos (1989) and Fulginiti and Perrin (1997). Battese and Rao (2002) employed the meta-frontier analysis for the comparisons of productivity differentials across countries. One of the advantages of meta-frontiers with respect to meta-production functions is that they are able to separate technological differences from the differences in technical efficiency. Battese et al. (2004) and O'Donnell et al. (2008) extended the idea and developed both parametric and nonparametric approaches.

Binam et al. (2008) employed the stochastic meta-production frontier to estimate the productivity of cocoa producers in West and Central Africa. The estimates of the elasticities with respect to cocoa area, labour, insecticide and fungicide (pesticide) expenses, and the age of the cocoa farms shows the differences in inputs used in production between the countries which implies that production structure and technology are different.

2.4.8 Conclusion

Agricultural productivity increase is an important policy indicator used to reduce rural poverty, create employment, improve rural infrastructure and increase industrialization thereby increasing the overall country GDP and livelihoods of the producers. Therefore measuring agricultural productivity is essential for policy making decisions by Government and other concerned stakeholders. Productivity is measured as output divided by input(s); there are two main types of productivity measurement, namely the partial and total factor productivities, the difference between these two types of measurement is in the denominator and the data requirement. Whereas the partial factor productivity measurement only considers one input in the denominator, the total factor productivity measurement considers all inputs used in the denominator.

This study seeks to estimate the level of productivity of individual inputs used in small-scale oil palm production; therefore marginal factor productivity is employed, because it will provide productivity estimates of the individual inputs like land, labour and fertilizer, which will provide a basic for policy decisions.

2.5 Efficiency

2.5.1 Introduction

In agriculture, efficiency is generally associated with the possibility of a farm producing at the maximum level of output from a given bundle of resources or a certain level of output with the least cost. Farrell (1957) posits that economic efficiency of a firm consists of two components: namely technical and allocative efficiencies. Technical efficiency measures the ability of the firm to obtain the maximum output from given inputs; whereas allocative efficiency measures the ability of the firm to use inputs in optimal proportions given their prices (Coelli et al., 2005). Moreover technical efficiency of a farm is the success of the farm to produce maximum output from a given set of inputs (Farrell, 1957). The potential importance of efficiency as a means of fostering production has yielded a substantial number of studies focusing on agriculture. Large numbers of frontier models have been developed based on Farell's work in 1957, which can be classified into two broad types: parametric and nonparametric and jointly they have monopolized recent literatures in calculating or measuring efficiency. The widely used non-parametric frontier technique is the Data Environment Analysis (DEA), while the parametric frontier technique is divided into the deterministic and stochastic.

2.5.2 Deterministic Frontier Analysis

Aigner and Chu (1968) used the deterministic approach to measure technical efficiency. They improved upon Farrell's work by measuring technical efficiency through a deterministic Cobb-Douglas production frontier obtained by using linear programming. The deterministic approach assumes that all deviations from the efficient frontier are under the control of the agents, as a result any resulting deviations are regarded as technical inefficiency. Hence no account is taken of noise. On the other hand, Coelli (1995) posits that The Deterministic frontier technique uses mathematical programming to constructs a non-parametric frontier. It is mathematically less demanding, does not specify a functional form of the frontier and easier to be used in professions where there are multiple outputs (banking, health, telecommunications, etc.). Hence it is simple to implement.

Shapiro and Muller (1977) measured technical efficiency by using the deterministic Cobb-Douglas production frontier obtained by linear programming. In their work, 'Sources of Technical Efficiency, they used modernization and information as variables and the measure of technical efficiency they employed differs ultimately from Farrell's concept of a frontier function. The major objective of their study was to investigate the roles of information and modernization in the production process of 40 cotton farms in Tanzania. By using correlation analysis, they found that technical efficiency had a high positive association with both modernization and information.

Russell and Young (1983) criticized the deterministic frontier production model, because it assumes that all deviations from the efficiency frontier are the result of technical inefficiency. On the other hand, two types of factors can affect the performance of a firm. They include exclusively factors outside the control of the firm and factors under the control of the firm. Factors fully outside the control of the firm are weather, climate, and failure of market and measurement errors; whereas, factors under the firm's control include socioeconomic characteristics and management practices. Thus, a stochastic parametric frontier production function was developed to incorporate these effects while estimating technical efficiency of the firms (Aigner et al., 1977; Meeusen & Van den Broeck, 1977).

2.5.3 Stochastic Frontier Analysis

Aigner et al. (1977) and Meeusen and Van den Broeck (1977) independently developed the stochastic frontier (SF) approach to estimate technical efficiency of producers/firms using parametric econometric techniques. The stochastic frontier production function takes into account the technical inefficiency and firm's specific random shocks separately in the analysis process. Aigner et al. (1977) and Meeusen and Van den Broeck (1977) pointed out that deviations from the production frontiers are because of two types of factors, such as factors entirely outside the control of the firm or producer and factors under the control of the firm or producer. This signifies that deviations are not completely under the control of the firm or producer, but some factors such as bad weather, measurement errors, etc. are totally outside the control of the firm or producer.

Mustapha (2011) applied the stochastic frontier analysis to investigate the relative performance of rubber smallholders in Besut District, Malaysia. The Maximum likelihood method was used to estimate the two statistical models normally adopted in stochastic frontier studies, namely the Cobb-Douglas and Translog production functions. The likelihood ratio test shows that the Cobb-Douglass could have explained better the relationship between the variables. The Technical Efficiency was estimated using the frontier 4.1. A total of 35 smallholders rubber producers where investigated and their technical efficiency scores varied significantly. These variations could have been due to factor under the control of the producers, such as agronomic practices, motivation and experience of the producers, species of rubber trees planted and whereas factors outside the control of the producers, such as weather condition.

2.5.4 Empirical Results of Previous Related Work

The empirical application of the study is consistent with the models developed by Aigner, et al. (1977) and Meeusen and Ven den Broeck (1977); Battese and Tessema (1993) and Battese and Coelli (1993). Hasnah et al. (2004) investigated technical efficiency for a sample of 80 smallholder oil palm producers in West Sumatra, over two years, 1999 and 2000. The maximum Likelihood method was used to estimate the translog SFPF. The output elasticities of the variables in the stochastic frontier production are 0.39, 0.13 and 0.35 for Total Weighted Trees (TWT), fertilizers, and labour respectively. The mean Technical Efficiency was estimated to be 0.66, which indicates that there is abundant room for increasing output through better extension work using informal education and selection of more suitable progressive producers without the need for producers to use more inputs.

Onumah et al. (2010) investigated technical efficiency of fish farms in Ghana and used the Ox version 3.40 (Windows) package to obtain the Maximum Likelihood estimate for the translog stochastic production frontier. They found that the expected elasticities for all inputs were significantly positive, meaning that all inputs have positive influence on fish farming. The inefficiency model revealed that the coefficients of experience was estimated to be significantly positive, indicating that older and more experienced fish producers are less technically efficient in their production than possibly new producers who are motivated, progressive and willing to implement new production system.

Ofori-Bah and Asafu-Adjaye (2011) examined technical efficiency of cocoa producers in three Regions of Ghana. The FRONTIER Version 4.1 computer programme was used to obtain the maximum likelihood estimates of the stochastic translog production function. The average technical efficiency level was 0.86, which indicated that diversified cocoa producers are more efficient than single crop cocoa producers.

2.5.5 Conclusion

Technical efficiency of a farm is the success it has to produce maximum output from a given set of inputs. Several methods have been employed to measure technical efficiency, which include the deterministic and stochastic approaches. Measuring efficiency using the stochastic approach is mostly preferred because it postulates that deviation from the production frontier are because of two types of effects, the noise effects (firms specific random shocks) and the inefficiency effect. The stochastic production frontier approach allows for technical inefficiency as do the deterministic technique and also captures the effects of random shocks. Furthermore, since it allows the measurement of technical efficiency and factors that influence technical efficiency simultaneously, therefore the stochastic production frontier is employed in this study.

2.6 Summary

Adoption measurement consists of measuring choices and it can be measure by estimating the rate of adoption and intensity of adoption. Adoption is a process that a producer passes through from first hearing about the technology to the final full stage of adoption. Rogers (1983) defined the adoption process as 'the mental process an individual passes through from first hearing about an innovation to final adoption". The rate of adoption is measured by taking the proportion of producers adopting the improved technology to the total number of producers, expressed as a percentage. Adoption is influenced by various social, technical, economic and institutional factors.

Technology plays a key role in improving agriculture. Agricultural productivity increase is an important policy indicator used to reduce rural poverty, create employment, improving rural infrastructure and increasing industrialization thereby increasing the overall country GDP and livelihood standards of the producers. Low productivity in the agricultural sector can only be mitigated by producers adopting new improved technology that will enhance their productivity and increase their technical efficiency.

Therefore measuring agricultural productivity is essential for policy decision by government and other concerned stakeholders.

Productivity is measured as output divided by input(s); there are two main types of productivity measurement, namely the partial and total factor productivities, the difference between these two types of measurement is expressed in the denominator and the data requirement. Whereas the Partial Factor Productivity (PFP) considers only one input in the denominator, the Total Factor Productivity (TFP) considers all inputs used in the denominator.

Technical efficiency is the ability of a farm to obtain maximum output from a given set of inputs. Methods employed to measure technical efficiency include the deterministic and stochastic approaches. Measuring efficiency using the stochastic approach is mostly preferred because it allows for technical inefficiency as do the deterministic technique and also captures the effects of random shocks.

In this study the intensity of adoption was measured by using proportion of improved technologies adopted by the producers to total improved technologies and the Poisson model was employed to estimate the factors that influence adoption. The level of productivity is measure by employing the partial factor productivity; also the stochastic production frontier approach was employed to measure technical efficiency and factors that influence technical efficiency simultaneously.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

This chapter presents the conceptual and theoretical frameworks of the study, the study area, sample size and variables used in the models as well as the methods of data analyses. The study also contains the empirical models for analyzing farm level productivity, adoption and technical efficiency of small-scale oil palm production. The method of data collection and sampling technique are also presented in this chapter.

3.2 Conceptual Framework for the Study

Typically, a producer that adopts improved technology is expected to have higher level of productivity and produce a higher level of output than one who does not adopt the technology. Given the available technologies, producers who produce the maximum possible output are more efficient.

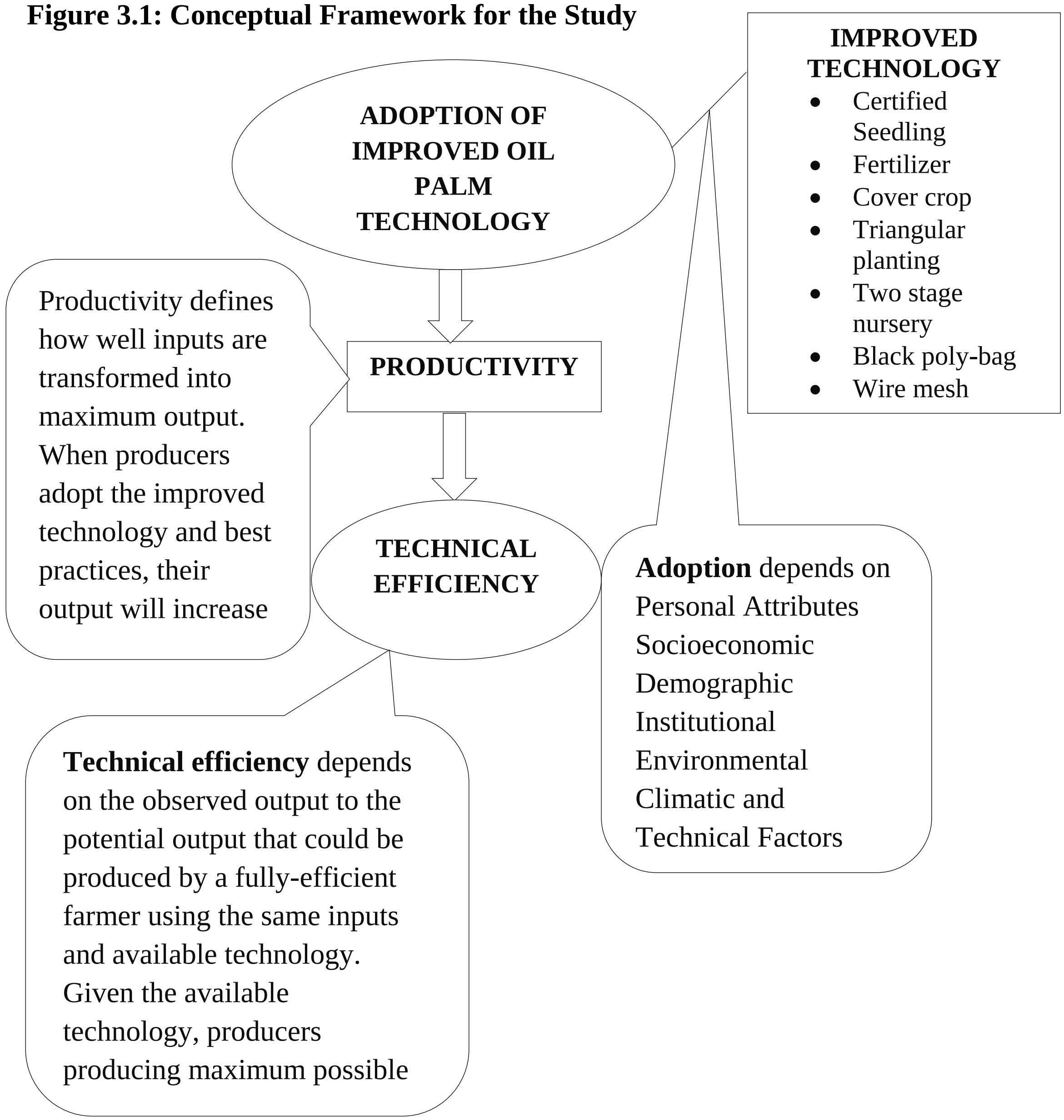
The concept of adoption is a behavioural choice at a particular time and space, which implies that some producers may adopt despite being aware of the choices and some may not adopt despite being aware. Furthermore, producers in the same geographical location are likely to adopt the improved technology if they are aware of its potential to increase output. The adoption literature shows that adoption of agricultural technologies is hypothesized to be affected by a host of personal attributes, socio-economic characteristics, demographic and institutional factors, environmental and climatic factors, producers' perception of the technology attributes, their attitude towards risk and technical factors (Feder et al., 1985; Shakya & Flinn, 1985; Kebede et al., 1990; Adesina

& Zinnah, 1993; Adesina & Baidu-Forson, 1995). According to Degnet and Belay (2001) farm level adoption of new technology varies over space and time. Factors influencing farm level adoption may be due to economic and social or cultural factors. These factors are essential motives influencing the producers' behaviour towards the new technology and its final adoption.

Productivity and efficiency are closely related and are often used interchangeably in economics literature and in other fields; however, they are two different terms. Productivity is defined in terms of how individual resources or a combination of resources are transformed into useful outputs within the production process. Efficiency on the other hand is defined as how well inputs or resources are combined to produce outputs given available technology relative to the frontier production (Fried, et al., 2008). Variations in productivity may be dued to differences in production technology, differences in the efficiency of the production process, and differences in the environment in which production takes place (Grosskopf, 1993).

The improved oil palm technologies considered in this study are: certified seedling, fertilizer, cover crops, triangular planting, two stage poly bag, black poly bag and wire mesh. Certified Seedling has fruits with thin shell and thick mesocarps (60 – 95%), as compared with the uncertified seedling that consists of 35 – 55% mesocarp and has up to 50% nuts. The certified seedling is Tenera and uncertified seedling is Dura (Tweneboah, 2000). Oil palm requires a lot of manure to provide the nutrient elements require for the formation of the vegetative bodies such as leaves, stem and roots, and reproductive organs of inflorescences and fruit clusters. Manuring involves application of empty fruit bunches and fertilizers. Where empty fruit bunches are not available, fertilizer is applied. The non-bearing palm requires mainly nitrogen while the bearing plant requires a lot of potassium. Application of potash to bearing oil palms increases the number of fruit clusters and also makes them bigger. Phosphorus may be required on specific soils but in most cases it only increases yield when the potassium requirement are satisfied. Leguminous cover crops are established soon after land clearing and burning and if possible before holing and planting. When properly established and maintained, cover crops will effectively smoother noxious weeds and help prevent erosion and soil nutrient depletion. It also provides some nitrogen and organic matter. The most common type of cover crop is Pueraria phaseloides. 5kg/ha of fresh Pueraria seeds is the standard for establishing cover crop on the farm. A recently introduced cover crop is Mucuna bracteata which has deeper roots and it produce more nutrients (MoFA, 2011). Triangular planting distance of 9m x 9m x 9m apart giving about 148 trees/hectares is recommended, this will allow each oil palm tree to receive equal solar radiation. The two-stage nursery involves a pre-nursery stage and a main nursery stage. The pre-nursery stage lasts 3 months, where germinated seedlings are sown in smaller black polyethylene bags. In the main nursery, the seedlings are placed in larger polythene bags where they are watered daily for the first 2 months before the frequency of watering is reduced. Black poly-bag use in nursing seedlings has demonstrated superiority in many respects, in terms of growth percent, blast diseases control and percent transportable seedlings. Wire mesh is place around newly transplanted oil palm seedling in the main field to prevent destruction by rodents (Tweneboah, 2000). Figure 3.1 below shows the conceptual framework of the study.

Figure 3.1: Conceptual Framework for the Study



Source: Author's Design

3.3 Theoretical Framework

3.3.1 Theoretical Framework for Adoption

The theory of adoption of new technology has provided the foundation for much of the research work on producers' behaviour in taking up improved technology to enhance their production. Adoption theory postulates that the rate and intensity of adoption of a new technology is dependent upon characteristics of the new technology, the producers and other factors including good agricultural policies (Rogers, 1983). This study is based on the theory of adoption and seeks to generate relevant information to distinguish between the intensity level of adoption of improved oil palm technology and those who have not adopted (without) the improved oil palm technology and factors influencing their choice.

The intensity of adoption is the degree of use of the improved technology, while the rate of adoption is the relative speed with which an improved technology is adopted by a producer (Rogers, 1983). The five main characteristics of the improved technology that explains the rate and intensity of adoption, are: 1) The relative advantage is the degree to which an innovation or improved technology is perceived as being better than the innovation or improved technology it supersedes; 2) Compatibility, reflects how the improved technology is perceived "consistent with the existing values, past experiences, and needs of the producers"; 3) Complexity reflects the perceived difficulty to understand and use the innovation or improved technology; 4) Trialability is "the degree to which the improved technology may be tested"; and 5) Observability reflects how the results of the improved technology are visible to others (Toborn, 2011). Moreover from theory, as stated by Feder et al., (1985) the personal characteristics affecting adoption include age, family size, perception, experience etc.; socio-economic characteristics include income, land tenure, farm size, age of plantation etc.; demographic and institutional factors include credit, market, extension, etc.; environmental and climatic factors include the pattern and amount of rainfall, soil type, topography, disease, pests; and technical factors include feasibility and availability of the technology. Therefore a complete analytical framework for investigating adoption processes at the farm level should include a producer's decision-making model determining the extent and intensity of use of the new technology at each point throughout the adoption process. This study used the Poisson regression model to address the above econometric problem. Similarly, Osgood (2000) and Slymen et al. (2006) used the Poisson regression to perform analysis using count data.

3.3.1.1 Count Data Analysis: The Poisson Model

The Poisson model is best suited model in the context of econometrics for estimation of count data dependent variable, and is the starting point for count data analysis (Cameron & Trivedi, 1990; Greene, 2003). It is employed for the estimation of the farmers' decision on how many improved oil palm technologies producer adopts. The probability of adopting k improved technology given n independent improved technology is represented by the binomial distribution:

$$P(Y = k) = \binom{n}{k} p^{k} (1 - p)^{n-k} \qquad (1)$$

where $\binom{n}{k} = \frac{n!}{k!(n-k)!}$ and p is the probability of adopting k improved technology.

Statistical theory states that a repetition of a series of binomial choices, from the random utility formulation, asymptotically converges to a Poisson distribution as n becomes large and p becomes small:

$$\lim_{n\to\infty}\binom{n}{k}p^{k}(1-p)^{n-k}=\frac{e^{-\lambda}\mu^{k}}{k!} \quad (2)$$

Where μ is the mean of distribution, such as the mean number of technology adopted by the farmer. The formula presented in (1) above allows modelling of the probability that a household adopts the number of improved oil palm technologies k given a parameter μ .

The oil palm farmers make series of discrete household decisions that sum across an aggregation of choices to a Poisson distribution. The Poisson regression model is the development of the Poisson distribution presented in (1) to a non-linear regression model of the effect of independent variables x_i on a scalar dependent variable y . The density function for the Poisson regression is

$$f(y/x_i)=\frac{e^{-\mu_i}\mu^{y}}{y!} \qquad \text{and } y = 0, 1, 2, \ldots.. \quad (3)$$

Where $f(y)$ denotes the probability that the variable y takes non-negative integer values, and where $y!$ stands for y factorial. μ is the mean of distribution, such as the mean number of technology adopted by the producer. Where the mean parameter as the function of the regressors x_i and a parameter vector β is given by

$E(y/x_i)=\mu=\exp(x'\beta)$ and $y=0, 1, 2, \ldots..$

Also note that $$\beta_i=\frac{\partial E[y/x_i]/\partial x_i}{E[y/x_i]}=\frac{\partial\log E[y/x_i]}{\partial x_i} \quad (4)$$

The β_i is the marginal effects of the Poisson model, which can be interpreted as the proportionate change in the conditional mean if the *jth* regressor changes by one unit. The Poisson model sets the variance to be equal to the mean. That is

$$V(y / x_i) = \mu(x_i, \beta) = \exp(x^{'} \beta) \tag{5}$$

The first two moments are:

$$E[y_i] = \mu \quad \text{and} \quad Var[y_i] = \mu \tag{6}$$

This displays a very strong assumption, which is the equality of mean and variance property of the Poisson distribution. Poisson regression has many extensions, such as the Negative Binomial and the Zero-inflated model. Since the dependent variables of a Poisson regression is a count variable, the coefficients are interpreted as: a one unit change in the independent variables, is expected to change the dependent variable (for example number of improved technologies adopted) by the respective regressor coefficient, given that the other regressors in the model are held constant, Wooldridge (2003), Cameron and Trivedi (1990) and Greene (2003).

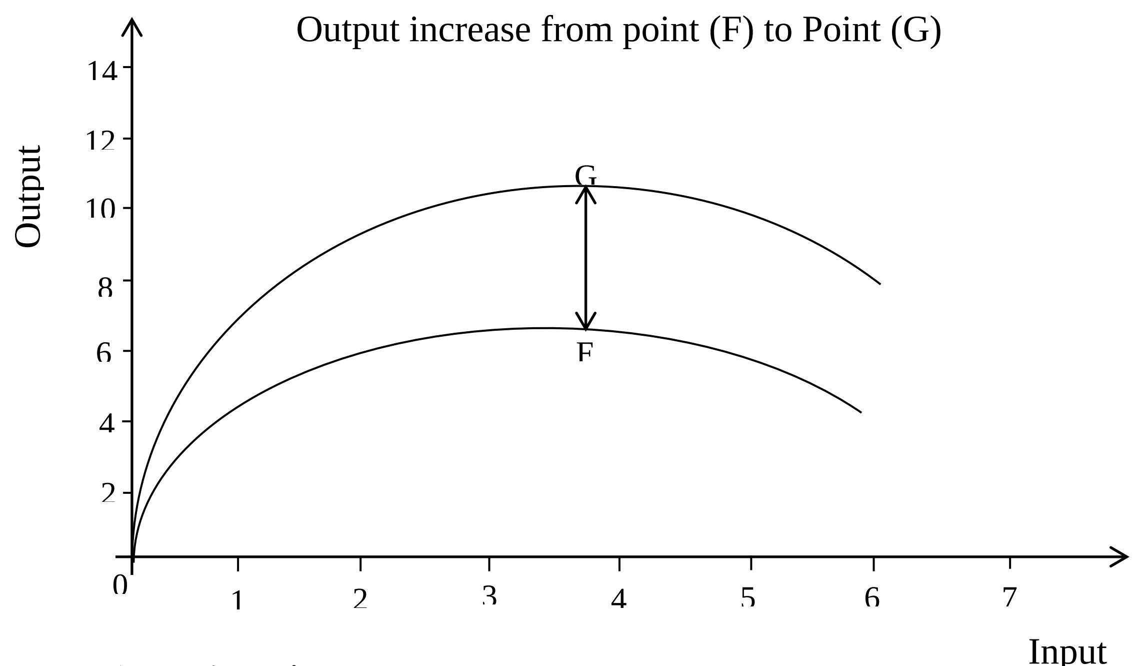
3.3.2 Theoretical Framework for Productivity

In economics, production is the process of converting inputs into output; moreover production theory assumes a technical relationship wherein inputs are combined to produce an output (Koutsoyiannis, 1985). Productivity gap between smallholder and independent producers is significant and the researcher must be able to capture the effects of such change on output. Capturing such effects can ideally be done within the production function in which output depends on various inputs such as land, labour, capital, etc. Hence the production function can be expressed as:

$$Q = f(X_1, X_2, X_3) \tag{7}$$

Where Q is the output and depends on how much of X_1 (land), X_2 (labour) and X_3 (capital) used. If the levels of land, labour and capital decreased/increased then we expect that Q will correspondingly decrease/increase, *ceteris paribus*. Conversely, Q can also be increased by using the same level of land, labour and capital. This is possible due to the use of an improved technology in the production process. Therefore, productivity increase can also be accredited to factors other than increase in conventional inputs. When this happens, then technical progress has taken place. In terms of the production frontier relationship, such a change represents a shift upward in the production frontier from point F to point G and can be displayed diagrammatically below:

Figure 3.2: Increment in Productivity



Source: Author's Design

Productivity is generally defined in terms of the efficiency with which inputs are transformed into useful outputs within the production method. Agricultural productivity increment is an essential source for increasing agricultural output, reducing poverty and enhancing food security. The concept of productivity growth has been a major indicator of aggregate output (Solow, 1957) and of agricultural output (Hayami and Ruttan, 1985).

3.3.3 Theoretical Framework for Stochastic Production Frontier Model

The stochastic frontier production function is defined as:

$$Y_i = f\left(X_i;\ \beta\right)\ exp\left(v_i - u_i\right)\ where\ i\ =\ 1,\ 2,\ \ldots,\ N \quad (8)$$

Where Y_i denotes the output level of the i^{th} sample farm, $f\left(X_i;\ \beta\right)$ denotes a suitable function such as Cobb-Douglas or translog production functions of the vector X_i, of input (comprising land, labour, fertilizer, intermediate cost etc) and a vector, β, of unknown parameters to be estimated. N represents the number of producers involved in the cross-sectional survey of the farms. Where v_i is a random error that is exogenous to the small-scale producers (e.g. measurement errors, extreme weather, industrial action, etc) not within the control of the agent and having zero mean, and it is assumed to be identically, independently normally distributed with mean zero and a constant variance, as $N(0,\sigma_v^{\ 2})$, (Coelli et al. 2005). The error term, u_i is also assumed to be distributed as a truncation of the normal distribution with mean μ_i and variance $\sigma_\mu^{\ 2}$; $\{u_i \sim N(\mu_i,\sigma_v^{\ 2})\}$ such that the inefficient error term is explained by some exogenous variables and it is specified as

$$\mu_i = f\left(Z_i;\delta\right) \quad (9)$$

Where Z_i is a 1 X n vector of exogenous variables which define inefficiency and δ_0 is an n X 1 set of unknown coefficients to be estimated.

Technical efficiency (TE) of an individual producer is the ratio of the observed output to the corresponding potential output, conditioned on the level of inputs and available technology used by the farm, which is evinced as:

$$TE_i = \frac{Y_i}{Y_i^*} = \frac{f\ (X_i;\ \beta)\ exp\ (v_i\ -\ u_i)}{f\ (X_i;\ \beta)\ exp\ (v_i)} = exp\ (-u_i) \qquad (10)$$

Where Y_i is the observed output and Y_i^* the potential frontier output. This expression implies that the difference between Y_i and Y_i^* is embedded in u_i. If $u_i = 0$, then $Y_i = Y_i^*$ meaning that the production lies on the frontier and hence technically efficient and the farm obtains its maximum potential output given the level of inputs. On the other hand, if $u_i > 0$, production lies below the frontier and the farm is technically inefficient ($Y_i < Y_i^*$).

Technical inefficiency can be measured by:

$$\text{Technical inefficiency} = 1 - TE_i \qquad (11)$$

The βs and δs are unknown parameters that are estimated by the method of maximum likelihood. Gamma (γ) is a measure of total variation of observed output from the frontier (deterministic) output and it is given as a ratio of the variance of the error associated with inefficiency (σ_μ^2) to the overall variation in the model (σ^2). The overall variation of the model is the sum of the variance of the error associated with inefficiency (σ_μ^2) and that associated with random factors σ_v^2.

The gamma (γ) estimate is given as $\gamma = \frac{\sigma_u^2}{\sigma^2}$ (12)

Battese and Corra (1977) considered the parameter γ to be bounded between zero and one. When the value of γ = 1 implies that the deviations from the frontier are completely due to technical inefficiency, whereas when the value γ = 0 means the deviations from the frontier are completely because of noise effects. Hence, when 0 < γ < 1, output variability is characterized by the presence of both technical inefficiency and stochastic errors.

3.4 Empirical Model Specifications

3.4.1 Intensity of Adoption

The intensity of adoption was calculated using the formula below:

Intensity of adoption = $\left[\frac{n}{N} x100\right]$ (13)

Where n is the number of producers that adopted a particular improved technology and N is the total number of producers. The intensity of adoption represents the percentage of small scale producers that have adopted the improved oil palm technologies in the study area.

3.4.2 Factors Influencing Adoption of Improved Oil Palm Technology

The empirical Poisson model used to assess the factors influencing adoption of improved oil palm technologies is specified below:

$$ADOPT = \beta_0 + \beta_1 GEN + \beta_2 AFR + \beta_3 EXV + \beta_4 HLB + \beta_5 TSH + \beta_6 HHS + \beta_7 ACR + \beta_8 AF + \beta_9 OC + \beta_{10} EDU + \beta_{11} RS + \mu_i \quad (14)$$

Where:

ADOPT = adoption (Count data is the weighted sum of improved technology adopted)

GEN = Gender of the producers (1 = male or 0 = Female)

AFR = Age the producer (in years)

EXV = Extension contact (1 if extension service available and 0 otherwise)

HLB = Hired labour (measured in man-days)

TSH = Type of Small-scale producer (1 = smallholder; 0 = independent producer)

HHS = Household size (measure in number)

ACR = Access to credit, dummy (1 if producer has access to credit and 0 otherwise)

AF = Age of farm (in years)

OC = Other income (measured in GH Cedis)

EDU = Education (in years)

RS = Residential status, dummy (1 if producer is native and 0 otherwise)

The dependent variable is a count data which is equal to the weighted sum of the improved technology adopted by each of the farmer. Maggino and Rubigloni (2011) posits that weights are assigned to variables because of the differences in contribution that each variable make to aggregate output, furthermore, weight should satisfy the following basic conditions: the weights are non-negative numbers, the weights for each case add up to unity, the weights may require to be rescaled in order to have an identical range, the weights are relating in some way to the corresponding score. Bobko et al. (2007) postulates that weights determined by using multiple regression maximizes the linear relationship between the independent variables and dependent variable (at least in the sample used to general the weights); it is statistically well defined and no additional inputs are needed from subject matter experts to generate weights; hence this procedure is more objectives them the experts opinion use to general weights for variables.

3.4.3 Empirical Model Specification for Stochastic Production Frontier

The translog model is assumed for the deterministic part of the production frontier; It is relatively flexible functional form, as it does not impose any assumption about constant elasticities of production nor elasticities of substitution between inputs. Also it does not impose an a priori assumption on the structure of the technology; instead, it allows the data to fit a technology and it is less restrictive and permits the combination of square and cross product terms to improve the fit of the model. Although the Cobb-Douglass model is used in the frontier studies and simple to implement, it restricts the return to scale to take the same value across all farms and assumes that the elasticity of substitution to be equal to one. It is specified as:

$$InQ_i = In\beta_0 + \sum_{j=1}^{7}\beta_j In\,X_{ji} + 0.5\sum_{j=1}^{7}\sum_{k=1}^{7}\beta_{jk} In\,X_{ji}\; In\,X_{ki} + \varepsilon_i \tag{15}$$

Where Q_i is the observed farm outputs measured in fresh fruit bunch harvested per hectare X_i's represent the input variables which are standardized by the farm size and are normalized by their respective sample means before they are log transformed and β_j denotes the estimated technology parameters. If, β_{jk} = 0 then the translog stochastic frontier model reduces to the Cobb-Douglass model given as:

$$InQ_i = In\beta_0 + \sum_{j=1}^{7}\beta_j In\,X_{ji} + \varepsilon_i \tag{16}$$

The empirical stochastic frontier production model applied in this research is:

$$InQ_{ij} = In\beta_0 + \alpha_1 InDF_i + \sum_{i=1}^{7} \beta_i In\,X_i + \frac{1}{2}\sum_{i=1}^{7}\sum_{j=1}^{7} \beta_{ij} In\,X_i\; In\,X_j + \varepsilon_i \qquad (17)$$

Where *i* and *In* are the i[th] producer and logarithm to base e, respectively; Y the quantity of fresh fruit bunch (in mt), X_1 is the land cultivated measured in hectares. DF is the dummy variable equal to one if the producers used fertilizer and zero otherwise; DF accounts for intercept change. The estimator for the responsiveness of oil palm output to fertilizer used could be bias without inclusion of DF (Battesa, 1997; Onumah et al., 2010); X_3 is the quantity of fertilizer measured in tons, X_4 is the hired labour used (measured in man-days), X_5 is the family labour used (measured in man-days), X_6 is the age of trees and X_7 is the intermediate cost measure in Ghana Cedis. It includes cost of agrochemicals, transportation and depreciated cost of capital inputs. And where $\varepsilon_i = v_i - u_i$.

3.4.4 Empirical Model Specification for Productivity

To measure the productivity levels of each of the inputs, the partial elasticity of production with respect to the individual inputs was computed from the translog production model. Since the model is of a translog form, the coefficients are not directly interpreted as elasticities of production as in the Cobb-Douglas form. Therefore, the elasticities are computed by rescaling the variables to have unit means which implies the coefficients of the squared term (β_{jj}) and the cross terms (β_{jk}) turn to zero and the first term (β_j) is interpreted directly as elasticities, as shown in the model below:

$$\varepsilon_q = \frac{\partial InE(Q_i)}{\partial InX_{ji}} = \left\{ \beta_j + \beta_{jj} InX_{ji} + \sum_{i=1}^{7} \beta_{jk} InX_{ki} \right\} = \beta_j \qquad (18)$$

Returns to scale (RTS) are computed for both independent and smallholder production functions and then compared. The RTS is the sum of the elasticities of output for the various inputs, given as:

$$RTS = \sum \varepsilon_q \tag{19}$$

Decision rule: RTS > 1 implies increasing returns to scale, RTS < 1 implies deceasing returns to scale and RTS = 1 implies constant returns to scale.

3.4.5 Empirical Model Specification for Technical Inefficiency

The technical inefficiency model is specified as follows:

$$\mu_i = \delta_0 + \sum_{i=1}^{8} \delta_i Z_i \tag{20}$$

Where the inefficiency factors are Z_1, Z_2, Z_3, Z_4, Z_5, Z_6, Z_7, and Z_8, which are defined in Table 3.1 below:

Table 3.1: Description of Variables in the Inefficient Model

Variable	Description	Unit
Z_1	Adoption	Number
Z_2	Land ownership	Dummy (1 = own land or 0 = otherwise
Z_3	Formal education	Year
Z_4	Access to credit	Dummy (1 = access to credit or 0 = otherwise
Z_5	Household size	Number
Z_6	Extension visit	Number
Z_7	Experience	Nears
Z_8	Smallholder	Dummy (1 = smallholder or 0 = independent)

These variables have direct influence on the producers' efficiency and are included in the model to indicate their possible contribution and influence on technical inefficiencies of the producers; hence they are determinants of technical efficiency that indicate possible effects of producers characteristics on technical efficiency in order to be able to come out with recommendations concerning how government policy could be used to influence these variables so as to enhance the technical efficiency of the producers.

3.4.6 Description and Measurement of Variable Used in the Frontier Model

Output: this is the total quantity of fresh fruit bunch harvested, measured in metrics ton during the 2011/2012 production season.

Land size: land is prime input for agricultural production. Land size refers to the land under oil palm cultivation for each individual producer and it is measured in hectares. The size of the farm land influences output positively, all things being equal.

Fertilizer: this is the quantity of fertilizer applied to the oil palm, measured in Kg during the 2011/2012 production season.

Labour: this is defined as the number of people who work on the oil palm farm throughout the production season and it is measured in man-days. It is assumed that oil palm production increases with labour input, all things being equal. Labour performs activities such as weeding, fertilizer application, harvesting, pruning and transportation. This study considered both hired and family labour in terms of male, female and children.

Age of trees: this is the model age of the most oil palm trees on the farmed mesued in years. This variable is included because it is expected to affect yield in a quadratic form.

All things being equal, we expect that output increases from first harvest over time, reaches a peak and then declines.

Intermediate cost: this variable captured cost used in production for capital item, transportation to factory, due to association and weedicide used.

The stochastic production frontier is run separately for the independent producers, smallholder producers and for the combination of the producers.

3.4.7 Statement of Hypothesis

The following hypotheses are tested to ascertain adequacy of the functional form adopted for the data, to determine whether adoption of improved oil palm technology and technical inefficiency significantly explains output variability, and whether the exogenous variables and the conventional input variables in the technical inefficiency model play a role in explaining technical inefficiency. Hypothesis two and three do not considered smallholder because all the smallholders are using fertilizer and adopting all the improved technologies, therefore there was no dummy variables to cater for non-use of fertilizer in the smallholder model and no adoption variables. The hypothesis are specified as below:

Table 3.2: Hypothesis Tested and their Description for the Three Model Used

Null hypothesis	**Description**
1. Independent Smallholder Combined	
$H_0: \beta_{ij} = 0$	Coefficients of the second-order variables in the translog model is zero
$H_1: \beta_{ij} \neq 0$	Coefficients of the second-order variables in the translog model is not equal to zero
2. Independent Combined	
$H_0: \alpha_i = 0$	Intercept coefficients is zero
$H_1: \alpha_i \neq 0$	Intercept coefficients is not equal to zero
3. Independent Smallholder Combined	
$H_0: \gamma = \delta_0 = \delta_1 \ldots\ldots \delta_8 = 0$	There are no inefficiency effects
$H_1: \gamma \neq \delta_0 = \delta_1 \ldots\ldots \delta_8 = 0$	There are inefficiency effects
4. Independent Smallholder Combined	
$H_0: \gamma = 0$	Inefficiency effects are non-stochastic
$H_1: \gamma \neq 0$	Inefficiency effects are stochastic
5. Independent Smallholder Combined	
$H_0: \delta_0 = \delta_1 = \delta_2 \ldots\ldots = \delta_8 = 0$	The inefficiency error term follows a half normal distribution
$H_1: \delta_0 \neq \delta_1 = \delta_2 \ldots\ldots = \delta_8 = 0$	The inefficiency error term does not follows a half normal distribution
6. Independent Smallholder Combined	
$H_0: \delta_1 = \delta_2 \ldots\ldots = \delta_8 = 0$	Farm specifics factors do not influence the inefficiencies
$H_1: \delta_1 \neq \delta_2 \ldots\ldots \neq \delta_8 \neq 0$	Farm specifics factors do influence the inefficiencies
7. Independent Combined	
$H_0: \delta_1 = 0$	Adoption has no influence on technical efficiency
$H_1: \delta_1 \neq 0$	Adoption has influence on technical efficiency

Source: Survey Data 2011/2012

3.4.8 Statistical Testing Technique for the Hypotheses

The Generalized Likelihood Ratio Statistic (LR) was used to test the hypotheses. It is given as

$$LR = -2\left[In\left\{L(H_0)\right\} - In\left\{L(H_1)\right\}\right] \tag{21}$$

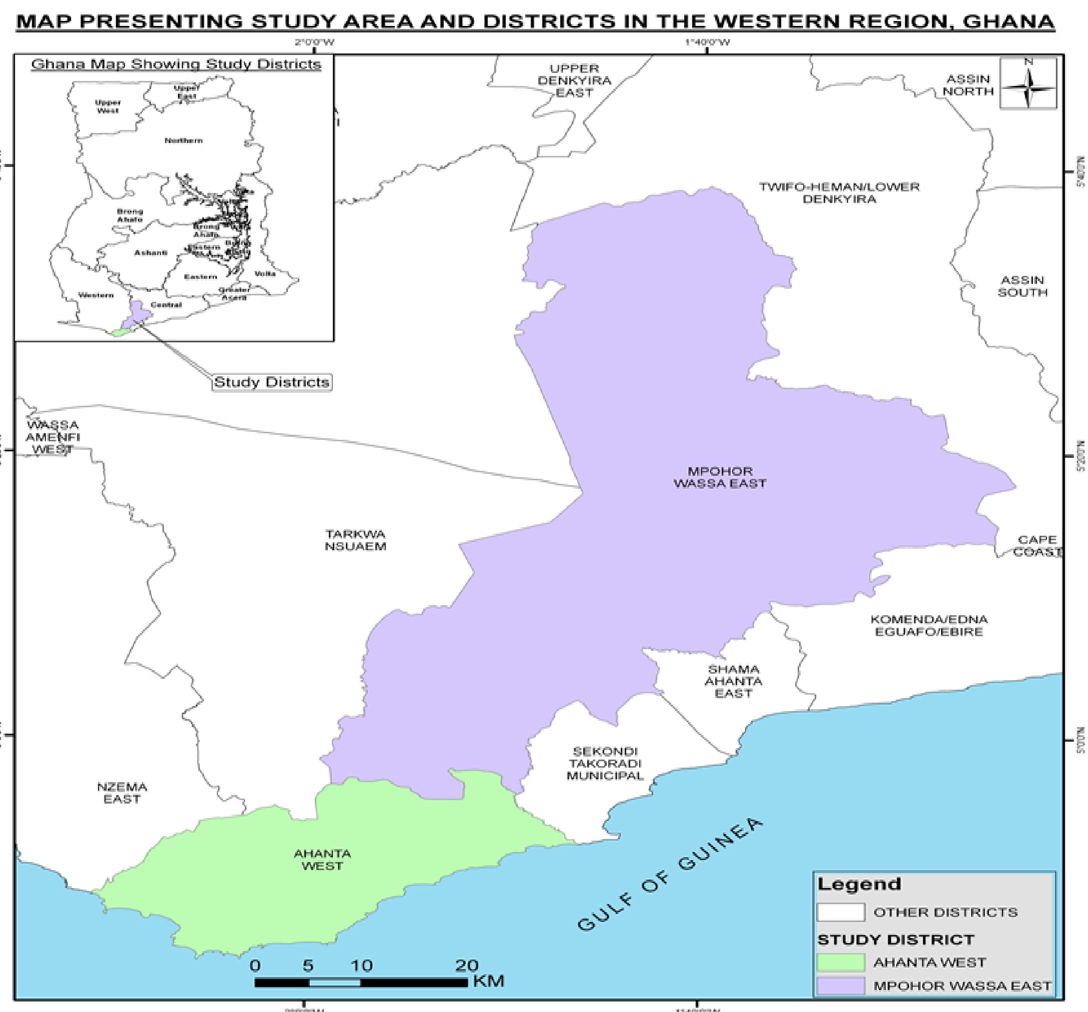
Where $L(H_0)$ and $L(H_1)$ are values of likelihood function under the null (H_0) and alternative (H_1) hypotheses (restricted and unrestricted models), respectively. LR has approximately a Chi-square (or mixed Chi-square) distribution if the given null hypothesis is true with degrees of freedom equal to the numbers of estimated parameters assumed to be zero for (H_0). However, where the test of the hypothesis involves $\gamma = 0$, then the asymptotic distribution requires the use of the mixed Chi-square distribution (Kodde and Palm 1986).

3.5 Description of the Study Area

The study was conducted in the Western Region of Ghana, an important oil palm production region that accounts for the second highest area (28%) under oil palm cultivation in Ghana (MoFA, 2011). It is bordered on the East by the Central Region, to the West by La Côte d'Ivoire, to the North by Ashanti and Brong-Ahafo Regions, and to the South by the Gulf of Guinea, moreover the southernmost part of Ghana lies in this region, at Cape Three Points near Busua, in the Ahanta West District. The Western Region has co-dominated the oil palm sector with the Eastern Region from its unset and is home to three large-scale plantations and mills, few medium-scale plantations and several small-scale farms.

The Western Region contains twenty one districts including the four new districts added in 2012 and oil palm is mainly produced in four districts namely: Ahanta West, Mpohor, Wassa East and Juaboso. Agricultural activities are mainly subsistence and complemented by large-scale agriculture. Major categories of crops grown in the region include staples food and cash crops. The output per yield is substantially low in the district due to traditional methods of farming with an average farm size of one acre per producer (MoFA 2012).

Figure 3.3: Study Area and Districts in the Western Region



Source: RS/GIS Laboratory, University of Ghana

Oil palm is cultivated on a large-scale by Benso Oil Palm Plantation (BOPP), NORPALM and Ayiem Oil Mills. Some indigenous and settlers producer also cultivate oil palm on medium and small-scales. Hence the study was conducted in three Districts including Ahanta West, Mpohor, Wassa East Districts. Note that the map captured only two Districts because Mpohor Wassa East was divided into two Districts in 2012 (Mpohor and Wassa East Districts) and the border demarcation has not yet being finalized. These districts contain the highest number (1182) of small-scale oil palm producers in the region with 1976.6ha area cropped in 2005 **(**SRID/MoFA, 2006).

3.5.1 Climate

The climate of Western Region ranges from cool to warm. It has 75% of its vegetation within the high forest zone of Ghana, and lies in the equatorial climatic zone that is characterized with moderate temperatures. The average temperature of the area is 22^0c. Generally the climate of the area is characterized as tropical rain forest zone. The region has two seasons, the dry season (November – February) and rainy seasons (major from March to July and minor from September to November). It is the wettest part of Ghana and is characterized with an average rainfall of 1600mm per annum and the major dry season drought is not severe, therefore the oil palm crop is subjected to markedly less severe water stress during the dry season (MoFA, 2012). These climatic conditions are conducive for the growth of the oil palm in the region.

3.5.2 Population

According to the 2010 population and housing census from the Ghana Statistically Service, the Western Region has a total population of 2,376,021 (GSS, 2005) of which male and female are 1,149,812 and 1,157,583 respectively.

3.5.3 Economic Activities

According to MoFA (2012) the region is endowed with extensive natural resources which give it a significant economic position and potential within the framework for national development. It is the longest producer of cocoa, rubber, and coconut in the country and one of the major producers of oil palm. Moreover the recent discovery of oil in commercial quantities has boasted economic activities in the region. In the Western Region (www.ghanadistricts.com), agriculture accounts for about 60% of the region’s GDP and is the main occupation of its citizenry, employing about 57 percent of the total labour force in the Region. There are more females (59.5%) than males (56.7%) in agriculture. The main crops grown in the region are maize, cassava, plantain, yam, cocoyam, rice, cocoa, coconut, rubber, oil palm and coffee. There is also poultry production, grass-cutter and fish production.

From the Table 3.2 below, the arable land available in the Region for agricultural production is 73.8%, of which 38.1% is currently under cultivation and the balance 34.7% is yet to be cultivated.

Table 3.3: Land Allocation of the Western Region

Land type	Land size	Percent
Arable land	17,641 km^2	73.8% of land area
Land under cultivation	6,720 km^2	38.1% of arable land area

Source: MoFA 2012

3.6 Data type, Sampling and Data Collection Methods

Cross sectional farm level data on output, inputs variables and relevant socioeconomic characteristics using structured questionnaires was collected from 250 producers in the Western Region of Ghana. The respondents included 122 smallholder producers from the large plantations and 128 independent small scale producers, who don't received any support from the companies. A structured questionnaire with both open and close ended questions was used to collect the data from the respondent. Interview with key informers was also conducted with the management and staff of BOPP and NORPALM to collect information on oil palm production under the plantation system. Where it was necessary the producers' responses were validated from their record books. The enumerators recruited were knowledgeable in oil palm production and trained on the data collection techniques. The researcher monitored each enumerator during the collection of the data. A pilot survey was conducted in the districts to help improved upon the questionnaire.

The independent producers' data were collected across the three Districts, 50 from Ahanta West and Mpohor and 28 from Mpohor/Wassa East. On the other hand for the smallholder producers' data were collected from two plantations namely NORPALM located in Ahanta West with sample size of 10, while BOPP located in the Mpohor/Wassa East had sample size of 115 (See Appendix 2).

The sample was selected using purposive and random sampling techniques. Purposive sampling technique was used to select the districts and communities, because oil palm production in the region is mainly concentrated in these districts and communities. Following this, the respondents were randomly selected from the two different groups. This procedure was adopted to take into account the differences in production conditions and to compare and analyse production efficiencies across the two small-scale farms in the study area.

3.7 Method of Data Analysis

Data was analysed using the descriptive and inferential statistics and econometric model. Stata was used to provide frequencies, mean, median, standard deviations and estimates regression. The Frontier 4.1 was used to estimate the maximum likelihood estimates of the stochastic production frontier.

3.8 Conclusion

The conceptual framework describes various factors that affect adoption and technical efficiency. Moreover if these factors affect adoption negatively, they reduce productivity. In the theoretical model, the Poisson model was used to analyse factors that influence the adoption of improved technology. Also the stochastic frontier production function was used to analyse the technical efficiency and the factors influencing the efficiency of the producers. The software Stata and Frontier 4.1 were employed to analyse the models of adoption and technical efficiency. The research covered Three Districts and two companies' area in the Western Region where palm oil is predominantly produced and the sample size is 250 small-scale oil palm producers.

CHAPTER FOUR

RESULTS AND DISCUSSION

4.1 Introduction

This chapter presents the results and discussion of the study. It describes the socio-economic characteristics of the respondents in the study area, and analyses the estimates of productivity, adoption model and technical efficiency. The factors that influence technical inefficiency are also discussed.

4.2 Socioeconomic Characteristics of Respondents

The socioeconomic characteristics of the respondents discussed in this section are the age of the producer, gender, education level, household size, residential status, access to credit, farming experience and member of a farming organization.

The ages of the producers range between 20-86 years, with an average of 50 years (Table 4.1). The majority (62.8%) of the producers are aged between 41-60 years. This implies that oil palm production is dominated by middle aged producers; moreover, it serves as a means of employment for the producers and provides income to meet the basic needs of the family. Furthermore it provides a source of livelihood for the aged.

Men dominate oil palm production (76.8%). This is because oil palm cultivation and maintenance are labour and cost intensive which discourages most females from investing their little share of household resources into oil palm production. Moreover, in Ghana land is mostly owned and controlled by the male head of the household.

Table 4.1: Socioeconomic Characteristics of Oil Palm Producer

Socioeconomic variables	Independent producers (n = 128)		Smallholder producers (n = 122)		Combined (250)	
	Freq.	%	Freq.	%	Freq.	%
Producer age range						
20-30	8	6.3	6	4.9	14	5.6
31-40	26	20.3	12	9.8	38	15.2
41-50	49	38.3	36	29.5	85	34.0
51-60	36	38.3	36	29.5	72	28.8
61-70	8	6.3	21	16.8	29	11.6
71-86	1	0.8	12	9.0	13	5.2
Mean	46.5		54.3		50	
Minimum	20		26		20	
Maximum	74		86		86	
Gender						
Female	24	18.8	31	25.4	55	22
Male	106	81.2	91	74.6	197	78.8
Education level						
None	18	14.1	31	24.8	49	19.6
Primary	19	14.8	12	9.6	31	12.4
Middle school/JHS	76	61.7	66	52.8	142	56.8
Senior Secondary school	5	4.7	12	9.6	17	6.8
Vocational/polytechnic	5	3.1	3	2.5	8	3.2
University	2	1.6	1	0.8	3	1.2
Mean	9.9		8.9		9.4	
Minimum	0		0		0	
Maximum	19		21		21	
Household size						
1 – 5	53	41.4	44	35.2	97	38.8
6 – 10	71	55.5	67	53.6	138	55.2
11 – 15	4	3.1	11	8.8	15	6.0
16 – 20			3	2.4	3	1.2
Mean	6.0		7.2		6.6	
Minimum	3		3		3	
Maximum	13		20		20	
Residential status						
Native	103	80.5	102	83.6	205	82.0
Settler	25	19.5	20	16.4	45	18.0
Access to credit						
Yes	8	6.3	122	100	130	52.0
No	120	93.7			120	48.0
Farming experience						
1 - 10	47	36.6	11	8.8	58	23.2
11 – 20	64	50	84	68.9	148	59.2
21 – 30	13	10.2	24	19.2	37	14.8
31 – 41	4	3.2	3	2.4	7	2.8
Membership of farming organization						
Member	5	4	122	100	127	50.8
Non-member	123	96			123	49.2

Source: Survey Data, 2011/2012

According to Goldstein and Udry (2002), the primary source of land in rural communities is allocated family land and it is mainly controlled by the man who is the head of the family; women rely more on allocated household land, which is given to them by their husbands or other family members.

The majority (56.8%) of the oil palm producers have middle school or junior high education. This implies that most of the producers have attained basic level education. Furthermore 19.6 percent have no formal education.

The sizes of the households range from 2-20 members, with an average of 7 and the majority (56%) of the producers have household sizes that range between 6-10 members. Mugisha et al. (2012) observed that producers had an average household size of seven members in Uganda and a large household is an endowment and a reliable source of labour given the labour intensive nature of agricultural technologies, if household members are available to work on the farm as family labour.

The majority (80.8%) of the producers were natives of the community. This implies that oil palm cultivation is mainly in the hands of indigenes of the District, and therefore income generated from oil palm production by the natives of the Districts is likely to be used to improve the livelihood of the community members. Moreover, any policy geared towards investing in improving small-scale oil palm production that includes partnership with the community will be most appropriate because the indigenous population own the land and this will minimize issues surrounding land.

The companies used credit to establish and maintain the farms for the smallholder producers, unlike their independent counterpart who do not have access to credit for the establishment and maintenance of their farms. Referring to Table 4.1, all the smallholder producers have access to credit compared to only 5.5% of the independent producers who have access to credit. Access to credit by the independent producers should be improved because it may enable the producers to adopt improved technologies and use other productivity enhancing inputs which enhance productivity.

The farming experience of the respondent as depicted in Table 4.1 range between 5 - 41 years. The majority (59.6%) of the oil palm producers have farming experience between 11 - 20 years, and the average producer experience is 17 years. In cocoa farming, as found by Aneani et al. (2011), the average experience of cocoa producers was 19.6 years. These results imply that the relatively old age of the producers translates into more years of farming experience as most started farming at an early age. The long years of experience can increase their confidence in adopting improved oil palm technologies.

The majority (52%) of the producers are members of the producer based organization for the plantations (Table 4.1); the rest of the producers were not members of any producer organizations or the farming organization they belonged to had stopped functioning four years earlier. One hundred and twenty two (122) producers are smallholders producing for the plantation; membership in plantation’s producer groups is compulsory. Producer organizations play a pivotal role in negotiating input and output prices and providing a good working environment for it members. This implies that since the independent producers lack strong organization, there is no uniformity in the prices for sale of their outputs and they are unable to negotiate for credits and lower prices for inputs.

4.3 Adoption of Technology

4.3.1 Intensity of Improved Oil Palm Technology Adoption

The improved oil palm technologies that are essential for increasing productivity in the oil palm sector are: certified seedling, fertilizer, cover crop, triangular planting distance, two stage nurseries, black poly-bag and wire collar mesh. The numbers of improved oil palm technologies all producers adopted range from 0 to 7 (Table 4.2). The mean level of intensity of adoption of technology for independent farmers is 3.41 and for smallholder farmers is 7. For the combined effect, the mean level of intensity of adoption of technology is 4.3. About 10.9 percent of independent producers adopted none of the improved technologies. A majority of 53.1 percent of independent producers adopted 4 – 6 of the technologies. On the contrary, smallholder producers adopted all the technologies and are the most productive with an estimated average productivity of about 16.7 ton/ha. This is followed by the independent producers who adopted six of the improved technologies with an estimated average productivity of 9.10 ton/ha. This implies that oil palm productivity increase as the number of improved technologies adopted increases. The Ghana Tree Crop Policy based on FASDEP II, which was developed in 2010 by MoFA, sought to intensify the use of improved technologies to increase productivity and ensure competitive and sustainable tree crops subsector (MoFA, 2011).

Table 4.2: Intensity of Improved Oil Palm Technology Adoption and Productivity

Type of producer	Number of improved oil palm technologies	Number of adopter	Percent of adopter	Yield (tons/ha)
	0	14	10.9	3.67
	1	16	12.5	4.13
Independent	2	20	15.6	4.50
Producer	3	10	7.8	6.78
	4	14	10.9	7.20
	5	29	22.7	8.00
	6	25	19.5	9.10
	Total	**128**		
Smallholder Producer	7	122	100.0	16.7
	Group total	**250**		

Source: Survey Data 2011/2012

4.3.2 Determinants of Intensity of Adoption of Improved Technologies

Each of the improved technologies does not contribute equally to output and as such weights are estimated based on the contribution of each improved technologies to output. These weights are assigned to each improved technologies to cater for the differential importance and are used to assign weight to each improved technologies, to estimate the regression. From the estimated marginal effects (See Appendix 4) of each of the improved technologies, fertilizer contributed the most to output and thus has the largest weight, followed by certified seedlings. The technology that contributed the least to output is black ultraviolet (UV) stabilized poly-bag used in nurseries (See Table 4.3 below).

The improved technologies considered in this study do not contribute equally to output, weights are estimated and assigned to each of the improved technologies based on their contribution to aggregate output. Maggino and Ruvigloni (2011) asserts that choice of weights should be preferably derived from objective principle and that weights are assigned because of the difference contributions each input makes to aggregate output. The weights in Table 4.3 below are assigned to each improved technologies and used to estimate the dependent variable for the Poisson regression since it has a count dependent variables. The argument is that each improved technology made different contributions to output. Moreover, Bobko et al. (2007) assert that weights determined by using multiple regressions is statistically well defined and no additional inputs are needed from subject matter experts to generate weights.

Table 4.3: Relative Weights Assigned to Technologies Adopted by Producers

Variable	Weights
Fertilizer	0.33
Certified Seedling	0.21
Leguminous cover crop	0.19
Two stage nurseries	0.12
Wire mesh	0.07
Triangular planting distance	0.06
Use of black poly bag in nurseries	0.02
Total weight	1.00

Source: Survey Data 2011/2012

Table 4.4 presents the estimates of the Poisson regression model. The results indicate that Extension contact, use of hired labour, smallholder and producers' access to credit are the main factors that significantly influence the intensity of adoption of improved technologies. Extension contact was positive and significant, which implies that exposing more producers to extension services will help producers to adopt more improved oil palm technologies.

Table 4.4: Poisson Model for Factors Influencing the Intensity of Adoption. Dependent variable is the assigned weights multiply by the number of improved technology adopted

Explanatory variable	Coefficient	Robust Std. Err.	P > |z|
Gender	0.0227	0.0487	0.642
Age of the producer	0.0014	0.0018	0.440
Extension contact	0.4221***	0.9700	0.000
Hired Labour	0.0026***	0.0008	0.002
Type of Smallholder	0.2986***	0.0944	0.002
Household size	0.0038	0.0053	0.467
Access to credit	0.1823*	0.0967	0.060
Age of farm	-0.0120	0.0130	0.105
Other source of income	0.0805	0.0570	0.158
Education	0.0032	0.0036	0.368
Resident Status	0.0383	0.0434	0.378
Number of observation	250		
Pseudo R^2	0.0516		
Wald Chi^2	208.27		
Log pseudo-likelihood	-217.166		

*** and * represents 1% and 10% significance levels respectively **Source: Survey Data, 2011/2012**

The use of hired labour had a positive and significant influence on the intensity of adoption. The result is particularly important for oil palm production which is labour intensive and producers who used hired labour can supplement family labour to cope with the labour requirements of improved technologies in oil palm production.

The positive and significant effect of smallholder variables suggests that as more farmers become smallholders, this will help to increase their intensity of adoption of improved oil palm technology. Hence this emphasize the need for independent producers to come under the supervision of the plantation to receive similar inputs and services like the smallholder producers.

Access to credit as expected increases the intensity of adoption of improved oil palm technologies and it highlights the importance of providing producers with credit to support their agricultural activities in securing productivity enhancing inputs. Mugusha et al. (2012) have reported that access to credit had a positive and significant influence on the rate of technology adoption and in some cases is a significant condition to adopting a particular technology package.

4.4 Productivity Differentials of Independent and Smallholder Producers

The mean output of smallholder and independent producers are 56.8 ton and 21 ton respectively (Appendix 5), with average land size of 3.4 ha and 3.1 ha, and mean yields of 16.7 ton/ha and 6.8 ton/ha, respectively. These estimated yields are slightly higher than national yield of 7-10 ton/ha and 3 ton/ha for smallholder and independent producers respectively (MoFA, 2012). The mean hired labour and family labour are 80.8 man-days and 31.6 man-days, respectively for the two groups of producers combined. This is expected, given the tedious task involved in oil palm production. The intermediate cost, which includes cost of weedicide, transportation and depreciated cost of capital inputs, for both independent and smallholder producers is high, with means of 529.8 and 764 Ghana Cedis respectively. This is expected because on average, farms operated in the study districts are medium sized (3.2 ha) and require more labour input, operating cost and other inputs cost.

On average there is high usage of fertilizer of 1505.3 kg; this is expected because it is the main nutrient source for oil palm growth and productivity, Most of the soils in the district is gradually being depleted of nutrients and therefore require high fertilizer input. The high usage of fertilizer is mainly among the smallholder producers who used 2838 kg on the average; the independent producers on average used 150 kg fertilizer. This is due to the fact that independent producers are not aware of the effects of fertilizer and are often discouraged by their prices, especially when compared to the price of subsidised fertilizer. Furthermore, the dosage and frequency of application is often not known by the independent producers who have little access to extension services to access information on the adequate usage of inputs.

The average age of the farm is 13 years; this implies that the farms are well into their productive life span and those that have the maximum age of 29 are into the declining period. In this case replanting is required because the productivity of trees will have dropped drastically. According to Hasnah et al. (2004), improved oil palms usually start producing at three to four years and yields peak between 9 – 12 years. Yield starts to decline by the fifteenth year.

The maximum likelihood estimates for parameters of the frontier model are presented in Table 4.5; the estimates are explained in terms of the output elasticities. For the independent producers a percentage increase in the size of land, quantity of fertilizer, levels of hired and family labour, and intermediate costs will increase output. This scenario is expected as the level of output depends to a large extent on the quantities of these inputs used on the farm. Conversely, the opposite is observed in the average age of the oil palm trees. This implies that as oil palm tree gets older, as productivity reaches its peak, it gradually starts to fall. This was also observed by Onumah et al. (2013) in their study on productivity and technical efficiency cocoa production in Eastern Region of Ghana.

On the other hand, all the input variables influence smallholder producers as in the independent model. The negative effect of average age of oil palm trees is an indication for producers to replace their trees with new ones. Oil palm yield starts to decline after fifteen years of production; hence according to Ismail and Mamat (2002), the optimum replanting age of the oil palm is between 24 – 26 years, when yield is at its lowest. The three models exhibited increasing returns to scale, which implies that a percentage increase in the level of all input factors utilized will result in 1.05 percent and 1.159 percent increase in the level of output observed, respectively.

Table 4.5 Productivity Estimates (Elasticity and Returns to Scale of Production)

Variable	Independent	Smallholder	Combined
Land (hectare)	0.649	0.609	0.767
Fertilizer (Kg)	0.364	0.286	0.261
Hire Labour (man-day)	0.052	0.071	0.095
Family Labour (man-day)	0.070	0.002	0.023
Age of Farm (year)	-0.302	-0.187	-0.117
Intermediate cost (Ghana cedis)	0.217	0.249	0.145
RTS	**1.05**	**1.03**	**1.174**

Source: Survey Data, 2011/2012

4.5 Hypothesis Testing of Frontier Models

The following hypotheses are important to determine the adequacy of the specified model used, the presence of technical inefficiency and the significance of the technical inefficiency model. Seven hypotheses are tested using the LR tests to assess whether the effects of these variables on technical efficiency are significant. Results are presented in Table 4.6 below. The null hypothesis that the Cobb-Douglass model is an adequate representation was rejected in favour of the translog at 5% significant level. Similarly Chen et al. (2009), used the translog to estimate stochastic production frontier for farm groups in four regions in China over the period from 1995 – 1999.

The second hypothesis for the intercept coefficients for fertilize (DF) in the independent and combined models are both negative and significant for the independent model, indicating that there could be biased estimators of the parameter in the frontier function without inclusion of the dummies.

The third hypothesis tested for the presence of technical inefficiency effects in the model and it was rejected at 1% level of significance, hence suggesting that inefficiency effects are present in the model. The third hypothesis that inefficiency effects are non-stochastic is also rejected at 5% level of significance suggesting that inefficiency effects are stochastic. This indicates that the stochastic production model is appropriate to use compared to the average production response function. The fourth hypothesis that the technical inefficiency effect has a traditional half-normal distribution with mean zero as against the truncated normal distributional assumption was rejected. The traditional half-normal distribution assumes that the mean of the inefficiency error term to be zero, on the other hand the truncated normal assumes a mean, μ for the inefficiency error component.

Table 4.6: Results of Hypothesis Tested

Null hypothesis	Test Statistic	Critical value	Decision
1. Independent	33.24	32.67	Reject H_0
Smallholder	106.2	32.67	Reject H_0
Combined	61.68	32.67	Reject H_0
$H_0: \beta_i = 0$			
$H_1: \beta_i \neq 0$			
2. Independent	8.98	3.84	Reject H_0
Combined	5.54	3.84	Reject H_0
$H_0: \alpha_i = 0$			
$H_1: \alpha_i \neq 0$			
3. Independent	65.02 [A]	20.97 [B]	Reject H_0
Smallholder	46.53 [A]	20.97 [B]	Reject H_0
Combined	94.55 [A]	20.97 [B]	Reject H_0
$H_0: \gamma = \delta_0 = \delta_1 \ldots.. \delta_8 = 0$			
$H_1: \gamma \neq \delta_0 = \delta_1 \ldots.. \delta_8 = 0$			
4. Independent	3.24 [A]	2.71 [B]	Reject H_0
Smallholder	19.37 [A]	2.71 [B]	Reject H_0
Combined	2.98 [A]	2.71 [B]	Reject H_0
$H_0: \gamma = 0$			
$H_1: \gamma \neq 0$			
5. Independent	32.33	23.21	Reject H_0
Smallholder	27.18	23.21	Reject H_0
Combined	93.52	23.21	Reject H_0
$H_0: \delta_0 = \delta_1 = \delta_2 \ldots\ldots = \delta_8 = 0$			
$H_1: \delta_0 \neq \delta_1 \neq \delta_2 \ldots\ldots \neq \delta_8 \neq 0$			
6. Independent	64.66	20.09	Reject H_0
Smallholder	26.4	20.09	Reject H_0
Combined	88.26	20.09	Reject H_0
$H_0: \delta_1 = \delta_2 \ldots\ldots = \delta_8 = 0$			
$H_1: \delta_1 \neq \delta_2 \ldots\ldots \neq \delta_8 \neq 0$			
7. Independent	57.72	6.64	Reject H_0
Combined	27.58	6.64	Reject H_0
$H_0: \delta_1 = 0$			
$H_1: \delta_1 \neq 0$			

Values with [A] are test of one sided error from the Frontier 4.1 output of the maximum likelihood estimates.
Values with [B] are the critical values under the mixed chi-square distribution
The correct critical value for the hypotheses involving γ are obtained from Table 1of Kodde and Palm (1986, p. 1246)
Source: Survey Data, 2011/2012

The fifth hypothesis that all coefficients of the inefficiency model are zero except for the constant term is also rejected. This implies that the joint effects of inefficiency factors involved in the model are important in explaining the variation in production of oil palm production in the Western Region, even some individual effects of some variables may not be significant. The sixth hypothesis that adoption has no effects on productivity and technical efficiency is core to the research. The hypothesis was strongly rejected for the independent and combine data, revealing that adoption have significance effect on technical efficiency.

The variance parameters are integral components of the stochastic frontier production function and are represented by sigma squared and gamma and both are significantly different from zero at one percent. This implies that the ordinary least squares estimate (OLS) is not adequate to explain the inefficiencies on oil palm farms; the specification of a stochastic frontier production function is therefore justified. The gamma estimates, which measure the deviation of the observed output from the frontier output are 0.99 and 0.99 for the independent and smallholder producers, respectively (Table 4.8 and Table 4.9) and 0.96 for the combined data. This implies that most of the deviations in total output in both models are largely due to inefficiencies in inputs used and other farm practices, whereas random factors contribute 1% each to deviations of actual output from the frontier output for the independent and smallholder producers and 4% for the combined model, respectively. Some of the random shocks could be unfavourable weather conditions (rain fall patterns and sun shine duration), pest and disease infestation and statistical errors in data measurement and model specification.

4.6 Parameter Estimates of the Stochastic Frontier Production Function

The estimates of the stochastic frontier models for the independent and small-scale oil palm producers are presented in Table 4.8 and Tables 4.9 respectively.

All the input variables in the model for independent producers met the apriori signs. The contribution of land, fertilizer, hired and family labour, intermediate cost to output was positive, whereas that of the age of the tree is negative. Land and fertilizer contributions are significant. This implies that land and fertilizer are critical factors in oil palm production in the study area, thus a percentage increase in the quantity of land and fertilizer will result in a 0.649% and 0.364% increase in total output respectively. It can be observed that, output response to land is greater than fertilizer. This suggests that more attention should be given to land amendment to increase its fertility level, as a means of increasing productivity of oil palm, because most of the land is gradually being depleted of require nutrients and as such any programme to complement the existence fertilizer subsidize programme, will help increase output in the sector. Moreover, Oil palm needs a lot of fertilizer when it is young to help form its leaves and make the fruit clusters bigger when the palm is bearing fruits.

Table 4.7: Parameter Estimates of Independent Producers Model

Variable	Parameter	Coefficient	t-ratio
Constant	β_0	3.745***	4.306
Ln (Land size)	β_1	0.649**	1.674
Fertilizer Dummy	α_1	-3.469***	-4.105
Ln (Fertilizer)	β_2	0.364***	4.136
Ln (Hired labour)	β_3	0.052	0.424
Ln (Family labour)	β_4	0.070	0.840
Ln (Age of tree)	β_5	-0.302	-1.196
Ln (Intermediate cost)	β_6	0.217	1.159
Ln (Land square)	β_7	-1.229*	-1.305
Ln (Fertilizer square)	β_8	-0.119*	-1.584
Ln (Hired labour square)	β_9	-0.085	-0.354
Ln (Family labour square)	β_{10}	-0.234*	-1.351
Ln (Age of tree square)	β_{11}	0.015	0.027
Ln (Intermediate cost square)	β_{12}	-2.686***	-3.362
Ln (Land*Fertilizer)	β_{13}	-0.246***	3.326
Ln (Land*Hired labour)	β_{14}	-0.034	-0.07
Ln (Land*Family labour)	β_{15}	-0.285	-0.76
Ln (Land*Age of tree)	β_{16}	1.148*	1.34
Ln (Land*Intermediate cost)	β_{17}	2.403	3.63
Ln (Fertilizer*Hired labour)	β_{18}	0.017	0.59
Ln (Fertilizer*Family labour)	β_{19}	0.004	0.17
Ln (Fertilizer*Age of tree)	β_{20}	-0.063**	-1.69
Ln (Fertilizer*Intermediate cost)	β_{21}	0.162***	4.09
Ln (Hired labour* Family labour)	β_{22}	-0.064	-0.42
Ln (Hired labour*Age of tree)	β_{23}	0.311	0.57
Ln (Hired labour*Intermediate cost)	β_{24}	-0.068	-0.17
Ln (Family labour*Age of tree)	β_{25}	-0.231	-0.65
Ln (Family labour*Intermediate cost)	β_{26}	0.427**	1.85
Ln (Age of tree*Intermediate cost)	β_{27}	-1.002*	-1.53
Gamma		0.99***	1.83E07
Log-likelihood value		128.796	
LR test for one-side error		46.530	
Sigma square (σ^2)		0.098***	7.896

***, ** and * represents 1%, 5% and 10% significance levels respectively

Source: Survey Data, 2011/2012

On the other hand, all inputs variables of the smallholder model are positive, except for age of the tree, and all the inputs variables in the model of independent producers are significant except for family labour. From Table 4.7, a percentage increase in the land size, fertilizer, hired labour and intermediate costs will respectively result in 0.609%, 0.286%, 0.071% and 0.248% increases in total output. However, a percentage increase in age of the trees results in a 0.187% decrease in total smallholder output. This suggests that as the age of the oil palm tree increases, the lesser the yield derived from it. As posited by Ismail and Mamat (2002) Oil palm yield starts to decline after fifteen years of production and output drastically reduced between 24 – 26 years. It can be observed that in the smallholder model, output is most responsive to land size and the quantity of fertilizer used. One of the foremost principles that smallholder production strives on is to adopt improved technologies similar to the plantation, thereby increasing output without necessarily increasing the land size and applying fertilizer adequately to improved soil fertility. This suggests that to achieve higher outputs under the smallholder model, producers are required to effectively utilize the appropriate improved technologies, which include the right fertilizer usage and other management practices, because land is limited and expansion of land as a means of increasing productivity is not the best option. Therefore, independent producers should learn from the methods applied by smallholders to boost land productivity and other environmentally friendly management practices that are within their reach.

Table 4.8: Parameter Estimates of the Smallholder Model

Variable	Parameter	Coefficient	t-ratio
Constant	β_0	0.090***	4.055
Ln (Land size)	β_1	0.609***	3.438
Ln (Fertilizer)	β_2	0.286***	2.766
Ln (Hired labour)	β_3	0.071**	1.786
Ln (Family labour)	β_4	0.002	0.041
Ln (Age of tree)	β_5	-0.187**	-2.216
Ln (Intermediate cost)	β_6	0.249***	6.857
Ln (Land square)	β_7	6.651**	2.124
Ln (Fertilizer square)	β_8	-0.100	-0.741
Ln (Hired labour square)	β_9	-0.162	-1.078
Ln (Family labour square)	β_{10}	0.193**	1.850
Ln (Age of tree square)	β_{11}	-2.375***	-3.045
Ln (Intermediate cost square)	β_{12}	1.504***	9.973
Ln (Land*Fertilizer)	β_{13}	-1.794**	-2.320
Ln (Land*Hired labour)	β_{14}	0.165	0.370
Ln (Land*Family labour)	β_{15}	-0.477	-1.151
Ln (Land*Age of tree)	β_{16}	1.309**	2.115
Ln (Land*Intermediate cost)	β_{17}	-2.245***	-4.933
Ln (Fertilizer*Hired labour)	β_{18}	-0.184*	-1.613
Ln (Fertilizer*Family labour)	β_{19}	0.421***	3.044
Ln (Fertilizer*Age of tree)	β_{20}	0.559**	1.987
Ln (Fertilizer*Intermediate cost)	β_{21}	0.165*	1.575
Ln (Hired labour* Family labour)	β_{22}	-0.086	-1.021
Ln (Hired labour*Age of tree)	β_{23}	0.123	0.469
Ln (Hired labour*Intermediate cost)	β_{24}	0.160	0.962
Ln (Family labour*Age of tree)	β_{25}	-0.457**	-1.839
Ln (Family labour*Intermediate cost)	β_{26}	-0.054	-0.535
Ln (Age of tree*Intermediate cost)	β_{27}	-0.009	-0.052
Gamma		0.99***	959.24
Log-likelihood value		128.796	
LR test for one-side error		46.530	
Sigma square (σ^2)		0.335***	2.232

***, ** and * represents 1%, 5% and 10% significance levels respectively

Source: Survey Data, 2011/2012

4.7 Technical Efficiency Estimates

The mean technical efficiency estimated for independent and smallholder producers is 0.61 and 0.91 respectively (Table 4.9). The difference in mean level of technical efficiency between smallholder and independent producers is tested using the Z-value.

Table 4.9: Distribution of Technical Efficiency Scores

Technical Efficiency Score	Min	Max	Mean
Independent	0.18	0.99	0.62
Smallholder	0.44	0.99	0.91
Combined	0.28	0.98	0.75

Source: Survey Data, 2011/2012

The hypothesis here is that producers that received improved technologies and support from the plantation are more technical efficient. The result as depicted in Table 4.10 shows significance difference in the mean technical efficient level between the smallholder and independent producers as depicted by the Z-value, which suggests that smallholder producers are more technical efficient than the independent producers.

Table 4.10: Z-Test for the Difference in the Mean TE Level Between the Groups

Types of Producers	Number of Producers	Mean	Difference	Z-value
Smallholder	122	0.91	0.29	12.63***
Independent	121	0.62		

***Significance at the 1% level **Source: Survey Data, 2011/2012**

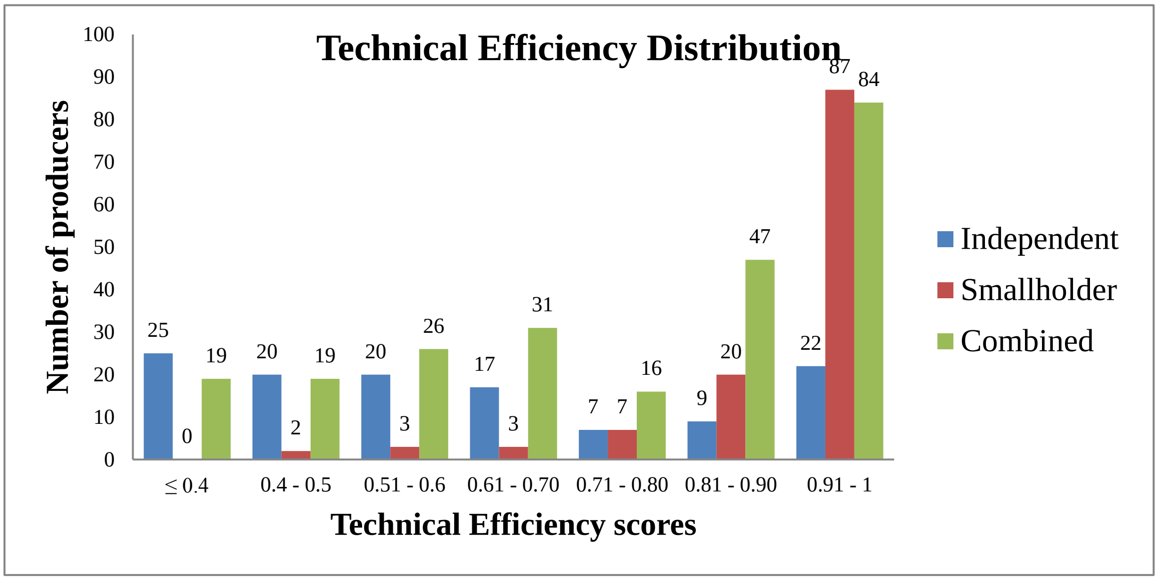
In other words, on average independent producers and smallholder incur about 39% and 9% losses, respectively in output due to technical inefficiency. This implies that on the average, in the short run, independent and smallholder producers can increase output by 39% and 9%, respectively by utilizing best management practices exhibited by producers operating on the frontier. Hence to bridge the gap and achieve 100% level of technical efficiencies, the producers have to address some of the inefficiency factors.

In the study area the predicted technical efficiency scores vary substantially among the independent and smallholder producers. The technical efficiency scores range from 0.18

to 0.99 and 0.44 to 0.99, for independent and smallholder producers, respectively (Table 4.9). The technical efficiency scores for the combined stochastic frontier model ranged between 0.28 and 0.98. Iwala et al. (2006) also observed in the Nigeria Oil Palm sector technical efficiency scores ranging between 0.463 and 0.999.

The distribution of the individual efficiency level of the independent and smallholder producers is depicted using the histogram in Figure 4.1. The results show that majority (54.2%) of independent producers and 4.1% of the smallholder producers have technical efficiency scores that lie between 0.18 and 0.60. Moreover 20% of independent producers and 8.2% of smallholder producers have efficiency scores that lie between 0.61 and 0.80. On the other hand, majority (89.2%) of the smallholder producers and minority (25.8%) of the independent producers have efficiency scores between 0.81- 0.99. This indicates that most of the independent producers have low technical efficiency scores compared to the smallholder producers. The low technical efficiency could be attributed to low utilization of the existing improved oil palm technologies and best practices by the independent producers. On the other hand smallholder producers are achieving higher technical efficiency because of the use of best management practices introduced to them by the plantation company. Ojo and Ajibefun (2000) also estimated a mean technical efficiency of 0.93 for trained producers, who are also using trained hired labour from plantations; producers without training achieved technical efficiency of 0.51.

Figure 4.1: Technical Efficiency Distribution



Source: Survey Data 2011/2012

4.8 Determinants of Technical Inefficiency

The results of the inefficiency model are presented in Table 4.10. The farm specific factors that have significant effects on technical inefficiency are adoption of improved technologies, education of the producers, access to credit, extension visit, experience and smallholder.

Table 4.11: Parameter Estimates of the Inefficiency Model

Variable	Independent	Smallholder	Combined
Constant	1.358***	-0.298**	0.898***
Adoption	-1.328***	n.a.	-0.824***
Landownership	-0.008	n.a.	-0.042
Education	0.015	0.061**	-0.0005
Access to credit	0.004	1.668**	-0.122
Household size	0.011	0.005	0.014
Extension visit	-0.042	-0.014**	-0.037*
Experience	-0.017**	-0.073*	-0.003
Smallholder	n.a.	n.a.	-0.374**

***, ** and * represents 1%, 5% and 10% significance levels respectively.

Source: Survey Data, 2011/2012

Adoption of improved technology is expected to increase farm productivity and technical efficiency of producers in the independent and combined models. The coefficient for adoption is negative and significant in the independent and combined models; indicating that as independent and combined producers adopt more of the improved technologies and best practices their technical efficiency will increases.

The estimated coefficient of education and access to credit were positive and significant. This suggests that producers who have higher education may regard farming as secondary activities and focus on their other income earning activities more than oil palm production. Hence the coefficient of the education attainment variable implies that farmers with more years of formal education tend to be less efficient, such that education attainment has a negative impact on technical efficiency in oil palm production. Similar result was observed by Hasnah et al. (2004), where the coefficient for education was significant and positive. Similarly access to credit was positive and significant, suggesting that smallholder producers may be using some of the credit to meet domestic and social needs and are not investing all the credit provided to them to improved their farming activities. It should be recognized that credit contributed positive to adoption in the Poisson model, but this was due to combined effects of both independent and smallholder producers.

Extension visit has negative and significant effect on inefficiency for the smallholder and combined models. Agricultural extension agents are vehicles through which improved technologies and information from the research station reaches the producers and is the same means through which the results from the producer fields are transmitted to the researchers. An increase in the number of extension visits with oil palm specific information improves producers' technical efficiency of producers in the smallholder and combined models. The result suggests that, since the plantations have special extension programmes for smallholder producers, this has reduced their technical inefficiency. The result further indicates that smallholder producers had higher productivity, because they had a higher frequency of extension visits.

Experience of the producer is an asset for farming because the producer has over the years practically utilized or has field experience with most of the practices (improved and traditional practices) and is able to clearly indicate which of them gives the highest output. The estimated coefficient for producers' experience in the independent and smallholder models are negatively related to inefficiency and is statistically significant at 5% and 1% level, respectively. This result implies that, with more experience, producers are able to apply best practices to minimise losses and adopt improved technologies to increase their productivity. Moreover as producers increase their experience level, they get more information and are able to use the information to help boost their productivity, therefore making them efficient in oil palm production. It can be concluded that producers with more experience adopt more of the improved technologies; they have higher productivity and produce with less inefficiency.

The estimated coefficient of smallholder in the combined model was negative and significant. This implies that becoming a smallholder reduces your technical inefficiency of production, because smallholder received improved technologies, extension services and supervision from the plantation. Similar result was observed for smallholder in the Poisson count model for smallholder.

CHAPTER FIVE

SUMMARY, CONCLUSION AND POLICY RECOMMENDATIONS

5.1 Introduction

This chapter summarises the main findings of the study and draws major conclusions stemming from the results and analysis of the study. Based on the major findings of the study, policy recommendations are also made for future interventions in the oil palm sector by producers, the Government of Ghana and other stakeholders.

5.2 Summary

This study was carried out to assess the role of improved technology adoption on technical efficiency of small-scale producers, by estimating the productivity, intensity of adoption and technical efficiency of the producers. Factors affecting efficiency of the individual farms were also analyzed and discussed.

The objectives of the study were analyzed using relative frequencies, Poisson regression and stochastic frontier models. Intensity of adoption measured the number of technologies adopted. Relative frequencies were used to estimate the intensity of adoption of improved technologies (proportion of producers adopting a certain number of technologies), while the Poisson regression was used to analyze factors that influence adoption. The stochastic frontier model was used to estimate the productivity, technical efficiency levels and inefficiency of the producers simultaneously. The translog model was tested against the Cobb-Douglass and the former provided the best fit for the data with consistent estimates. Tests for the absence of inefficiency and the adequacy of the half normal distribution were also conducted; they were both rejected. The data used for the study was collected for farming period 2011/2012, from 250 small-scale producers (128 independent and 122 smallholder producers) through field survey conducted by the researcher in the Western Region of Ghana in 2012.

The results show that smallholder producers adopted all the seven improved technologies compared to the independent producers who adopted six and less of the improved technologies. As a result smallholder producers had higher productivity level of 16.7 ton/ha compared with 6.8 ton/ha obtained by independent producers. Producers who adopted more of the improved technologies had higher productivity. The estimates for productivity are explained in terms of the output elasticities. All the inputs variables were positive and therefore increased output, except for the average tree age, that decreases output. The technical efficiency analysis indicated that smallholder producers are more technically efficient than independent producers. Independent producers that adopted more of the improved technologies and had more experience were more efficient. Smallholder producers that had frequent contact with extension and more experience were more efficient.

5.3 Conclusion

The study concludes that the productivity estimates demonstrate increasing returns to scale for the independent, smallholder and the combined models, respectively. Therefore oil palm producers can expand output by using more of the inputs. The age of the oil palm tree was found to have negative influence on output, which implies that as the average age of the tree increase, productivity of oil palm in the study area declines. .

Also, as producers increase the intensity of adoption of improved technologies their productivities increases accordingly. Hence, since the smallholder producers adopted all the improved oil palm technologies, they are more productive compared to the independent producers who are non-adopters or are partial adopters of the technologies. Access to credit is among the factors that influence the adoption of improved technologies; credit enables producers to access inputs such as improved seedling, fertilizer, hired labour, establish two stage nurseries and acquire other farm tools that may be required in the production process; it is therefore necessary for producers to have access to credit to help improved their farming activities. Hired labour also significantly influenced the adoption of improved oil palm technologies in the study area; since oil palm production is labour intensive, producers employ hired labour to cater for their farm labour requirements.

Smallholder producers are closer to the productivity frontier compared to the independent producers. Therefore, the potential for further expansion in output to meet the maximum potential output is much higher for the independent producers than the smallholder producers. Efforts to increase oil palm production in the short run should focus on the independent producer.

The occurrence of inefficiency was found among both the independent and smallholder producers. The amount of improved technologies adopted was found to increase efficiency of the independent producer. The years of experience in oil palm production was found to increase efficiency among both independent and smallholder producers and number of extension visit was also found to increase efficiency among smallholder producers. In other words, if the producers are able to get access to improved technologies, extension services and acquire more experience, it may help to reduce the inefficiencies in oil palm production. On the other hand, levels of formal education achieved and access to credit increase inefficiency. Educated farmers are more likely not to dedicate more time to farming because they have other sources of income and farmers who received credit may use the credit for other pressing social needs rather than for only farming.

5.4 Policy Recommendation

Overall, three main empirical findings emerge from this study. Firstly, oil palm productivity increases as the number of improved technologies adopted increase; indicating that cultivating with improved technologies will shift the production frontier upwards. Therefore it is recommended that independent producers adopt improved technologies and best practices on their farms, to increase their productivity. Smallholder producers who are not operating at the frontier should also endeavour to adopt the best practices exhibited by producers operating at the frontier. The improved technologies are certified seedlings, application of fertilizer at the right time, two stage nurseries and establishment of the plantation with cover crops; the best management practices are, applying the right quantity and quality of fertilizer, and timely pruning, weeding and harvesting.

Secondly, the study reveals that access to extension and hired labour positively influenced the intensity of adoption, productivity and technical efficiency. The study also recommends that producers should endeavour to increase their contact with extension agents and use hired labour on the farms. Government and NGO extension services should be strengthened by increasing the number of extension contact with oil palm producers. Furthermore oil palm plantations should encourage independent producers to become out-growers for the plantations since they provide more effective services compared to the Government extension system. It is further recommended that independent producers use hired labourers on their farms and their remuneration be catered for from sale of output from their farms. This is because family labour may not be sufficient for the labour needed for oil palm production. It is also recommended that Government and other stakeholders should provide training to oil palm producers and hired labourers on the application of agrochemicals and fertilizer.

Thirdly, the performance of smallholder producers in terms of technology adoption, productivity and technical efficiency is much better than the independent small scale producers. Therefore, it is highly recommended that independent producers be encouraged to become out-growers for the larger oil palm plantations. The plantations are also encouraged to permit independent producers participate in their smallholder programme for effective supervision. It is also recommended that all producers replant aged trees with improved seedlings, which have higher productivity. Moreover, there should be deliberate programmes, like the PSI, by Government and stakeholders geared towards increasing producer access to improved technologies. Extension agents should endeavour to provide knowledge, skills and information to producers on the utilization of said technologies to boost their efficiency level. This should include access to fertilizer at lower cost in the producers' communities

Banks and microfinance institutions should be encouraged to initiate credit programmes for producers so that they can maintain their farms.

5.5 Direction for Future Research

Further research using panel data to compare productivity and technical efficiency over the years among oil palm producers in the different regions in Ghana is highly commended. This will provide empirical results that can be used across the country to improved productivity and efficiency. Moreover this comparison can be conducted across the border to compare Ivory Coast oil palm sector with that of Ghana, using meta-frontier analysis this will encourage learning and knowledge sharing between the sub- regional neighbours.

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APPENDICES

APPENDIX 1: Questionnaire

ADOPTION OF IMPROVED TECHNOLOGY AND FARM LEVEL TECHNICAL EFFICIENCY OF SMALL-SCALE OIL PALM PRODUCERS IN THE WESTERN REGION OF GHANA

Department of Agricultural Economics and Agribusiness, University of Ghana

This questionnaire is meant for data to address the above topic in partial fulfillment for the award of Master of Philosophy Degree in Agricultural Economics at the University of Ghana. Your respond to the questions would encourage the researcher to get appropriate findings that will contribute to knowledge in the academia. Your confidentiality is assured.

Identification Code

District………………………………...….

Town……………………………………..

Interviewer……………………………….. Date.…/.…/.…

A. Socioeconomic characteristics of the primary decision maker on oil palm

1. Name of respondent/primary decision maker on oil palm…………………………………
2. Gender 1 = Male [ ] 2 = Female[ ]
3. Age of primary decision maker …..…… **4**. Household size…………………….
5. Marital Status 1=Single [ ] 2=Married [ ] 3=Divorced/Separated [ ] 4 = Widowed [ ]
6. Level of Education Attained 0 = No Schooling [ ] 1 = Primary [ ] 2 = MSLC/JSS [ ] 3 = SSS [ ] 4 = Vocational [ ] 5 = polytechnic level [ ] 6 = University (bachelor) Level [ ] 7 = University (Graduate or Above) Level [ ] 8= years of formal education ………
7. Residential Status: 1=Native [ ] 2=Settler [ ]
8. Land own: 1=Owner (eg. family, purchase) [ ] 2 = Otherwise (eg. lease, rent, contract,) [ ]

B. Oil palm production Information

1. Number of year's respondent has been growing oil palm in this community..........
2. Do you depend on oil palm as the only source of income? 1=Yes [ ] 2=No [ ]

Other income sources	Amt earn monthly	Amt earn per season	Amt earn yearly

3. Please indicate the output, sales and self-consumption of the oil palm bunch produced during 2011/2012

Total Quantity Harvested	Quantity Sold		Self-Consumption
Quantity in FFB (ton)	Quantity in FFB (ton)	Price/unit	Quantity in FFB (ton)

4. Please list all inputs and cost for 2011/2012 production year

Types of inputs	Quantity of inputs	Unit cost	Total cost
Labour			
Fertilizer			
Pesticide			
Herbicide			
Weedicide			
# of trees			

5. Please indicate other expenses and services for 2011/2012 production year

Type of Services	Unit Cost	# of time/Quantity	Total cost
Harvesting			
Weeding			
Transportation			
Supervision			

6. Please indicate quantity, years of purchase and current price of the following capital items used in oil palm production

Inputs	Quantity	Year last purchase		Current price	Lifespan in years
		Year	Amount/price		
Hoe					
Cutlass					
Tractor					
Power tiller					
Snapsack sprayer					
Others					

7. Main source of labour for 2011/2012? i) hire labour….. ii) family labour……
8. Farm Labour activities and cost for 2011/2012 for oil palm production

Farm Activity	Hired Labour							
	Male			Female			Total	
	Qty	# of days	Wage/day	Qty	# of days	Wage /day	Total Wage	Total man day
1st Weeding								
1st Harvesting								
1st Fertilizer application								
1st Chemical application								
1st Pruning								
2nd Weeding								
2nd Harvesting								
2nd Chemical application								
2nd Pruning								
2st agrochem app.								
2nd Weeding								
2nd Harvesting								
2nd Chemical application								
2nd Pruning								
2st agrochem app.								

Farm Activity	Family Labour – Adult							
	Male			Female			Total	
	Qty	# of days	Wage/day	Qty	# of days	Wage /day	Total Wage	Total man day
1st Weeding								
1st Harvesting								
1st Fertilizer application								
1st Chemical application								
1st Pruning								
2nd Weeding								
2nd Harvesting								
2nd Chemical application								
2nd Pruning								
2st agrochem app.								
2nd Weeding								
2nd Harvesting								
2nd Chemical application								
2nd Pruning								
2st agrochem app.								

Farm Activity	Family labour - children							
	Male			Female			Total	
	Qty	# of days	Wage/day	Qty	# of days	Wage /day	Total Wage	Total man day
1st Weeding								
1st Harvesting								
1st Fertilizer application								
1st Chemical application								
1st Pruning								
2nd Weeding								
2nd Harvesting								
2nd Chemical application								
2nd Pruning								
2st agrochem app.								
2nd Weeding								
2nd Harvesting								
2nd Chemical application								
2nd Pruning								
2st agrochem app.								

C. Oil palm adoption Information

1. Kindly indicate your knowledge and use of improved oil palm technology

Type of improved technology	**awareness**		**Utilizing on farm**	
	Yes	No	Yes	No
Certified Tenera Seedling				
Cover crops				
9 x 9 x 9 triangular planting				
Two stage nurseries				
Use of black poly-bag in nursing seeds				
Wire mesh				
Fertilizer/compost				

2. How long since you first heard about improved oil palm varieties?

   ....Years

3. Whom/where did you first hear about the improved oil palm varieties?

   …….…………….

4. How many times have you purchased improved oil palm seedlings since you started using it? ……………………times.

5. From where do you usually get improved seedlings?

....

6. Can/do you purchase the amount you need to plant? 1= Yes [ ] 2 = No [ ]

7. If no, why? i) not available …… ii) too expensive……… iii) cash shortage ………

iv) was not sure of benefit …. v) not available on time …. vi) not better than local ….

8. Are you cultivating both traditional and improved varieties? 1= Yes [ ] 2 = No [ ]

9. Are your oil palm trees planted at different interval? 1= Yes [ ] 2 = No [ ]

10. Please indicate the proportion of improved variety planted on your farm.

Number of trees	Variety	Year planted	Land size	Proportion of total land

11. Please indicate the proportion of traditional variety planted on your farm

Number of trees	Variety	Year planted	Land size	Proportion of total land

12. Please indicate the quantity and type of fertilizer used for oil palm

Quantity (# of 50kg bags)									
Yr app.	Plt stg	Qnty Org.	Price/unit	Fert. type	Oil palm variety	Qnty Inorg.	Price/unit	Fert. type	Oil palm variety

13. Kindly indicate the types of agro-chemical used on your oil palm

Type of agro-chemical	Quantity in liter	Price/Unit
Field pesticide		
Weedicide		
Fungicide		
Others		

14. Do you perceive any personal risk and uncertainty concerning oil palm production? 1= Yes [ ] 2 = No [ ]

15. If yes, please state……..……………………………………………..……………

D. Credit and Extension

1. Do you use credit in the production and maintaining of your farm? 1= Yes [ ] 2 = No [ ]
2. Please provide the following information on credit

Amt of credit	Time taken	Payback pd	Credit source	Int. rate	Prop. of total working capital

3. Are you a member of producer organization in your District/Region? 1= Yes [ ] 2 = No [ ]
4. If yes, provide the name...
5. What are the contributions of the organization to your production? ....
6. Source of extension services1= Government [ ] 2 = NGO [ ] 3 = Others ……………...
7. What type of extension services to you get ……….

i) weed control ii) during input/tools provision iii) during nursery iv) whenever disease/ pest occur v) using transplanting vi) during credit collection vii) others

(Specify)………………………………………………………………….………

8. How frequently do the extension agents visit you? ....

i) never ii) annually iii) monthly iv) bi-weekly v) weekly

9. Do you visit/invite extension agent? 1= Yes [ ] 2 = No [ ]

10. If yes, when do you visit/invite? ………………………

i) Weed control ii) during input/tools provision iii) during nursery iv) whenever disease/ pest occur v) during transplanting vi) during credit collection vii)others

(Specify)…………..……………………………………………………..………………

11. What are your other sources of information for oil palm production and how often you use/ have contact with them?

..……………………………………………………….…….

APPENDIX 2: Research Communities and sample

Districts	Communities	Sample size	Total
	Santian	21	
	Fasin	10	
Ahanta West	Camp	5	60
	Aboade	6	
	Miawan	8	
	Yabiw	4	
	Eusiejoe	6	
	Adum Banso	52	
	Benso	45	
	Danpim	12	
Mpohor/Wassa East	Mamponso	9	140
	Bufoyedur	4	
	Aboboso	18	
	Ayiem	10	
Mpohor	Cargo	6	50
	Mpohor	34	

Survey Data, 2011/2012

APPENDIX 3: Improved Technologies Contribution to Output.

Linear regression

Number of obs =	250
F(7, 242) =	32.91
Prob > F =	0.0000
R-squared =	0.3848
Root MSE =	17.998

OUTPUT	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
seedlin	9.047688	3.830992	2.36	0.019	1.501341	16.59403
ferti3	20.55456	2.586418	7.95	0.000	15.4598	25.64933
covercro	6.916266	2.966004	2.33	0.021	1.073787	12.75875
Twostage	6.181919	3.150452	1.96	0.051	-.0238886	12.38773
Triangula	5.276809	3.318464	1.59	0.113	-1.259951	11.81357
black	.4871693	3.448993	0.14	0.888	-6.306709	7.281047
wire	.126852	2.754308	0.05	0.963	-5.298626	5.55233
_cons	-2.809809	3.736869	-0.75	0.453	-10.17075	4.551132

Source: Survey Data, 2011/2012

APPENDIX 4: Marginal Effects Regression

Marginal effects after regress
y = Fitted values (predict)
= 34.451892

variable	dy/dx	Std. Err.	z	P>|z|	[95%	C.I.]	X
Dferti~r*	14.6417	3.42481	4.28	0.000	7.92919	21.3542	.676
Seedling*	9.351438	3.8236	2.45	0.014	1.85732	16.8456	.764
Covcrop*	8.276492	2.87812	2.88	0.004	2.63549	13.9175	.732
Twostage*	5.124906	6.24203	0.82	0.412	-7.10925	17.3591	.78
Wire*	3.144358	3.18962	0.99	0.324	-3.10719	9.39591	.692
triangu*	2.674121	4.72631	0.57	0.572	-6.58927	11.9375	.772
Adaptb~k*	.8751793	7.19074	0.12	0.903	-13.2184	14.9688	.748

(*) dy/dx is for discrete change of dummy variable from 0 to 1

Source: Survey Data, 2011/2012

APPENDIX 5: Poisson Regression Result

```
. poisson Totaladopted Gender Farmerage Extensioncontact Hiredlabour Smallholder Hhsize ACCRE Agfarm OTHSOU EDUC RESTA, vce(robust)
note: you are responsible for interpretation of noncount dep. variable

Iteration 0:   log pseudolikelihood = -217.14513
Iteration 1:   log pseudolikelihood = -217.14477
Iteration 2:   log pseudolikelihood = -217.14477

Poisson regression                              Number of obs   =        250
                                                Wald chi2(11)   =     209.92
                                                Prob > chi2     =     0.0000
Log pseudolikelihood = -217.14477               Pseudo R2       =     0.0516
```

Totaladopted	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
Gender	.0226765	.048731	0.47	0.642	-.0728344	.1181875
Farmerage	.001386	.0017931	0.77	0.440	-.0021284	.0049005
Extensioncontact	.4221418	.0970255	4.35	0.000	.2319753	.6123083
Hiredlabour	.0026022	.0008428	3.09	0.002	.0009504	.004254
Smallholder	.2985565	.0944446	3.16	0.002	.1134484	.4836646
Hhsize	.0038426	.0052798	0.73	0.467	-.0065055	.0141908
ACCRE	.1823052	.0967468	1.88	0.060	-.0073151	.3719254
Agfarm	-.021001	.0129504	-1.62	0.105	-.0463834	.0043814
OTHSOU	.0805114	.0570198	1.41	0.158	-.0312454	.1922681
EDUC	.0032391	.0035963	0.90	0.368	-.0038096	.0102878
RESTA	.038274	.0434164	0.88	0.378	-.0468205	.1233685
_cons	-1.070019	.1777909	-6.02	0.000	-1.418483	-.7215553

Source: Survey Data, 2011/2012

APPENDIX 6: Summary Statistics of Output and Inputs Variables

Variables	Unit	Independent			Smallholder			Combined		
		Min	Max	Mean	Min	Max	Mean	Min	Max	Mean
Output	Ton	2.3	85	21	17.9	99	56.8	2.3	99	39
Farm Size	Hectare	1	7.2	3.1	2	3.9	3.4	1	7.2	3.3
Fertilizer	Kg	0	1050	150	250	3450	2838	0	3450	1505.3
Hired labour	Man-day	24	178.5	77.8	39.4	269.9	83.8	24	269.9	80.8
Family labour	Man-day	4.9	45	15.4	13.1	148.1	47.5	4.9	148.1	31.6
Farm Age	Years	6	29	10	9.9	21.1	16.3	6	29	13
Intermediate cost	GH Cedis	45.3	1762	529.8	132	1665	764	45.3	1762	647.84

Source: Survey Data, 2011/2012

APPENDIX 7: Respondents Distributed by Districts

Name of District/Company	Number of respondents
Ahanta West	60
Mpohor	50
Mpohor/Wassa East	140
Total	**250**

Source: Survey Data, 2011/2012.

APPENDIX 8: Parameter Estimates of the Combined Model

Variable	Parameter	Coefficient	t-ratio
Constant	β_0	0.641	1.20
Ln (Land size)	β_1	0.717***	4.375
Dummy for Fertilizer	β_0^*	-0.394	-0.901
Ln (Fertilizer)	β_2	0.104**	1.913
Ln (Hired labour)	β_3	0.158*	1.31
Ln (Family labour)	β_4	0.068	-0.788
Ln (Age of tree)	β_5	-0.237	-1.272
Ln (Intermediate cost)	β_6	0.309***	2.783
Ln (Land square)	β_7	-0.963***	-8.328
Ln (Fertilizer square)	β_8	0.021**	1.742
Ln (Hired labour square)	β_9	0.053	0.249
Ln (Family labour square)	β_{10}	-0.358***	-3.606
Ln (Age of tree square)	β_{11}	0.139	0.456
Ln (Intermediate cost square)	β_{12}	0.400***	3.699
Ln (Land*Fertilizer)	β_{13}	-0.034***	-6.306
Ln (Land*Hired labour)	β_{14}	0.724***	11.588
Ln (Land*Family labour)	β_{15}	0.888***	8.026
Ln (Land*Age of tree)	β_{16}	0.253	0.348
Ln (Land*Intermediate cost)	β_{17}	-0.027	-0.106
Ln (Fertilizer*Hired labour)	β_{18}	0.034***	14.491
Ln (Fertilizer*Family labour)	β_{19}	0.006	0.148
Ln (Fertilizer*Age of tree)	β_{20}	-0.050*	-1.432
Ln (Fertilizer*Intermediate cost)	β_{21}	-0.006	-0.407
Ln (Hired labour* Family labour)	β_{22}	-0.274	-1.074
Ln (Hired labour*Age of tree)	β_{23}	0.007	0.067
Ln (Hired labour*Intermediate cost)	β_{24}	-0.504***	-2.744
Ln (Family labour*Age of tree)	β_{25}	-0.184	-0.648
Ln (Family labour*Intermediate cost)	β_{26}	-0.273***	-10.573
Ln (Age of tree*Intermediate cost)	β_{27}	0.147	0.852
Gamma		0.99***	280.4
Log-likelihood Value		19.895	
LR test for one-side error		25.23	
Sigma square (σ^2)		0.056***	10.222

***, ** and * represents 1%, 5% and 10% significance levels respectively

Source: Survey Data, 2011/2012