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ACRONYMS AND ABBREVIATIONS

ADP	Agricultural Development Project
AE	Allocative Efficiency
APMEU	Agricultural Projects Monitoring and Evaluation Unit
BNARDA	Benue State Agricultural and Rural Development Agency
CADP	Commercial Agriculture Development Programme
CBN	Central Bank of Nigeria
CD	Cobb-Douglas
CE	Cost Efficiency
COLS	Corrected Ordinary Least Squares
CRS	Constant Returns to Scale
CSIS	Centre for Strategic and International Studies
DEA	Data Envelopment Analysis
DFID	Department for International Development
DFRRI	Directorate of Food, Roads and Rural Infrastructure
EE	Economic Efficiency
FACU	Federal Agricultural Coordinating Unit
FAO	Food and Agriculture Organization
FAOSTAT	Food and Agriculture Organization Statistics
FAS	Agricultural Service of United States Department of Agriculture
FCT	Federal Capital Territory
FEAP	Family Economic Advancement Programme
FMARD	Ministry of Agriculture and Rural Development
FRN	Federal Republic of Nigeria
GDP	Gross Domestic Product
Ha	Hectare
HDR	Human Development Report
ICARRD	International Conference on Agrarian Reform and Rural Development
IDRC	Development Research Centre
IFPRI	International Food Policy Research Institute
IITA	International Institute of Tropical Agriculture
Kg	Kilogram

LR	Likelihood Ratio
MLE	Maximum Likelihood Estimates
NACB	Nigerian Agricultural and Cooperative Bank
NACRDB	Nigerian Agricultural, Cooperative and Rural Development Bank
NAFPP	National Accelerated Food Production Project
NALDA	National Agricultural Land Development Authority
NBS	National Bureau of Statistics
NCRI	National Cereals Research Institute
NDE	National Directorate of Employment
NEEDS	National Economic Empowerment and Development Strategy
NERICA	New Rice for Africa
NPC	National Population Commission
NPFS	National Food Security Programme
NPN	National Party of Nigeria
NSS	National Seeds Service
OFN	Operation Feed the Nation
OLS	Ordinary Least Squares
PCU	Projects Coordinating Unit
R&D	Research and Development
SAP	Structural Adjustment Program
SFPF	Stochastic Frontier Production Function
SIDF	Stochastic Frontier Input Distance Function
TE	Technical Efficiency
TFP	Total Factor Productivity
TL	Translog
UNDP	United Nations Development Programme
USAID	United States Agency for International Development
VRS	Variable Returns to Scale

CHAPTER 1

INTRODUCTION

1.1 Background to the Study

Nigeria is blessed with huge physical, human and natural resource endowments yet the majority of its population live below both the absolute and relative poverty lines. The national survey conducted between 2003 and 2004 shows that slightly above half of the population (51.6 percent) live below US$1 dollar per day and the relative national poverty incidence was found to be 54.4 percent (National Bureau of Statistics (NBS), 2005, 2008). However, the most current Human Development Report by the United Nations Development Programme (UNDP, 2009) shows that about 64.4 and 83.7 percent of the population lives below $1.25 and $2 a day, respectively. This poverty situation is worse in the rural areas where over 70 percent of the people reside and earn their living through agriculture than in the urban areas. More than 86.5 percent of the rural population is engaged in agriculture (NBS, 2005). This invariably leaves agriculture as a key sector capable of affecting majority of Nigerians in diverse ways. Therefore, the persistence of hunger and poverty in Nigeria must be, to a large extent, the failure of the agricultural sector to fully impact positively on the people.

Agriculture plays a cardinal role in Nigeria's economy contributing the greatest share to the nation's gross domestic production (GDP). For instance, 2008 agriculture's contribution to total real GDP was 42.07 percent with crop, livestock, forestry and fishery accounting for 37.52, 2.65, 1.37 and 0.53 percent, respectively (NBS, 2007; Central Bank of Nigeria (CBN), 2008). This implies that the crop sub-sector contributed 89.2 percent of agriculture GDP. Further, agriculture generates employment for over 70 percent of the total labour force, accounts for about 60 percent of the non-oil exports and, perhaps most important, provides over 80 percent of the food needs of the country (Adegboye, 2004; Onwuemenyi, 2008; CBN, 2008). Despite these indicators, Nigeria's agricultural performance in recent times remains inadequate and indeed far less than its potentials. Food demand exceeds the supply thus leading to large importations of food, which further erodes the economies foreign exchange. The growing food import over the years gave rise to escalating foreign exchange expenditures, which could have been invested in other areas of the economy. The food import bill for Nigeria rose from N3.474 billion in 1990 to N 654 billion in 2007 where as it could only boast of agricultural export worth of N73.3 million (CBN, 2007); and this trend has not yet changed. At the heart of this inadequacy of the sector lies the foremost problem of low productivity, as will be clarified later in this introduction. Low productivity in the country could be as a result of a number of factors, which may be direct or indirect. With the fast increase in human population in the country, there is no doubt that resources are becoming scarcer than ever before and therefore development strategies should focus on strategies that are intended to increase the productivity of scarce resources.

Although small scale farmers dominate agricultural production in Nigeria and individually exert little influence, collectively they form the foundation upon which the economy rests. About 90 percent of Nigeria's total food production comes from small farms and at least 60 percent of the country's population earns their living from these small farms with farm sizes generally less than 2 hectares (Oluwatayo et al. 2008). Unfortunately, these small scale farmers are subsistence farmers and use crude and traditional production techniques. This has contributed to the poor performance of the sector. Therefore, effective economic development strategy will depend critically on promoting productivity and output growth, particularly among small-scale producers since they make up the bulk of the nation's agriculture. To boost the agricultural production base of the country, a number of policies have been put in place and these in a broad sense, include: (i) the achievement of self-sufficiency in basic food supply and the attainment of food security; (ii) increased production of agricultural raw materials for industries; (iii) increased production and processing of export crops, using improved production and processing technologies; (iv) generating gainful employment; (v) rational utilization of agricultural resources, improved protection of agricultural land resources from drought, desert encroachment, soil erosion and flood, and the general preservation of the environment for the sustainability of agricultural production; (vi) promotion of the increased application of modern technology to agricultural production and (vii) improvement in the quality of life of rural dwellers.

Maize is one of the main staple crops in Nigeria and featured among the five food crops (cassava, maize, wheat, rice and sugar) whose production is to be promoted for attainment of food self-sufficiency as revealed by the Minister of Agriculture and Water Resources (Sayyadi, 2008). In Nigeria, maize production ranks third after sorghum and millet among the cereal crops (Food and Agriculture Organization Statistics (FAOSTAT), 2009). A survey conducted in Nigeria reveals that maize accounts for about 43 percent of calorie intake, with income elasticity of demand of 0.74, 0.65 and 0.71 for low income, high income and all sample households, respectively and contributes to 7.7 percent of total cash income of farm households (Nweke et al. 2002; Nweke, 2004; Alabi and Esobhawan, 2006). Apart from being a food crop, maize has equally become a commercial crop on which many agro-based industries depend on for raw materials (Oluwatayo, et al. 2008 and Babatunde et al. 2008). Maize contributes about 80 percent of poultry feeds and this has great implication for protein intake in Nigeria (FAO, 2008). Thus, maize can be considered very vital to the economic growth of the nation through its contribution to food security and poverty alleviation.

Land area under maize increased from 653,000 ha in 1984 to 5m ha as at 2007 and production also increased from 1m to 7m tons during the same period (International Institute of Tropical Agriculture (IITA), 2007). The average yield of 1.4-1.5 tonnes/ha being obtained in Nigeria is low compared to other places. For instance, FAOSTAT (2009) production statistics from 1990-2007 shows that world maize average yield was 4.3 tonnes/ha, average yield for Kuwait was 18.4 tonnes/ha, Jordan, 16.2 tonnes/ha, New Zealand, 10.2 tonnes /ha, Chile, 9.5 tonnes/ha, Egypt, 7.1 tonnes/ha, Mauritius 5.8 tonnes/ha, South Africa, 2.5 tonnes/ha, Algeria 2.4 tonnes/ha, Cameroon, 1.9 tonnes/ha, Ethiopia, 1.8 tonnes/ha and Kenya, 1.7 tonnes/ha. According to IITA (2007, 2009), Nigeria's low maize productivity was attributed to poor seed supply system, little or no use of improved seeds, herbicides and fertilizers, increased levels of biotic and abiotic constraints, low investment in research for development, inefficient marketing systems, the fact that prices of inputs have tripled in the last ten years and also global warming and its associated effects which have contributed to this by changing the rainfall pattern leading to erratic and unreliable rainfall, in some cases resulting in drought.

Maize is planted in all the six ecological zones (namely Northcentral, Northeast, Northwest, Southeast, South-south, and Southwest) in the nation and serves as an important source of income to farm households. Until recently, the bulk of the maize grain produced in Nigeria was from the south-western zone. However, it has been acknowledged that dry grain maize production has shifted dramatically to the Northern Guinea Savannah (located in the north central zone), which is now regarded as the maize belt of Nigeria (Ogunbodede and Olakojo, 2001; Iken and Amusa, 2004) and the study area, Benue State is located in this zone. Further, Manyong et al. (2003) identified the north central zone to have a comparative advantage in maize production over the rest five zones. Due to high solar radiation and low night temperatures in the Northern Guinea Savanna (NGS), the area has high potential for maize production (Carsky et al., 1998).

The federal government under the leadership of President Olusegun Obasanjo in 2006 initiated a programme to double maize production in the country both for national consumption and international export through promotion of improved agricultural technologies (United States Agency for International Development (USAID), 2006). Since then, several stakeholders have alleged their support for this program. Apart from the federal government policy to promote increased application of modern technologies, several research institutes in the nation like International Institute of Tropical Agriculture in collaboration with Institute of Agricultural Research and Training, National Rice/Maize Center, National Accelerated Food Production Program, Institute for Agricultural Research, National Cereals Research Institute, National Agricultural Extension and Research Liaison Services also came up with the initiative of doubling maize production by 2008. This is in view of the high level demand for maize in industries (flour mills, breweries, confectioneries etc), for human and animal consumption. More over, maize is among the crops of interest in the 2008 President Umaru Yaradua seven-point agenda. Thus, every attempt to boost its production is expected to enhance food security, serve as import substitution and earn foreign exchange for the country through export to food deficit countries (IITA, 2007).

Given the consistent low maize productivity and the technological innovation polices in Nigeria aimed at increasing the productivity of maize, it becomes essential to understand the efficiency with which farmers use the production technologies and since the development of technological innovations often come at a cost, ascertaining their feasibility in terms of impact on farm households in general and farm efficiency in particular is very crucial for policy analysis. The investigation of farm efficiency has fuelled a large body of literature globally and is of vital importance both from microeconomic and macroeconomic points of view. Improving the efficiency with which farmers use the available technologies is very crucial to increasing productivity, household income, food security, and overall economic growth and poverty reduction. There are three main efficiency measures namely technical, allocative and cost efficiency. In microeconomic theory, the primal production frontier describes the maximum output that may be obtained from given inputs. Any deviation from the maximal output is typically considered technical inefficiency. A firm that operates at the production frontier has a technical efficiency of 100 percent. Even though farmers may be technically efficient, they may not be cost efficient because they are allocatively inefficient. That is, they do not utilise the inputs in optimal proportions, given the observed input prices, and hence do not produce at minimum possible cost. Hence the modelling and estimation of both technical and allocative efficiency of agricultural production is often motivated by the need for a more complete representation of economic or cost efficiency of farmers implied by the economic theory of production.

Two broad approaches are usually followed in efficiency analysis in the literatures; parametric and non-parametric approaches. The parametric approach requires specification of the underlying technology and or assumption about the distribution of the inefficiency term while the non-parametric approach neither require a specific functional form nor an assumption about the inefficiency term but rather requires solving linear programs in which an objective function envelops the observed data; then efficiency scores are derived by measuring how far an observation is positioned from the "envelope" or frontier.

1.2 Problem Statement

The global food crisis is increasing with alarming speed and force, necessitating nations and international organizations all over the globe to respond with a strategic and long term approach. It has been observed that the current crisis is caused by a web of interconnected forces involving agriculture, energy, climate change, trade, and new market demands from emerging markets and therefore has grave implications for economic growth and development, international security, and social progress in developing countries (Centre for Strategic and International Studies (CSIS), 2008). Nigeria too is currently experiencing food crisis. This has been attributed to low productivity in the agricultural sector necessitating huge food imports. Maize being a major staple in Nigeria is of vital concern to agricultural policy decisions. Current production is about 8 million tonnes and average yield is less than 1.5 tonnes per hectare. This is far below the potentials of the Nigerian maize sector. A recent empirical research shows that local maize farmers in Nigeria can raise yield to about 4.2 tonnes/ha and national production could hit 20 million (IITA, 2009). The average yield is low when compared to world average of 4.3 tonnes/ha and to that from other African countries such as Egypt and Mauritius with 7.1 and 5.8 tonnes/ha, respectively (FAOSTAT, 2009). Thus, there has been a growing gap between the demand for maize and its supply arising from low productivity. The stronger force of demand for maize relative to supply is evidenced in frequent rise in the price of maize and therefore has great implication for the food security status and economic development of the Nigerian economy. The price of maize increased by about 70 percent between 2006 and 2008 (Badmus and Ogundele 2009).

The limited capacity of the Nigerian maize economy to match the domestic demand raises a number of pertinent questions both in the policy circle and amongst researchers. For instance, what factors explain why domestic maize production lags behind the demand for the commodity in Nigeria? To bridge the demand-supply gap, effort has to be channeled towards increasing its productivity. Theoretically, increasing the productivity of maize production would require either increased input use especially acreage expansion, improvement in resource use efficiency and or technological change derived from use of new technologies. Given the constant population pressure and other social and economic constraints in Nigeria, acreage expansion as a source of increased productivity has little application. Hence, the country is left with the option of improving efficiency of farmers by improving on their condition or removing existing institutional, market and socio-economic constraints and introduction of improved technologies.

For more than a decade, it was thought that adopting food import as a policy would address the nation's food shortage problem. However it has become obvious that such policy rather than bring solutions, has fuelled inflation, discouraged local production and created poverty among many farm households and helped to cause food insecurity. This therefore necessitated alternative policy actions. Consequently, speedy and extensive introduction of technological change has become one of the crucial concerns in the development of Nigeria's agriculture (International Development Research Centre (IDRC), 2005). Much effort has been geared towards increasing the availability and adoption of improved technologies in maize production in Nigeria both at the National and State levels. Specifically, the federal government in 2006 initiated a programme of doubling maize production in Nigeria through promotion of improved production technologies such as fertilizer, hybrid seeds, pesticides, herbicides and better management practices. Several improved maize varieties that are drought-tolerant, low nitrogen-tolerant, Striga-tolerant, stemborer-resistant and early maturing has been deployed to address the challenge faced by resource-poor farmers in maize production. Despite theses efforts, maize productivity remained low thus raising question about the efficiency with which resources are used by maize farmers. More, importantly, for a justification of further investment in agricultural production and technology development in general and maize in particular, there is a need to assess the feasibility of investment made so far.

It is against this background that this study analyses the technical, allocative and cost efficiency of smallholder maize production and evaluates the impact of technological innovations on these efficiency measures. To the best of my knowledge, no previous study has been conducted on simultaneous analysis of technical, allocative and cost efficiency of the maize sub-sector in Nigeria. Different approaches exist for efficiency analysis and different approaches may produce different results leading to different policy conclusions. However, if different approaches give similar results, it implies that the measures of efficiency and the explanations of relative efficiency in terms of the variables of interest (for instance technological innovation and other policy variables as in this study) can be used as basis for policy recommendations. Two competing broad approaches are usually employed in efficiency analysis namely parametric and non-parametric approaches with each having both advantages and disadvantages. While there are a number of parametric approaches, the data envelopment analysis has dominated the non-parametric approach. The choice between the various variants of these two approaches has been an issue of debate with some preferring the parametric approach while others prefer the non-parametric approach. Even within the parametric approach, a choice needs to be made whether to employ a production or distance or cost frontier especially when the analysis extends beyond technical efficiency to allocative and cost or economic efficiency.

The traditional approach in using a parametric frontier for analyzing allocative and cost efficiency is to specify the production technology either as a production or cost function. The problem with the direct estimation of cost frontiers is that it will not be practical when input prices do not differ among firms, a case that is very common in developing country agriculture. It will also not be appropriate when there is systematic deviation from cost-minimising behaviour. In this situation, the duality between the cost and production functions breaks down, and the resulting bias in the cost frontier estimates will make the cost efficiency calculation and decomposition biased as well (Bauer, 1990; Coelli et al., 2003). The problem with the production frontier (e.g. Bravo-Ureta and Riegger, 1991) approach is that a production function is estimated when one is clearly assuming that the input quantities are decision variables thus leaving the approach to criticism that simultaneous equation bias may afflict the production frontier, and efficiency estimates may be biased (Coelli et al., 2003; Alene and Hassan, 2005). The problems with the conventional cost and production frontiers motivate interest in distance functions. The distance function approach does not require behavioural assumptions to provide a valid representation of the underlying production technology, does not suffer from simultaneous equations bias when firms are cost minimisers or shadow cost minimisers, easily accommodates multiple outputs and does not require variation in input prices across firms to provide valid estimates of allocative and cost efficiency. This study contributes to the understanding of the sensitivity of efficiency results to the methodological approach employed using the Nigerian maize sector as a case study.

The present study is by no means the first to investigate the sensitivity of efficiency estimates to parametric and non-parametric approaches. However, the sensitivity of results to analytical approaches has not been fully explored and results from different studies have been mixed. For instance, most studies compared efficiency scores from the parametric stochastic frontier production function (SFPF) and data envelopment analysis (DEA) which is non-parametric (e.g., Ferrier and Lovell, 1990; Kalaitzandonakes and Dunn, 1995; Sharma et al., 1997,1999; Wadud and White, 2000; Mbaga et al. 2000; Bojnec and Latruffe, 2007; Ajibefun, 2008). The parametric stochastic production frontier approach however has been critiqued for simultaneity bias especially when analysis extends to that of allocative and cost or economic efficiency. Few studies have compared results from parametric distance functions to other approaches (Coelli and Perelman, 1999; Alene and Manfred, 2005; Alene et al. 2006). These studies compared technical efficiency estimates only and none of the approaches accounted for the possible stochastic noise in the data. In other words, the parametric distance functions employed were deterministic in nature. Further, with exception of few comparative studies (Coelli and Perelman, 1999; Alene et al. 2006, Azadeh et al. 2009) which provided a method for calculating final efficiency scores and ranks of the units studied, majority simply calculated the correlation between efficiency scores from different approaches. Even these few studies limited their analysis to obtaining final technical efficiency scores without consideration of overall efficiency and determinants and Alene et al. (2006) is the only study related to agriculture.

Few studies (Umeh and Asogwa 2005; Chirwa, 2007; Oyekale and Idjesa, 2009) attempted analyzing the impact of technology on technical efficiency without due consideration to allocative and cost efficiency. More so, the sensitivity of impact to methodological approach and the selectivity bias and thus potential endogeneity of adoption decisions was not considered in these studies. The current study fills these knowledge gaps by employing a parametric stochastic frontier input distance function (SIDF) approach that accounts for stochastic noise and avoids simultaneity bias and compares the results to the non-parametric counterpart, that is, the input oriented data envelopment analysis, DEA. Also a comparison is made with the conventional SFPF approach. The sensitivity of technical, allocative and cost efficiency estimates and their determinants from these approaches is analysed. Based on the consistency of efficiency results from the different approaches, an integrated model is developed to obtain final efficiency scores and for policy analysis. To illustrate the potentialities of this approach, application is made to analysis of technology and other policy impact on technical, allocative and cost efficiency in the maize sector of Nigeria with the aim of providing the direction and magnitude of impact. To the best of my knowledge, no previous study has taken similar dimension both in terms of content and comprehensiveness as proposed in this study.

1.3 Objectives of the Study

The broad objective of this study is to evaluate the sensitivity of efficiency results estimated from both parametric and non-parametric frontier approaches with application to Nigeria's maize sector. The specific objectives are to:

(1) compare the performance of technical, allocative and cost efficiency measures from both parametric stochastic and non-parametric distance functions;
(2) assess the impact of measuring technical, allocative and cost efficiency relative to a distance function frontier versus a production function frontier;
(3) analyse and compare the effect of technology and other policy variables on technical, allocative and cost efficiency of maize farmers in Benue State Nigeria using results from the different frontier models;
(4) integrate technical, allocative and cost efficiency scores from different frontier models into a single index of technical, allocative and cost efficiency respectively and subsequently analyse the impact of technology and other policy variables on these combined scores.

1.4 Hypotheses

The following hypotheses were tested in the study.

(1) Technical, allocative and cost efficiency scores from both parametric and non-parametric approaches are similar with respect to their means.
(2) TE, AE and CE scores from both parametric and non-parametric approaches are similar with respect to their distributions.
(3) TE, AE and CE scores from both parametric and non-parametric approaches are similar with respect to their variances.
(4) TE, AE and CE scores from both parametric and non-parametric approaches are similar with respect to their rankings of farm households.

1.5 Justification for the Study

This study is motivated by the important position of maize production in the Nigerian economy. Maize production not only serves as an important food staple to a majority of the citizens of Nigeria but also a source of revenue to both farm households and the nation at large. Nigeria has a great potential for better economic growth both in the short and long run than is currently experienced through increased maize production. Therefore, the need to efficiently allocate productive resources for development purposes cannot be overstressed. In that case, every resource should be efficiently and effectively mobilized to reduce the gap between actual and potential national output. But most importantly is to ensure that the nation's concerted effort to improving agricultural technology is remunerated with sufficient gains in food security and economic growth since technologies are developed, disseminated and adopted at a cost. Given the comparative nature of this study, the outcome in terms of the consistency or otherwise of the results will form a basis for policy recommendations. Thus, the study will contribute to literature on economic efficiency in the context of appropriate analytical methodology to employ. Measurement of efficiency is justified for a number of reasons: firstly, it is an indicator of performance measure by which production units are evaluated, thus indicating the potentials there is to improve productivity and household welfare by improving efficiency. Therefore, knowledge of production efficiency will assist policy makers to identify which farmers need support most, thus assisting in better targeting and priority setting. Secondly, measurement of causes of inefficiency makes it possible to explore the sources of efficiency differentials and elimination of causes of inefficiency. Finally identification of sources of inefficiency indicates which aspect of the farm's physical and human resources need to be targeted by public investment to improve performance.

This study is further justified, as it will help the research and extension agents to know specifically the various problems faced by the farmers and how best to ensure that their production potentials are realized by facilitating technology generation and diffusion thus reducing production inefficiencies. The farmers themselves will also benefit from this study as the revelation of their true situation could attract more favourable policies to them, which will help in improving their access to the modern technologies and thus increasing their productivity and efficiency. As there is a dearth of empirical work explicitly linking efficiency and agricultural technologies, this study will therefore contribute to the existing literatures not simply by testing the difference in the mean efficiency of users and non-users of improved technologies but also by determining the direction and magnitude of impact of such adoption decisions on farmers' technical, allocative and cost efficiency and also the sensitivity of such impact to different methodological approach. Finally, the building of an integrated model will serve as an important tool to production economists and agricultural policy analysts as this is expected to ease the problem of model selection for efficiency and policy analysis.

1.6 Organization of the Thesis

The thesis is organized into eight chapters. The next chapter (chapter two) presents an overview of agricultural policies and programmes in Nigeria. Chapter three gives a detailed account of theoretical and empirical issues relating to technical, allocative and cost efficiency. In chapter three, the review of empirical studies is limited to comparative studies in agriculture, comparative studies in other sectors that employed distance functions in efficiency analysis and efficiency studies in Nigerian agriculture. This is because of the large volume of theoretical and empirical literature in the field of efficiency measurement and it will help in giving the study a proper focus. The analytical framework and empirical specifications for the alternative approaches are discussed in chapter four. Chapter five describes the study area, sampling procedures, data and socioeconomic characteristics of sampled households. Chapter six is dedicated to discussion of results from different approaches and their comparison. The integrated model and results from the model is discussed in chapter seven. Chapter eight provides a summary of the research problem, study approach, main findings and policy implications, limitations of the study and recommendations or scope for further research.

CHAPTER 2

A REVIEW OF AGRICULTURAL POLICIES AND PROGRAMMES IN NIGERIA

2.1 Introduction

Agricultural policy is the combination of the outline and strategies designed to achieve overall agricultural development and growth. Agricultural development refers to the process of making fuller and more rational the use of agricultural resources of a country, with a special reference to improving the efficiency of agriculture and the living standards of the agricultural population (FAO 1953 cited in Famoriyo and Raza, 1982). Agricultural policies and programmes can be evaluated by their ability to promote not only agricultural development but also overall economic growth, the capacity to bring about structural transformations and their poverty reducing impacts. Farmers are generally confronted with many risks and uncertainties ranging from weather, drought, floods, fire, diseases and pest, unstable market conditions, falling product prices and constant increase in the prices of production inputs among others. These risks in the production and socioeconomic environment in which farmers operate make it very essential to make deliberate developmental efforts to prevent agricultural productivity from declining or remaining static and promote agricultural development in general.

The Nigerian government has made several developmental efforts aimed at improving the performance of the agricultural sector. The national policy on agriculture can be viewed either as a process or as an output (or product) or both. Viewed as an output, the national policy on agriculture becomes roughly equivalent to the national policy statement(s) on agriculture. These statements are usually contained in government publications and documents. An agricultural policy statement usually consists of the objectives, the strategies for their realization, and the operational targets for measuring performance (Oji, 2002). The policy documents identifies the ultimate goal of Nigerian Agricultural Policy as the attainment of self-sustaining growth in all the sub-sectors of agriculture as well as the realization of the structural transformations necessary for the overall socio-economic development of the rural areas. Viewed as a process, the national policy on agriculture reflects the cumulative experiences and lessons learned from implementing various policies in the agriculture sector right from the nation's independence in 1960 (Igbokwe et al., 2004).

The purpose of this chapter is to present an overview of the agricultural policy and programmes in Nigeria and their impact on agricultural productivity and development. The next section provides a review of agricultural policies and programmes in Nigeria. The third section evaluates the impact of development strategies on agriculture's performance. The last section concludes by providing a summary.

2.2 Agricultural Policy and Programmes in Nigeria

Since Nigeria's independence in 1960, successive governments as well as international donors, bilateral and multilateral agencies have designed and implemented different agricultural policies and programmes. The agricultural policies and strategies adopted in Nigeria since independence are discussed under four distinct periods. These include the pre-1970 era, the period 1970-1985, the period 1986-1999, and post 1999 era.

2.2.1 The Pre-1970 Era

The pre-1970 era was characterized by minimum direct government intervention in agriculture. As such, government's attitude to agriculture was relaxed, with the private sector and particularly the millions of small traditional farmers bearing the brunt of agricultural development efforts. Government efforts were merely supportive of the activities of these farmers and these largely took the form of agricultural research, extension, export crop marketing and pricing activities. Most of these activities were regional-based towards the end of the colonial era with federal government's contribution being confined largely to agricultural research. The low visibility of governments in agricultural development efforts was borne out of a general philosophy of economic laissez faire. Some governments were bent on making their presence felt in agriculture, especially in the 1950s and 1960s, by creating government-owned agricultural development corporations and launching farm settlement schemes. But these actions found their justification more in welfare considerations than in hard-core economic necessities (Manyong et al., 2003).

The first National Development Plan for the years 1962-68 was enacted during this era. This Development Plan was aimed at exploiting the abundant natural resources for improvement of the living standards and GDP growth target was set at 4 percent per annum (Federal Ministry of Economic Development, 1963). However, the share of investment to the primary sector was only 13.6 percent whereas the shares of industries, electricity, and the transportation system added up to 50 percent (Shimada, 1999). This development plan focused mainly on infrastructure provisions and it was designed such that regional governments would also implement their own development plans in addition to that of the federal government. During this period, much emphases was laid on export crops through research, extension, subsidies and export-crop marketing and development programmes for cocoa, groundnut and palm produce. Little attention was given to food crop production.

By the end of the 1960s, it became obvious that the Nigerian agricultural economy was heading towards big catastrophe. Signs of emerging agricultural problems included declining export crop production and some mild food shortages. Even then, most of these problems were attributed to the civil war and as such, were considered to be only ephemeral in nature. But events soon proved these optimistic assumptions wrong as the agricultural sector sank deeper and its problems became much more intractable than anticipated (Manyong et al., 2003).

2.2.2 The 1970-1985 Era

The second era, 1970-1985, is the period spanning the post-civil war years to the era just before economic adjustment, and it was characterized by change from minimum intervention, to that of active intervention and programming. This phase witnessed massive government involvement in all facets of agricultural production. The feeling was pervasive that the solutions to the increasingly serious problems of agriculture and especially those of food supply required the heavy clout of government in the form of multi-dimensional agricultural policies, programs and projects, some of them requiring the direct involvement of government in agricultural production activities. The sudden smile of oil fortune on Nigeria reinforced this feeling (Manyong et al., 2003). Hence, the decade of the l970s and early 1980s witnessed an unprecedented deluge of agricultural policies, programs, projects and institutions. Direct and indirect agricultural interventions were implemented with public resources from oil earnings.

During this period, the second National Development Plan for the years 1970/71-1973/74 was enacted. The main aim of this development plan was to restore the economy damaged by the war, and agriculture was still its utmost priority. However, again the budgetary share for agriculture was only 10.5 percent, and the expenditure realized was 7.7 percent of the total (Federal Ministry of Economic Development, 1975; Shimada 1999). Within the agricultural sector itself, the emphasis was on restoration of export crop production, and the food-producing sector attracted only little attention. The food shortages which resulted from the Biafran war and subsequent effects of the 1972-74 droughts destabilized the optimistic view on agriculture that was prevalent in the 1960s. Imminent crisis was felt, but no action was taken. The government chose to rely on imports of maize, wheat, and rice, rather than to address measures to strengthen food production (Shimada, 1999).

In 1974, the National Accelerated Food Production Project (NAFPP) was initiated and it was aimed at increasing the production of rice, maize, millet, sorghum, cassava, and wheat. The program assisted supply of improved seeds, chemical fertilizers, and pesticides, education of farmers, sales of agricultural products, and stock management and processing. Agro Service Centres were built all around the country to ensure effective service delivery to the public. However, these services failed to provide agricultural inputs at the right time, and before it could achieve any substantial results, the main constituents were transferred to the Agricultural Development Project (ADP) in 1975 (Okuneye, 1992, Shimada, 1999). The ADP was set up in all states of the federation to help organize farmers into more productive agriculture through the provision of modern inputs. It however, included more comprehensive measures in addition to the provision of agricultural inputs, such as construction of agricultural roads, building of small-scale dams, and setting up of Agro Service Centres. At the end of 1985, there were 470 Agro Service Centres all over the country (Okuneye, 1992).

During this era, other programmes aimed at boosting food production were also in place. These include Operation Feed the Nation (OFN) and the Green Revolution Scheme. These projects were innovative in the history of Nigerian agricultural policy in that they proved a shift of the government's attitude toward active participation in food production. The OFN was actively advertised to public, using mass media, and was substantially implemented. The aim of the project was to build a stable and self-sufficient socio-economic system by increasing food production to the level sufficient to feed the growing population, and to lower the import dependency ratios. Thus, not only the farmers but all citizens were called for co-operation. Distribution of fertilizers and improved breeds, extermination of insects and diseases, and lending of agricultural tools and machines were pursued not only by farmers but also by all citizens, including military men and civil servants. Mobilization of university and polytechnic students in farming during the summer vacation was also pursued.

In October, 1979, there was a change from military government to a democratic one which led to the election of Shehu Shagari as the president of Nigeria and the Fourth National Development Plan (1981-1985) was enacted thereafter. The scale of this plan with a total budget of 70,500,000,000 Naira reflected the oil revenues of the late 1970s. The plan aimed at improvement in real earnings, equality in income distribution, lowering of unemployment and under-employment rates, increased skilled labour, diversified economic activities, growth with equality among regions and sectors, and strengthened self-sufficiency of the economy by utilizing domestic resources more efficiently. The agricultural sector and the agricultural processing sector were designated as the first priorities for development, and the largest share of budget, 13.1 percent (9,260,000,000 Naira) was allocated to the agricultural sector (Federal Ministry of National Planning (undated) cited in Shimada, 1999).

Regardless of the OFN, the food shortage in Nigeria worsened. To counteract this situation, the government additionally set out the Green Revolution Plan Scheme in 1980. Improved rural road and education facilities were election promises of the National Party of Nigeria (NPN) led by President Shagari (Udo, 1982). Thus, the abolition of the OFN and the enactment of the Green Revolution were not merely about a change in agricultural development policy but also a reflection of political matters (Shimada, 1999). The scheme was set up to encourage all Nigerians in both urban and rural areas to go into agriculture for both commercial purposes and provision of food for home consumption. This scheme aimed to achieve self-sufficiency in food provision by 1985, when the Fourth National Development Plan terminated. For this goal, the scheme emphasized the need for comprehensive development of the rural areas. Thus emphasis was not only on food production, but also on building food processing firms, developing rural roads, providing houses, improving education and health facilities, and installation of water and electricity systems. Given the much dependency on imported inputs and foreign direction in irrigation projects that prevailed prior to this period, the scheme emphasized that dependency on foreign powers should be avoided as much as possible in terms of both manpower and technology. There are doubts about the impact of these programmes or schemes. They failed as efforts aimed at developing the agriculture sector. For instance, the green revolution led to increasing inequality in the rural areas whereby larger landowners became richer while the poorer farmers who produce the bulk of Nigeria's food needs were disadvantaged (Famoriyo and Raza 1982; Shimada, 1999; Manyong et al., 2003).

2.2.3 The 1986-1999 Era

The failure of the state led approach to development, Nigeria's declining fortune in the petroleum export market, an escalating debt burden and an unhealthy investment climate led to the realization that the country's economy required some drastic restructuring. These gave impetus to the structural adjustment program (SAP) launched in July 1986. A structural adjustment program comprises a mix of demand-side policies, supply-side policies and other policies designed to improve a country's international competitiveness. Generally, structural adjustment policies in Nigeria were aimed not only at correcting existing price distortions in the economy but also structural imbalances and for promoting non-price factors which would enhance the effectiveness of price factors (Manyong et al., 2003). The SAP period was characterised by contracting fiscal policies, deregulatory monetary and exchange rate policies, institutional restructuring and government divestiture from direct agricultural production and marketing.

According to Manyong et al. (2003), structural adjustment policies in Nigeria could be categorized into four broad groups. In the first group were expenditure reducing or demand-management policies, which were designed to influence the economy's aggregate domestic absorption mainly through fiscal and monetary policy instruments. The second group included expenditure switching policies that were designed to alter domestic relative prices in favour of tradable commodities and improve the price competitiveness of export commodities and import -competing goods. The most important policy instrument for this was the devaluation of the national currency. Thirdly, there were market liberalization policies that were designed to give the free interplay of market forces more roles in the economy, reduce administrative controls as well as government intervention in the operation of the economy and, generally, render the economy more flexible and more resilient. Policy instruments required for these included those aimed at reducing import and export taxes, eliminating export and import prohibitions, relaxing input and output marketing controls, withdrawal of subsidies and price controls, and so on. Fourthly, there were institutional or structural policies that were designed to eliminate those structural constraints that tended to inhibit the effectiveness of other adjustment policies. Some major structural policy instruments were those designed to promote the flow of technological innovation, provide better input delivery systems, provide more infrastructure and utilities, improve national information systems, provide institutional framework for the smooth operation of free market system and, generally, create a more favourable environment for increased investment in the economy, efficient allocation of resources and enhanced profitability of public enterprises through commercialization and privatization.

With respect to the agricultural sector under SAP, the tariff structure was adjusted to encourage local production and to protect agricultural and local industries from unfair international competition. The marketing boards for scheduled crops were abolished. Bans were placed on the importation of a number of food items including most livestock products, rice, maize, wheat and vegetable oils. Subsidies for agricultural input subsidies were substantially cut. For instance, in the first half of the 1980s, the retail prices of fertilizers and pesticides were only 25 percent and 20 percent of real prices, respectively. The subsidizing rate for fertilizers, for example, was dropped from 75 percent to 60 percent (CBN, 1992). A number of new institutions were created for agricultural and rural development namely; the Directorate of Food, Roads and Rural Infrastructure (DFRRI) and the National Directorate of Employment (NDE). Some existing institutions were also reorganised (e.g. the River Basin Development Authorities), while most public-owned agricultural enterprises were privatised or commercialized (Federal Ministry of Agriculture and Rural Development (FMARD), 2001).

Following SAP, the economic philosophy of the government for the agricultural sector are the key principles that (i) agriculture is essentially a private-sector activity, and the role of government must largely be facilitating and supportive of private-sector initiative; (ii) the agricultural economy should be as free of government administrative control as possible, as market forces are allowed to play a leading role in directing the economy and resource allocation; (iii) the agricultural economy should be more inward-looking and self-reliant by depending more on local resources, and at the same time ensuring self-sufficiency in food production and the supply of raw-materials to industries; (iv) the agricultural economy should serve as the primary avenue for the diversification of the export base of the economy. (v) the agricultural economy should provide the take-off and serve as the engine room for growth and development in the economy (Igbokwe et al., 2004).

According to FMARD (2001), these SAP measures to some extent had positive impact on the agricultural sector due mainly to price increase as a result of devaluation of the currency and ban on importation of wheat, rice and maize. The ban placed on the importation of some food items increased the output of local production, especially rice. However poultry and fishery production became less profitable because of the resultant exorbitant costs of imported inputs attendant on SAP. Sharp rises in imported inputs such as fertilizer, agro-chemicals etc. were also witnessed while the cost of providing large scale irrigation rose because of the high cost of foreign components. The increase in the cost of the import component of equipment for research and technology development reduced their further growth. Although SAP substantially addressed problems of price distortions to the farmers, new problems were created by the effects of the changes in macro-economic policies. Implementation bottlenecks arising from scarcity of basic farm inputs and slower rate of adoption of new technologies also contributed their quota in impeding the achievement of policy objectives. These reduced the expected benefits of yield increases accruable from the adoption and use of modern farm inputs such as improved variety of seeds. The withdrawal of subsidies which increased production costs substantially reduced the profitability of agricultural activities leading to reduction in size of farm holdings and enterprises. The problem of inefficient marketing persisted as a result of existence of imperfection in the markets, dwindling marketing infrastructures and limited availability of storage facilities.

In 1988, the first national policy on agriculture was adopted and was expected to remain valid up to the year 2000. The document, Agricultural Policy for Nigeria, released by FMARD (1988), itemized seven broad agricultural policy objectives along with their accompanying strategies for realization. The seven broad policy objectives include: (i) attainment of self-sufficiency in basic food commodities with particular reference to those which consume considerable shares of Nigeria's foreign exchange and for which the country has comparative advantage in local production; (ii) increase in production of agricultural raw materials to meet the growth of an expanding industrial sector; (iii) increase in production and processing of exportable commodities with a view to increasing their foreign exchange earning capacity and further diversifying the country's export base and sources of foreign exchange earnings; (iv) modernization of agricultural production, processing, storage and distribution through the infusion of improved technologies and management so that agriculture can be more responsive to the demands of other sectors of the Nigerian economy; (v) creation of more agricultural and rural employment opportunities to increase the income of farmers and rural dwellers and to productively absorb an increasing labour force in the nation; (vi) protection and improvement of agricultural land resources and preservation of the environment for sustainable agricultural production; (vii) establishment of appropriate institutions and creation of administrative organs to facilitate the integrated development and realization of the country's agricultural potentials.

The main features of the policy include the evolution of strategies that will ensure self-sufficiency and the improvement of the level of technical and economic efficiency in food production. This was to be achieved through the introduction and adoption of improved seeds and seed stock, husbandry and appropriate machinery and equipment, efficient utilization of resources, encouragement of ecological specialisation and recognition of the roles and potentials of small scale farmers as the major producers of food in the country. Reduction in risks and uncertainties were to be achieved through the introduction of the agricultural insurance scheme to reduce natural hazard factors militating against agricultural production and security of credit outlay through indemnity of sustained losses. A nationwide, unified and all-inclusive extension delivery system under the ADP was put in place in a joint federal and state government collaborative effort. Agro- allied industries were actively promoted. Other incentives such as rural infrastructure, rural banking, primary health care, cottage industries etc. were provided, to encourage agricultural and rural development and attract youth, including school leavers, to go back to the land.

The agricultural policy was supported by sub-policies aimed at facilitating the growth of the sector. These sub-policies covered issues of labour, capital and land whose prices affect profitability of production systems; crops, fisheries, livestock and land use; input supply, pest control and mechanisation; water resources and rural infrastructure; agricultural extension, research, technology development and transfer; agricultural produce storage, processing, marketing, credit and insurance; cooperatives, training and manpower development, agricultural statistics and information management. Implementation of the agricultural policy was however, moderated by the macro-economic policies which provide the enabling environment for agriculture to grow along side with the other sectors. These policies usually have major impact on profitability of the agricultural system and the welfare of farmers as they affect the flow of funds to the sector in terms of budgetary allocation, credit, subsidies, taxes etc and, therefore, must be in harmony and mutually reinforcing with the agricultural policy. The macro policies comprise the fiscal, monetary, trade, budgetary policies and other policies that govern macro-prices.

The experience gained over the years in the implementation of the agricultural policy and the trends in agricultural development during this era lead to the formulation of a number of sub-sectoral policies which include the Land Resources Policy which is expected to guide the sustainable use of agricultural lands, National Agricultural Mechanisation Policy, National Cooperative Development Policy, and the National Seed Policy which assigns primary responsibility for commercial seed supply to the private sector while Government was responsible for foundation and breeder seed development, seed certification and quality control and certification while providing the enabling environment for the seed industry development. The National Policy on Integrated Rural Development was also formulated and was expected to integrate the rural economy into the mainstream of national development process to ensure its effective coordination and management and make the rural areas more in tune with the urban areas so as to moderate the rural-urban drift, redress the past neglect through provision of critical rural infrastructure and empowerment of the rural population to create wealth and eradicate rural poverty (FMARD, 2001).

In view of the fact that agricultural and rural development is critical for generating economic growth, institutional arrangements were also adopted for realising sector objectives (FMARD, 2001). These include the relocation of the Department of Cooperatives of the Ministry of Labour and its merger with the Agricultural Cooperatives Division of the Ministry of Agriculture, the transfer of the Department of Rural Development from the Ministry of Water Resources to the Ministry of Agriculture; the scrapping of the erstwhile National Agricultural Land Development Authority (NALDA) and, the merging of its functions with the Rural Development Department; scrapping of the Federal Agricultural Coordinating Unit (FACU) and the Agricultural Projects Monitoring and Evaluation Unit (APMEU) and the setting up of Projects Coordinating Unit (PCU) and streamlining of institutions for agricultural credit delivery with the emergence of the Nigerian Agricultural, Cooperative and Rural Development Bank (NACRDB) from the erstwhile Nigerian Agricultural and Cooperative Bank (NACB) and the Peoples Bank and the assets of the Family Economic Advancement Programme (FEAP).

2.2.4 The Post 1999 Era

The federal government under the leadership of President Olusegun Obasanjo critically evaluated the 1988 agricultural policy in 2001; an evaluation which led to the approval of its latest policy entitled ‘‘The New Policy Thrust for Agriculture’’ in 2002 (FMARD, 2001; FRN, 2002). The new policy document share very similar features to that of 1988. However, this new policy thrust provided greater support for the underlying philosophy of allowing the private sector and market forces to dictate the pace of development in the agriculture sector, while governments at all levels are restricted to facilitating roles, support services, and providing the enabling environments for agricultural growth. In a broad sense, the objectives of the new agricultural policy are very similar to those of the old one. They include:(i) The achievement of self-sufficiency in basic food supply and the attainment of food security;(ii) increased production of agricultural raw materials for industries;(iii) Increased production and processing of export crops, using improved production and processing technologies; (iv) generating gainful employment; (v) rational utilization of agricultural resources, improved protection of agricultural land resources from drought, desert encroachment, soil erosion and flood, and the general preservation of the environment for the sustainability of agricultural production; (vi) promotion of the increased application of modern technology to agricultural production; and, (vii) improvement in the quality of life of rural dwellers.

The key features of the new policy are as follows: (i) Evolution of strategies that will ensure self-sufficiency and improvement in the level of technical and economic efficiency in food production. This is to be achieved through (i) the introduction and adoption of improved seeds and seed stock; (ii) adoption of improved husbandry and appropriate machinery and equipment; (iii) efficient utilization of resources; (iv) encouragement of ecological specialization; and (v) recognition of the roles and potentials of small -scale farmers as the major producers of food in the country; (vi) reduction of risks and uncertainties in agriculture, to be achieved through the introduction of a more comprehensive agricultural insurance scheme to reduce the natural hazard factors militating against agricultural production and security of investment; (vii) a nationwide, unified and all-inclusive extension delivery system under the ADPs; (vii) active promotion of agro-allied industry to strengthen the linkage effect of agriculture on the economy; (viii) provision of such facilities and incentives as rural infrastructure, rural banking, primary health care, cottage industries etc, to encourage agricultural and rural development and attract youths (including school leavers) to go back to the land.

The major content of the new policies include (i) agricultural resources (land, labour, capital, seeds, fertilizer, etc) whose supply and prices affect the profitability of agricultural business; (ii) crops, livestock, fisheries and agro-forestry production; (iii) pest control; (iv) mechanization; (v) water resources and irrigation; (vi) rural infrastructure; (vii) agricultural extension and technology transfer; (viii) research and development (R&D); (ix) agricultural commodity storage, processing and marketing; (x) credit supply; (xi) insurance; (xii) agricultural cooperatives; (xiii) training and manpower development and (xiv) agricultural statistics and information management.

According to the document (FMARD, 2001; FRN, 2002), the new agricultural policy will herald in a new policy direction via new policy strategies that will lay the foundation for sustained improvement in agricultural productivity and output. The new strategies involve: (i) creating a more conducive macro-environment to stimulate greater private sector investment in agriculture; (ii) rationalizing the roles of the tiers of government and the private sector in their promotional and supportive efforts to stimulate agricultural growth; (iii) reorganizing the institutional framework for government intervention in the agricultural sector to facilitate the smooth and integrated development of the sector; (iv) articulating and implementing integrated rural development programs to raise the quality of life of the rural people; (v) increasing budgetary allocation and other fiscal incentives to agriculture and promoting the necessary developmental, supportive and service-oriented activities to enhance agricultural productivity, production and market opportunities and (vi) rectifying import tariff anomalies in respect of agricultural products and promoting the increased use of agricultural machinery and inputs through favourable tariff policy.

The new agricultural policy spelt out definitive roles and responsibilities for the federal, state and local governments as well as the private sector in order to remove role duplication and overlapping functions among them. Under the new policy regime, the federal government are responsible for: (i) the provision of a general policy framework, including macroeconomic policies for agricultural and rural development and for the guidance of all stakeholders; (ii) maintenance of a reasonable flow of resources into agriculture and the rural economy; (iii) support for rural infrastructure development in collaboration with state and local governments; (iv) research and development of appropriate technology for agriculture, including biotechnology; (v) seed industry development, seed law enforcement and seed quality control; (vi) support for input supply and distribution, including seeds, seedlings, brood stock and fingerlings; (vii) continued support for agricultural extension services; (viii) management of impounded water, supervision of large dams and irrigation canals and maintenance of pumping facilities; (ix) control of pests and diseases of national and international significance and the promotion of integrated disease and pest management; (x) establishment and maintenance of virile national and international animal and plant quarantine services; (xi) maintenance of favourable tariff regime for agricultural commodities; (xii) promotion of the export of agricultural commodities through, among others, the Export Processing Zones (EPZs); (xiii) establishment of an agricultural insurance scheme; (xiv) maintenance of a Strategic National Grain Reserve for national food security; (xv) coordination of agricultural data and information management systems; (xvi) inventorization of land resources and control of land use and land degradation; (xvii) training and manpower development; (xviii) participation in the mapping and development of interstate cattle and grazing routes and watering points; (xix) promotion of micro-and rural credit institutions; (xx) promotion of agricultural commodity development and marketing institutions; (xxi) maintenance of fishing terminals and other fisheries infrastructure, including cold rooms; (xxii) promotion of trawling, artisanal and aquaculture fisheries; (xxiii) promotion of fish feed production; (xxiv) protection of Nigeria's Exclusive Economic Zone for fisheries resources and (xxv) periodic review of agreements on international agricultural trade.

The state governments are primarily responsible for: (i) the promotion of the primary production of all agricultural commodities through the provision of a virile and effective extension service; (ii) promotion of the production of inputs for crops, livestock, fish and forestry; (iii) ensuring access to land for all those wishing to engage in farming; (iv) development and management of irrigation facilities and dams; (v) grazing reserve development and creation of water access for livestock; (vi) training and manpower development; (vii) control of plant and animal pests and diseases; (viii) promotion of appropriate institutions for administering credit to smallholder farmers; (ix) maintenance of buffer stocks of agricultural commodities; (x) investment in rural infrastructure, including rural roads and water supply in collaboration with federal and local governments and (xi) ownership, management and control of forest estates held in trust for local communities.

The local governments are expected to take over progressively the responsibilities of state governments with respect to: (i) the provision of effective extension service; (ii) provision of rural infrastructure to complement federal and state governments' efforts; (iii) management of irrigation areas of dams; (iv) mobilization of farmers for accelerated agricultural and rural development through cooperative organizations, local institutions and communities; (v) provision of land for new entrants into farming in accordance with the provision of the Land Use Act and (vi) coordination of data collection at primary levels.

According to the policy document, since agricultural production, processing, storage and marketing are essentially private sector activities; the role of the private sector was to take advantage of the improved enabling environment provided by the public sector for profitable agricultural investment. In particular, the public sector is expected to play a leading role with respect to: (i) investment in all aspects of upstream and downstream agricultural enterprises and agribusinesses, including agricultural commodity storage, processing and marketing; (ii) agricultural input supply and distribution; (iii) the production of commercial seeds, seedlings, brood stock and fingerlings under government certification and quality control; (iv) agricultural mechanization; (v) provision of enterprise-specific rural infrastructure and (vi) support for research in all aspects of agriculture.

Following the redefined roles and responsibilities of tiers of government and the private sector, the main thrust of federal government programs and activities are directed at obviating the technical and structural problems of agriculture. These include research and development, (including biotechnology development), animal vaccine production, veterinary drug manufacture, agro -chemicals manufacture, water management, adaptive technology promotion, and the creation and operation of an Agricultural Development Fund. Supportive activities under the new policy comprise input incentive support and commodity marketing and export activities, support delivery activities cover input supply and distribution, agricultural extension, micro-credit delivery, cooperatives and farmer/commodity associations, commodity processing and storage, agro-allied industry and rural enterprise development, and export promotion of agricultural and agro-industrial products. For instance in the case of input supply and distribution the government is expected to create a more conducive environment for profitable investments in the production and distribution of inputs such as improved starter materials, animal health drugs, fertilizers, etc. Fertilizer supply is hinged on complete privatization and liberalization in the production, distribution and marketing of the commodity. The main role of the government therefore is to strictly monitor the quality standard of all fertilizers (both local and foreign) to ensure that only certified products reach the farmer. Government is also expected to encourage the use of organic fertilizers to complement the inorganic fertilizers currently in use. The seed industry development program is expected to be reinvigorated and community seed development programs promoted to ensure the provision of adequate and good quality seeds to local farmers. The organised private sector is to be mobilized, encouraged and given incentives to actively participate in the production of seeds, seedlings, brood stock, fingerlings, etc, and also to be involved in out-growers mobilization.

The successful implementation of the agricultural policy is, however, contingent upon the existence of appropriate macroeconomic policies that provide the enabling environment for agriculture to grow in equilibrium with other sectors. They affect profitability of agricultural enterprises and the welfare of farmers through their effects on the flow of credit and investment funds, taxes, tariffs, subsidies, budgetary allocation, etc. A range of macroeconomic and institutional policies as well as legal framework that affect agricultural investment in particular and agricultural performance in general was therefore considered under the new policy. The policies broadly cover fiscal, monetary and trade measures. There is also a large body of institutional policies that support not only the implementation of macroeconomic policies but also that of agricultural sector policies. Then, there is a set of national and international legal framework, including bilateral and multilateral agreements and treaties that provide the enabling environment for foreign and domestic private investment, promote international trade and, therefore, promote economic growth.

One of the important policies which is of interest to this study is the environmental policy. The goals of National Policy on the Environmental is to achieve sustainable development in Nigeria, and, in particular, to (i) secure a quality of environment adequate for good health and well being; (ii) conserve and use the environment and natural resources for the benefit of present and future generations; (iii) restore, maintain and enhance the ecosystems and ecological processes essential for the functioning of the biosphere to preserve biological diversity and the principle of optimum sustainable yield in the use of living natural resources and ecosystems; (iv) raise public awareness and promote understanding of the essential linkages between the environment, resources and development, and encourage individual and community participation in environmental improvement efforts; and (v) co-operate in good faith with other countries, international organisations and agencies to achieve optimal use of trans-boundary natural resources and for an effective prevention or abatement of trans-boundary environmental degradation.

In recognition of several longstanding challenges facing Nigeria which includes the fact that as at 2001, over 70 percent of Nigerians live below the poverty line of 1 US$ per day (UNDP, 2004), most of them in rural areas and depend on agriculture for sustenance, the federal government embarked on a series of economic reforms. In 2004, the federal government of Nigeria launched its National Economic Empowerment and Development Strategy (NEEDS) which identifies agriculture and reforming government and its institutions as core elements of economic growth. NEEDS is actually an important component of the new agricultural policy (International Conference on Agrarian Reform and Rural Development (ICARRD), 2006). In general terms, NEEDS offers a very promising strategic direction to achieve poverty reduction, food security, and accelerated economic development. NEEDS recognizes that a dynamic and competitive non-oil private sector is essential to rapid and sustained growth. Nigeria's key policy thrusts for agriculture and food security under this scheme were to: (i) provide the right policy environment and target incentives for private investment in the sector; (ii) implement a new agricultural and rural development policy aimed at addressing the constraints in the sector; (iii) foster effective linkages with industry to achieve maximum value-added and processing for export; (iv) modernize production and create an agricultural sector that is responsive to the demands and realities of the Nigerian economy in order to create more agricultural employment opportunities, which will increase the income of farmers and rural dwellers; (v) reverse the trend in the import of food (which stood at 14.5 percent of total imports at the end of 2001), through a progressive programme for agricultural expansion; (vi) strive towards food security and food surplus that could be exported; (vii) invest in improving the quality of the environment in order to increase crop yields. The main targets include; achieve minimum annual growth rate of 6 percent in agriculture; (ii) raise agricultural exports to $3 billion by 2007; (iii) drastically reduce food imports, from 14.5 percent by 2007; (iv) develop and implement a scheme of land preparation services to increase cultivable arable land by 10 percent a year and foster private sector participation through incentive schemes; (v) promote the adoption of environment friendly practices; (vi) protect all prime agricultural lands for continued agricultural production (National Planning Commission, 2004).

Apart from the agricultural sector wide policies and programmes, a number of single crop programmes were initiated to improve agricultural production and productivity in Nigeria in general and some strategic crops in particular. For instance, the Olusegun Obasanjo administration added some impetus to the global efforts in the development of cassava by putting in place a 'Presidential Committee on Cassava for Exports', with the mandate to ensure that the country becomes the world-acknowledged cassava-exporting nation. The presidential initiative on cassava production and export is therefore intended to raise the production level of cassava to 150million Mt by the end of year 2010. The programme is also expected to assist the country realize an income of US$5.0billion per annum from the export of 37.6million tons of dry cassava products such as starch, cassava chips, adhesives and other derivatives (Abdullahi, 2003, Umeh and Asogwa, 2005; ICARRD, 2006). Currently Nigeria has replaced Brazil as the World's largest producer of cassava (Nweke, 2004).

There is also the Presidential Initiative on increased Rice Production designed to reverse the rising import bill, which stood at N96.012 billion in 2002 to meet domestic demand by 2006 and export by end of 2007. By 2007, it is targeted that 3.0 million hectares of land would be put under cultivation to produce about 15 million tones of paddy or 9.0 million tones of milled rice. In order to achieve this goal, Government embarked on:-procurement and distribution of 81,505 R-Boxes to the States and Federal Capital Territory (FCT) at 50 percent subsidy. The R-Box contains rice seeds, agro-chemicals and extension messages to farmers on its applications. The package is required to cultivate one-quarter of a hectare of rice. Similarly, 250 units of Knapsack Sprayers have been distributed to farmers based on needs. Production of 4.92 Mt of breeder seeds and 25.23mt of foundation seed stage 1 of the new rice for Africa (NERICA) I and 12.6mt of lowland varieties of foundation seed stage 1 by

National Cereal Research Institute and West African Rice Development Association; production of 58mt of foundation seed of rice varieties by the National Seeds Service (NSS); establishment of Management Training Plots on R-Box in Twenty-five (25) states including the FCT. About 1,250 farmers participated in the programme to showcase the benefits derivable from the use of the R-Box to accelerate its adoption by farmers; provision of irrigation infrastructure and construction of water reservoir at National Cereals Research Institute (NCRI), Badeggi for all year round breeder seed production; Six train-the-trainer workshops for rice farmers and extension agents (one per geo-political zone) on rice production and processing technologies (ICARRD, 2006).

Further, in realization that, maize is among the most important crops in Nigeria, but poor seed supply, inefficient marketing system, and low investment in research are among the factors that have limited production, the federal government still under the leadership of President Olusegun Obasanjo initiated a programme to double maize production in the country both for national consumption and international export through promotion of improved agricultural technologies (USAID, 2006). The doubling maize programme began in 2006 and was funded by the Federal Ministry of Agriculture and Rural Development. Partners include IITA, the Institute of Agricultural Research and Training, National Rice/Maize Centre, National Accelerated Food Production Program, Institute for Agricultural Research, National Cereals Research Institute, the University of Ilorin and the National Agricultural Extension and Research Liaison Services. The target is to raise the production of maize from current 8 million tonnes to 20 million tonnes and productivity from the about 1.5 tonnes per hectare to 4.2 tonnes per hectare and the possibility of achieving this target proved successful with more than 1000 farmers used in experimentation (IITA, 2009). It is not known to what extent the intended productivity gains from improved agricultural production technologies have been realized through these policy initiatives. Therefore, it is of interest in this study to assess the impact of the promoted improved technologies (which serves as proxy for investment in research and development) on the economic efficiency of smallholder maize farmers.

At the inception of his administration in 2007, President Umaru Musa Yar' Adua who succeeded Chief Olusegun Obasanjo earmarked on a Seven-Point Agenda so that the nation can move forward and be among the 20 largest economies by the year 2020. Briefly, the Seven-Point Agenda include: Energy and power, Food Security and Agriculture, Wealth Creation, Education, Land Reforms, Mass Transit and the Niger Delta issue. The broad policy objectives of both Vision 2020 and the Seven-Point Agenda are sustenance of a rapid broad based GDP growth, poverty reduction, employment generation, macroeconomic stability and economic diversification. To achieve this, Nigeria would require growth rates of between 13-15 percent in the medium-term, a goal which supersedes the 5-6 percent growth rate obtained then (Foreign Agricultural Service of United States Department of Agriculture (FAS, USDA), 2009). Like the Obasanjo administration (1999-2007), the thrusts of the policy direction for agriculture and food security within the seven point agenda include: creating the conducive macro environment to stimulate greater private sector investment in agriculture so that the private sector can assume its appropriate role as the lead and main actor in agriculture; rationalizing the roles of the tiers of government in their promotional and supportive activities to stimulate growth; reorganizing the institutional framework for government intervention in the sector to facilitate smooth and integrated development of agricultural potentials; articulating and implementing integrated rural development as a priority national programme to raise the quality of life of the people; increasing agricultural production through increased budgetary allocation and promotion of the necessary developmental, supportive and service-oriented activities to enhance production and productivity and marketing opportunities; increasing fiscal incentives to agriculture, among other sectors, and reviewing import waiver anomalies with appropriate tariffication of agricultural imports and promoting increased use of agricultural machinery and inputs through favourable tariff policy (Akinboyo, 2008).

As a response to the Seven Point Agenda, the Federal Ministry of Agriculture & Water Resources launched its National Food Security Programme (NPFS) in September 2008, to combat the global food crisis and with a vision to ensure sustainable access, availability and affordability of quality food to all Nigerians. The programme's vision is to eventually become a significant net provider of food to the global community and for the next four years (2008-2011), the federal government set aside N200 billion, which is about USD 1.7 billion, for the development of the programme. The short-term goals of the programme are to significantly improve the country's agricultural productivity. In the medium term, the aim is to expand and improve large-scale production, improve storage as well as processing capacity and establish the required infrastructure. The long-term objective is to derive over 50 percent of the nation's foreign exchange through agricultural exports. (CBN, 2008; Corporate Nigeria, 2009). A number of agricultural initiatives are implemented under the NPFS which includes a significant increase in the quantity of assorted fertilizers distributed nationwide, the rehabilitation and expansion of existing irrigation schemes, as well as the retention of the policy of zero tariffs on imported agrochemicals (CBN, 2008).

Further, in a bid to fast-track the transformation of the agricultural sector, the federal government in collaboration with the World Bank, has established the Commercial Agriculture Development Programme (CADP). The Programme, which has five states (Cross River, Enugu, Kaduna, Kano and Lagos) participating in the first phase, aims at strengthening agricultural production systems for targeted value chains and facilitate access to markets. The project is estimated to cost US$185 million, with the World Bank providing US$150 million, while the federal and the participating state governments would provide the balance of US$35 million (CBN, 2008).

With respect to input supply and distribution, three key inputs have received attention namely fertilizer, improved seeds and agrochemicals. Currently, the federal government of Nigeria, under the Federal Market Stabilization Program, procures fertilizer for sale to states at a subsidy of 25 percent. State governments typically institute additional subsidies on fertilizer. Under the current marketing structure, companies make bids to the federal government to import and distribute subsidized fertilizer (International Food Policy Research Institute (IFPRI), 2009). The seed sector is also a key component of the crops sub-sector. Most farmers in Nigeria depend on self-saved seeds. There is a thriving market in locally saved seeds by farmers. The formal seed trade is very underdeveloped. The National Seed Policy provides for coordination, monitoring and implementation of quality control in the national seed system (as regards seed production, marketing and quality control activities) by the NSS of the Federal Ministry of Agriculture and Rural Development. The National Seed Policy makes provision for the withdrawal of public sector agencies in favour of private sector in key areas of the seed industry. Another important segment of the crops sub-sector is the crop protection chemicals the use of which is still very low among Nigerian farmers. Here the federal government's policy is to encourage the establishment of manufacturing plants to make agro-chemicals in Nigeria. But so far there are no manufacturers of agro-chemicals. Instead the companies that operate in Nigeria do only reformulation and packaging, relying on their parent companies abroad to do the basic manufacturing. A 50 percent subsidy is used to support machinery ownership in this sector (Department for International Development (DFID), 2005).

2.3 The Performance of Nigerian Agriculture

A critical review of the state and performance of the sector since independence will assist an understanding of the impact of the myriads of agricultural policies and programmes enacted and implemented over the years. Nigeria has the potential of supporting a heavy population of livestock, has 78.5 million hectares of agricultural land, of which 36.5 million hectares is arable land and 0.29 million hectares is equipped for irrigation as at 2008 (FAOSTAT, 2010). She also has 267.7 billion m^3 of surface water and 57.3 m^3 of underground water. The country is also blessed with abundant rainfall of between 3000 mm to 4000 mm per annum, as well as extensive coastal region that is very rich in fish and other marine products (Corporate Nigeria, 2009).

Despite Nigeria's rich agricultural resource endowment and well articulated agricultural policies and programmes by successive governments and international bodies, the sector has been growing at a relatively low rate. Less than 50 percent of the country's cultivable land is under irrigation and smallholder farmers, who use rudimentary production techniques, cultivate over 90 percent of this land (Corporate, 2009). Its current performance is poor relative to the pre-oil boom era. Prior to the 1970's and before the commercial exploration of petroleum, agriculture was a prime mover of the Nigerian economy. Agriculture's share of GDP was about 90 percent before 1960 and 56 percent between 1960 and 1969, supplying 70 percent of export, and 95 percent of food needs (CBN, 1992; Corporate Nigeria, 2009; Ojo and Ehinmowo, 2010). Currently its share of GDP is about 42 percent with the crop sector dominating the share. The growth rate of agriculture GDP has been increasing very slowly though it witnessed a fall from 7.1 in 2007 to 6.5 in 2008 (table 2.1). Prior to the 1970's, Nigeria was among the world's leading producers of cocoa, palm oil, groundnut, cotton, rubber and hides and skin. However, from 1970 upwards, agriculture has been unable to spear-head the development of the Nigerian economy. Its share of total export stood at 0.58 percent as at 2008 while its share of total non-oil exports value dropped from 72.26 percent in 1992 (CBN, 2000) to 58.3 percent in 2008 (table 2.1). From an era of booming export trade in agricultural commodities, the Nigerian agricultural sector has degenerated to an import dependent one. Subsequently, it has failed to generate significant foreign exchange, feed agro-allied industries, improve the living standards of farming households and rural dwellers and provide effective demand for industrial use. In most of the period (table 2.1), the index of agricultural production increased.

Table 2.1 Selected agricultural development indicators: 2000-2008

Indicator	2000	2001	2002	2003	2004	2005	2006	2007	2008
Crop share in GDP	37.88	37.55	37.38	36.51	36.48	36.69	37.20	37.48	37.52
Livestock share in GDP	2.78	2.73	2.74	2.60	2.60	2.61	2.63	2.64	2.65
Fisheries share in GDP	0.62	0.60	0.58	0.54	0.54	0.53	0.53	0.53	0.53
Forestry share in GDP	1.37	1.42	1.44	1.37	1.37	1.36	1.37	1.37	1.37
Agric. Share in GDP	42.65	42.30	42.14	41.01	40.98	41.19	41.72	42.02	42.07
Agric GDP Growth rate	2.96	3.86	4.22	6.64	6.50	7.06	7.40	7.19	6.50
Aggregate index of production	149.20	148.90	154.90	165.40	175.50	186.90	200.1	212.8	227.9
Share in non-oil export	-	-	-	-	33.00	41.70	37.80	43.00	58.30
Share in total export	-	-	-	-	1.22	0.61	0.69	0.90	0.58

Sources: Central Bank of Nigeria, 2002, 2004, 2005, 2008; National Bureau of Statistics, 2007

At 227.9 (1990=100), the aggregate index of agricultural production increased by 7.1 percent in 2008, compared with 6.4 percent in 2007. However, the growth was below the national sectoral target of 8.0 percent (CBN, 2008). The increase in agricultural production was propelled largely by the sustained implementation of the various agricultural initiatives under the National Programme for Food Security. Such initiatives included a significant increase in the quantity of assorted fertilizers distributed nationwide, the rehabilitation and expansion of existing irrigation schemes, as well as the retention of the policy of zero tariffs on imported agrochemicals (CBN, 2008). Even though, the index of agricultural production has been increasing, the concern of most Nigerians is that much of the increase is notional with little real impacts on the economy (Adekanye et al., 2009).

Food grain production increased relatively over the period though much of the noticeable increase was witnessed as from 1983 with about 5 percent decline in 2000 and 6 percent decline in 2001 and 2007 (figure 2.1). Total food grain production grew by 6 percent between 1961 and 2008. However, the productivity of food grain has been fluctuating, peaking at 7.42 in 1981, declined from 1982 to 2000, increased slowly from then throughout with exception of 2007 when there was a 5.04 percent decline (figure 2.2). This slight improvement in trend productivity of food grain from 2000 could be as a result of the strategic crop presidential initiatives during this period aimed at providing subsidized agricultural inputs (fertilizer and seeds) to farmers.

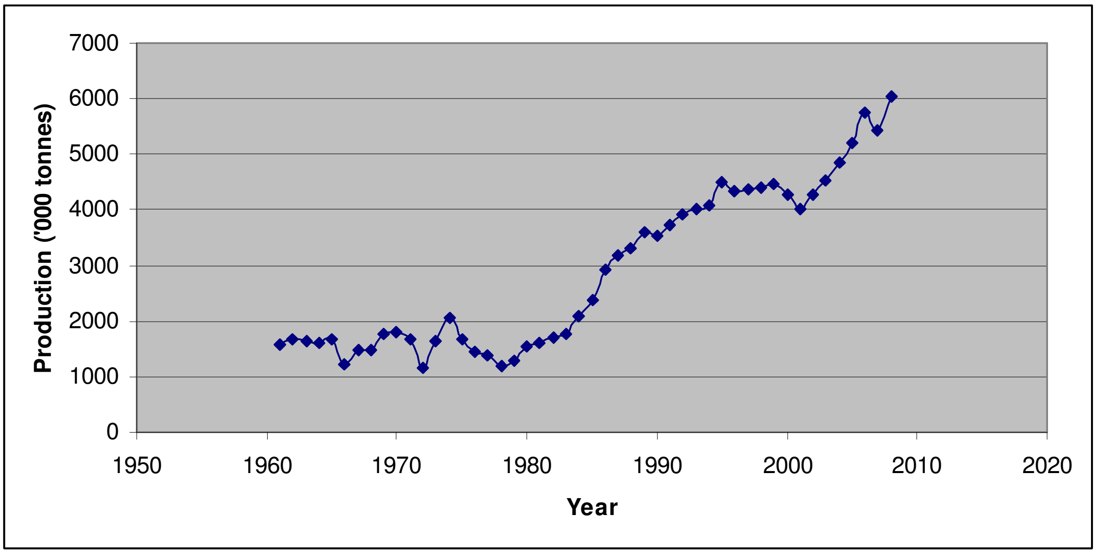

Figure 2.1: Trend in production of food grains

Source: Own computation using data from FAOSTAT (2010)

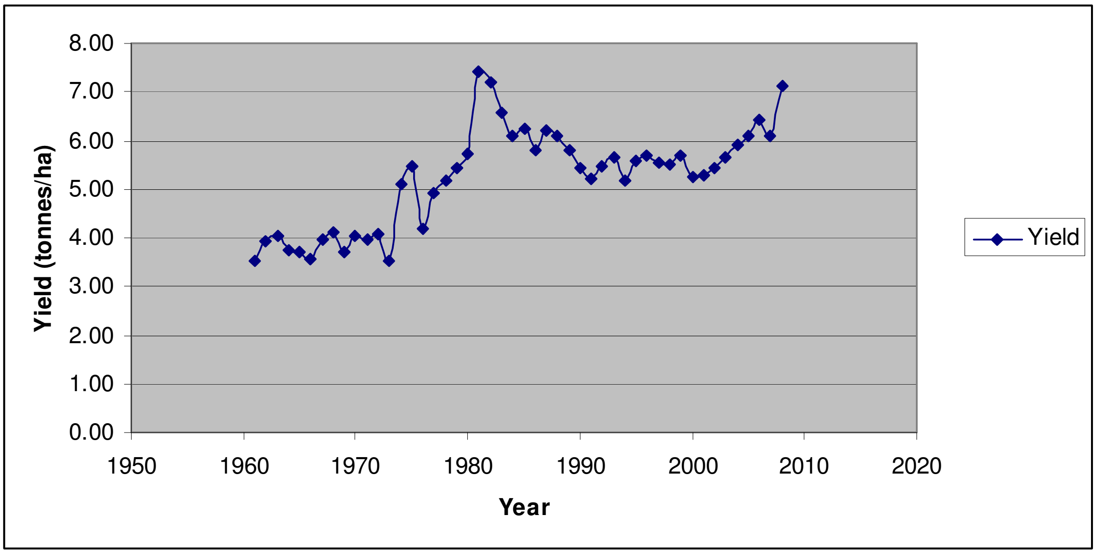

Figure 2.2: Trend in productivity of food grains

Source: Own computation using data from FAOSTAT (2010)

Prior to 1980, there was no noticeable increase in the production of major staple crops. However from 1980, there has been a general increase in the level of production (figure 2.3). For example the level of production of cassava, maize, millet, rice, sorghum, wheat and yam grew at 11, 12, 5, 65, 3 and 5 percent, respectively. The growth in cassava production in 2008 was attributed to increased use of improved cassava cuttings and an expansion of processing facilities across the country while growth in paddy rice production was attributed to the increased adoption of the high-yielding NERICA rice variety and the adoption of the Rice Box technology by farmers (CBN, 2008). In addition, good rainfall years coupled with crop protection measures contributed to the good harvest (USAID, 2006). The level and growth rate of productivity of major staple crops are very low and the later even turn negative in some years. For instance, whereas the average level of productivity of maize, millet, rice, sorghum and wheat for the period 1961-2008 were 1.22, 1.03, 1.64, 1.01 and 1.74, respectively (figure 2.4); their productivity grew at the rate of 3.04, 4.36, 2.05, 0.94 and -0.15 percent, respectively.

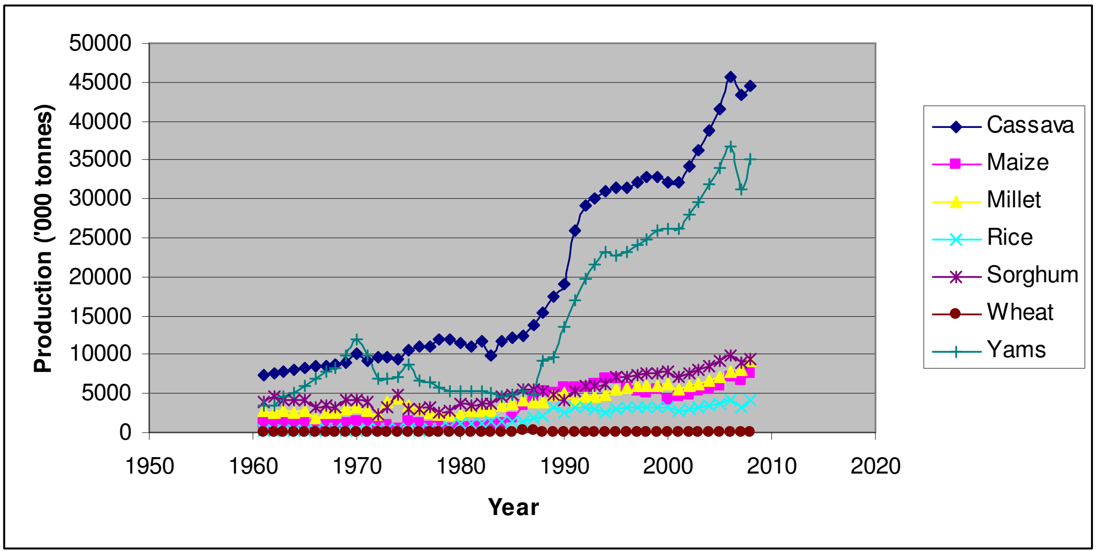

Figure 2.3: Trend in production of some major crops

Source: Own computation from FAOSTAT (2010)

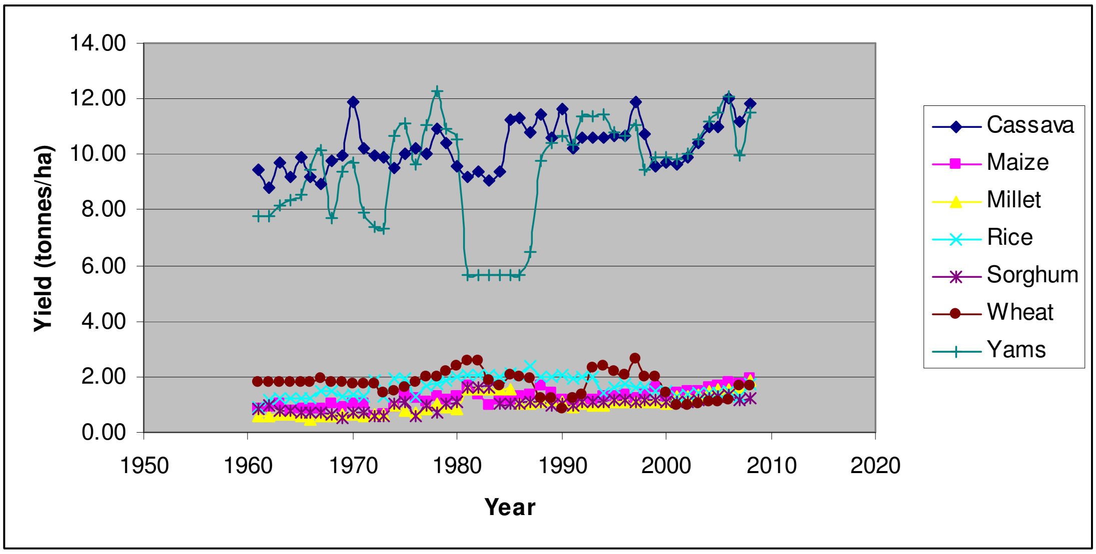

Figure 2.4: Trend in productivity of some major staples

Source: Own computation using data from FAOSTAT (2010)

One of the consequences of the low productivity is a widening demand-supply gap which resulted to huge food import bill incurred by Nigerian government over the years in order to bridge the demand-supply gap. About US$3.0 billion and US$3.99billion, representing about 8 percent and 8.1 percent of total foreign exchange disbursement on imports were utilized on food importation in 2007 and 2008, respectively (CBN, 2008). This amount is quite significant, particularly against the backdrop of the huge agricultural potential of the country. Most of the food items being imported can be grown abundantly and processed within the domestic environment. Another consequence is high food prices in the country. Food prices have generally been on increase. The surge in the prices of food and other essential commodities has been alarming. For example, the price of cassava, maize, millet, paddy rice, sorghum, wheat and yam grew by 60, 93, 75, 39, 63, 69 and 178 percent, respectively from 1991 to 2007 (figure 2.5). The price of a 50 kg bag of the premium brand of imported rice (caprice gold) which stood at about N7, 500 in December 2007 rose to N14, 000 by March 2008, representing an 87 percent price increase. Similarly, the prices of palm oil, maize, guinea corn, beans and garri rose by 36, 28, 16, 12 and 8 percent, respectively, over the same period (CBN, 2008).

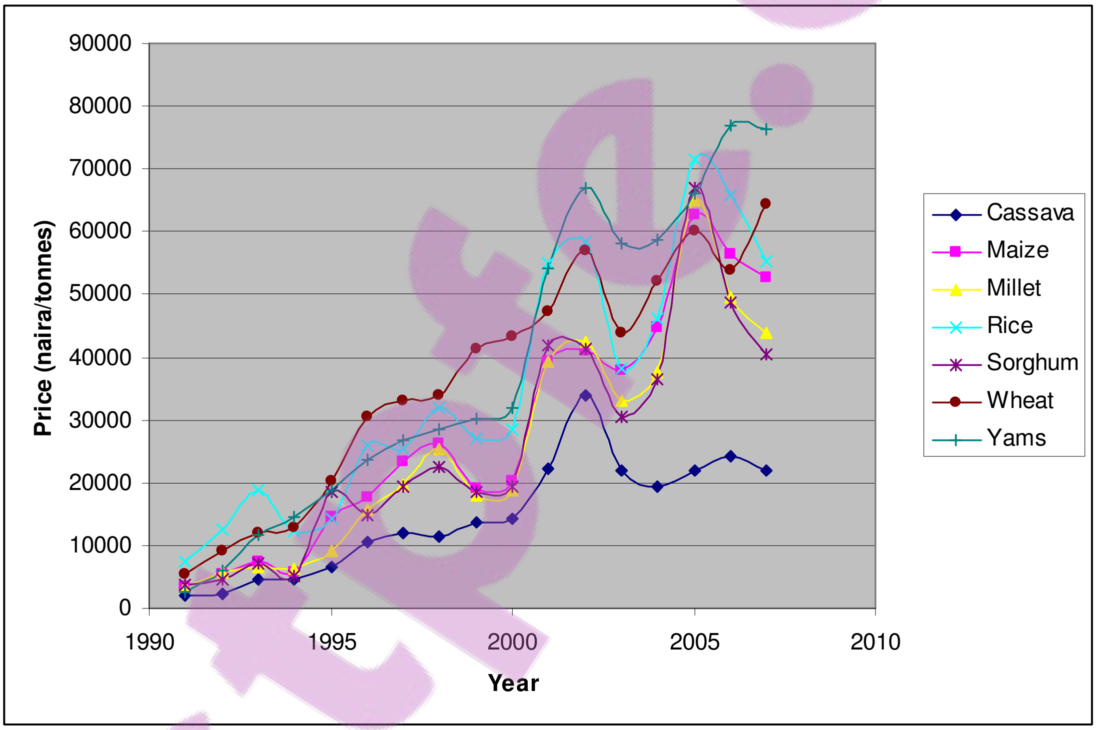

Figure 2.5: Trend in producer prices of some major staples.

Source: Own computation using data from FAOSTAT (2010)

CBN (2008) reported the remote and immediate causes of the current food price increases in Nigeria. First is the weak production structure in the agricultural sector. The farm landscape is dominated by smallholder farmers who still utilize crude implements and operate with traditional, inefficient production methods. The level of tractor use is still very low with the entire country having only about 30, 000 tractors, half of which are not functional. This compares unfavourably with India (also an emerging economy), where the state of Punjab alone can boast of 450,000 functional tractors. Also, the use of improved technologies has been sub-optimal. For instance the use of fertilizer has been on decline after reaching a peak in 1993 with only a slight increase between 1998 and 2001 (figure 2.6). The average global rate of NPK fertilizer application is 93 kg per hectare, while that of Nigeria is a mere 13 kg per hectare (CBN, 2008). The main constraints to fertilizer use are seen as high prices, low fertilizer quality and non availability of fertilizer at the time required (Banful et al. 2009). The government's stated reason for fertilizer subsidies is that farmers cannot afford a free market fertilizer price. However, most stakeholders and farm-level surveys indicated that quality and availability are the main constraints. While farmers will use more fertilizer if prices are lowered, farmers would use much more fertilizer at prevailing market prices if the quality was good and if fertilizer was available when needed (Nagy and Edun, 2002).

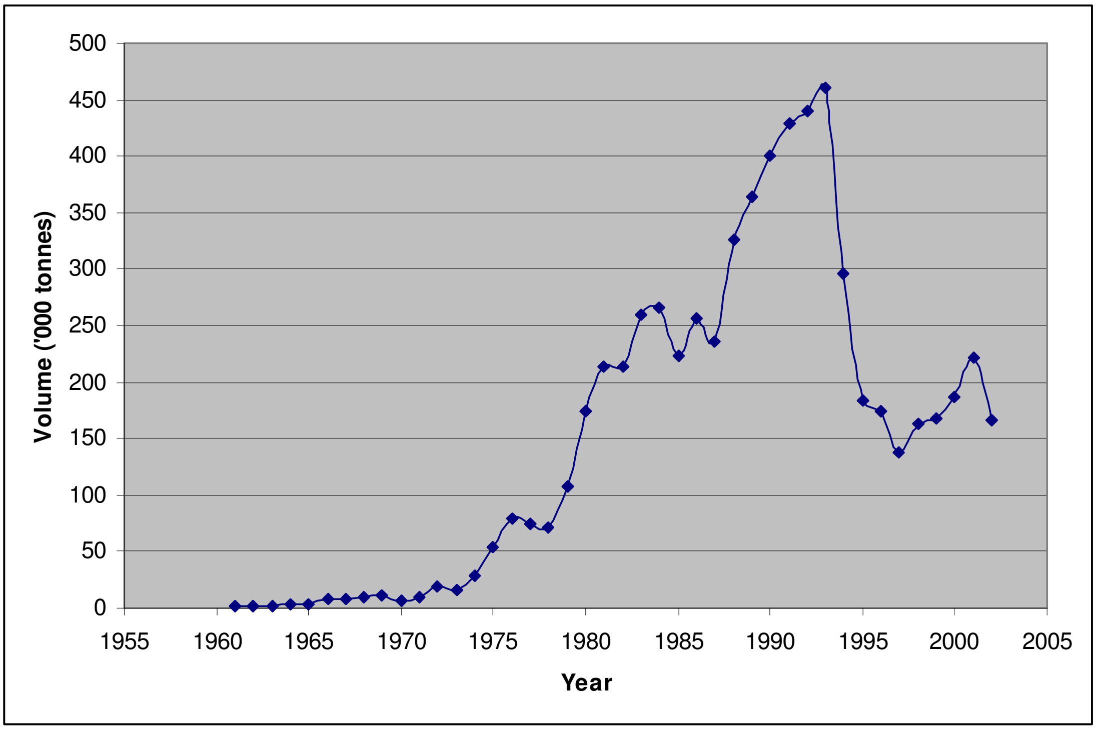

Figure 2.6: Trend in fertilizer utilization

Source: Own computation using data from FAOSTAT (2010)

Other causes of high food prices include grossly inadequate and inefficient storage and processing facilities, reflecting the high level of post-harvest losses, estimated at about 50 percent for fruits and vegetables, and 30 percent for root crops and tubers.

Second is the dearth of support infrastructure, notably an inefficient transportation system and the high cost of energy, both of which constrain the movement of farm produce from rural to urban centres. The railway system has virtually been grounded in the last two decades, thereby making the bulk movement of foodstuff from production centres to the markets impossible. The cost of diesel to power trucks that convey food stuffs across the country has been soaring and sold above N160 per litre in 2008.

Third, there is the inflation pass-through of international food prices. The dominance of imported food items in the menu of most urban families meant the easy and smooth transmission to the domestic economy of not only the global price changes of the commodities, but also the significant increases in freight charges. In this manner, the increases in the import prices of commodities have been transmitted to the domestic market. Fourth is the poor weather condition experienced in 2007, particularly in the Northern States. Widespread incidents of drought were reported in most grain producing areas such as Jigawa, Yobe, Sokoto, Katsina, Kebbi, Gombe, Kano and Borno States. In the North Central States, the rains stopped earlier than usual and these impacted negatively on food production in 2007 (CBN, 2008). Although, the foregoing analysis concentrated on the crop since it is the dominant sub-sector, the performance of other sectors is not quite different.

Perhaps the most disheartening challenge that Nigeria has faced since the 1980s is mass poverty. Given the large share of labour employment in the agricultural sector, it is expected that poverty level in Nigeria should be seriously abated if the sectors performance is to be applauded. The poverty level rose precipitously from about one quarter in 1980 to two thirds of the population in 1996. The trend has, however, been abated since 2004 when poverty fell to 54.6 percent, having dropped from over 65 percent in 1996. Yet, more than half of the population are still living below the nationally defined poverty line (NBS, 2005, 2007, 2008).

A catalogue of reasons has been advanced for the relative poor performance of the Nigerian agriculture sector. Key among these are macroeconomic disequilibria including interest and foreign exchange rate volatilities; poor infrastructure base; policy inconsistency and unnecessary intervention by the public sector which sends wrong signals to the private sector. Other important constraints include inadequate budgetary allocation to agriculture, over-dependence on crude oil revenue, rural-urban migration, inadequate processing and storage capacity, resource poverty and smallness of farm holdings, almost total dependence on rain-fed farming, aging farm population, use of inefficient traditional technologies, adoption of poor and non-sustainable agricultural practices, inadequate agricultural extension services, escalating environmental degradation, political instability and increasing population pressure, disincentive effects of low returns, weak/fragmented agricultural markets and other support institutions as well as dilapidated and mostly non-existent rural infrastructure, low levels of value-adding and insufficient investment in agricultural research and technology (Manyoung et al., 2003; Okoye, 2004; USAID, 2006; Banful et al., 2009).

2.4 Summary and Conclusions

This chapter provided a review of past government policies and programmes in agriculture and the performance of Nigerian agriculture. The review shows that agricultural policies and programmes were designed to facilitate increased agricultural development. Major policy instruments used in the various policy regimes included those targeted to agricultural commodity marketing and pricing, input supply and distribution, input price subsidy, land resources use, agricultural research, agricultural extension and technology transfer, agricultural mechanization, agricultural cooperatives, and agricultural water resource, irrigation development and environmental sustainability. Despite the existence of abundant natural resources and the implementation of agricultural policies in Nigeria over the years, the performance of the agricultural sector has hardly improved. Although agriculture still contributes a lion share of the gross domestic product which stands currently at 42 percent, this contribution is very poor compared to those of pre 1970 era when its contribution ranged between 60 to 90 percent. Agricultural export which once moved the economy forward had declined to as low as 0.58 percent of total export by 2008. Agricultural production essentially increased, but the productivity of major cereal and tuber crops such as cassava, maize, rice, millet, sorghum and yam only grew at a marginal rate ranging from 0.52 to 4.36 percent. The low productivity created demand-supply gap resulting in higher domestic food prices and high food import bills. This poor performance reflects underlying sector-wide and economy-wide constraints, which the national agricultural policy has been unable to tackle. In essence they reflect shortcomings in the national policy on agriculture. Slower rate of adoption of new technologies also contributed their quota in impeding achievement of policy objectives. Nigeria has not fully embraced science-based agriculture and the use of fertilizer, improved seeds, and agro-chemicals is limited. These reduced the expected benefits of yield increases accruable from the adoption and use of these improved technologies. Land expansion is limited and without the use of modern agricultural technology, agricultural production and productivity may decline further. Effective policies and programmes that encourage high investment and high growth rate are highly needed to revamp the Nigeria's agricultural sector.

CHAPTER 3

LITERATURE REVIEW ON EFFICIENCY, MEASUREMENT AND EMPIRICAL APPLICATIONS

3.1 Introduction

The objective of this chapter is to give an overview of the concept of efficiency and frontier models, the different approaches to its measurement in the context of frontier models and empirical studies on efficiency. Approaches to efficiency measurement are broadly specified into parametric and non parametric approaches. Given the large volume of theoretical and empirical literature in the field of efficiency measurement, the review of empirical studies is further subdivided into three namely: a review of empirical comparative studies in agriculture, a review of empirical comparative studies in other sectors where the distance function approach was used and finally a review of empirical studies in Nigerian agriculture. The review is intended not only to provide a proper understanding of the specific area of research but it also helps the researcher to establish a vivid framework to be employed for analysis.

3.2 The Concept of Efficiency and Frontier Models

In microeconomic theory a production function is defined in terms of the maximum output that can be produced from a specified set of inputs, given the existing technology available to the firms involved (Battese, 1992). The maximum possible output becomes relevant in order to answer certain economic questions such as the measurement of efficiency of firms, hence the introduction of frontier production functions which estimates the maximum output as function of inputs. Similarly, a cost frontier function would give the minimum cost as a function of output quantity and input prices.

The papers by Debreu (1951) and Koopmans (1951) mark the origin of discussion on the measurement of productivity and efficiency in the economic literature. The work of Debreu and Koopmans was first extended by Farrell (1957) in order to perform the measurement of productivity and efficiency. The productivity of an economic agent can be measured simply as a scalar ratio of outputs to inputs that the agent uses in its production process. Productivity could be measured either as partial productivity such as yield per hectare (land productivity) or output per person (labour productivity) or more appropriately as total factor productivity (TFP) which is defined as ratio of aggregate outputs to aggregate inputs. An economic agent's productivity may vary based on differences in production technology, in the efficiency of the production process, in the environment in which production occurs, and finally in the quality of inputs used by the agent (Haghiri, 2003). On the other hand, efficiency is measured by comparing observed and optimal values of the agent's outputs and inputs. Prior to Farrell's work, efforts were made to measure efficiency by interpreting the average productivity of inputs, then to construction of efficiency indexes. However, these methods were found unsatisfactory by economists and agricultural economists as the methods suffered from one shortcoming to another. The use of the traditional least squares methods for estimating the production function has been critiqued as this is not consistent with the definition of the production function. The estimated functions could at best be described as average or response functions because such regression estimates the mean output (rather than the maximal output) given quantities of inputs (Schmidt, 1986). This led to the development of a better-founded theoretical method for measuring efficiency, i.e. the frontier method. Frontiers models are described as bounding functions (Coelli, 1995b).

The frontier approach holds a number of advantages over average or response functions as well as over non-frontier models. There are two main benefits that result from estimating frontier functions, as compared to estimating average functions using ordinary least squares (OLS) approach. First, when a frontier function is estimated, the result is strongly influenced by the best performing firm, and therefore the frontier reflects the technology set that the most efficient firm employs. However, the estimation of an average function only reflects the technology set employed by an average firm. Second, frontier functions provide a useful performance benchmark. These functions normally represent best practice technology, against which the efficiency of other firms within the industry can be measured. Frontier models also provide a number of advantages over non-frontier models like the one proposed by

Lau and Yotopoulos (1971). A non-frontier model yields efficiency measures for groups of firms, whereas a frontier model can provide firm specific efficiency measures to the researcher. Another advantage of the frontier methodology is that the word 'frontier' is consistent with the theoretical definition of a production, cost, and profit function, i.e., a solution to a maximum and minimum problem. These advantages make the frontier methodology popular in applied economic research (Forsund et al., 1980; Bravo-Ureta and Pinherio, 1993; Haghiri, 2003; Alene, 2003).

Frontier functions can be classified based on certain criteria. First, based on the way the frontier is specified, frontiers may be specified as parametric function of inputs or non-parametric. Second, it may be specified as an explicit statistical model of the relationship between observed output and the frontier or it may not. Finally, a frontier function can be classified according to how one interprets the deviation of a group of agents or firms from the best performing agents in the sample. In this sense, frontier functions can be either deterministic or stochastic. In the sub-sections that follow, we broadly classify the frontier models into parametric or non-parametric frontiers.

3.3 Non-Parametric Frontier Approach

A non-parametric approach neither specifies a functional form for the production technology nor makes an assumption about the distribution of the error terms. In other words it is robust with respect to the particular functional form and to the distribution assumptions. The non-parametric approach is mainly deterministic in nature. In a deterministic production frontier model, output is assumed to be bounded from above by a deterministic (non-stochastic) frontier. However, the possible influence of measurement errors and other statistical noise upon the shape and positioning of the estimated frontier is not accounted for.

The original work of Farrell (1957) serves an important starting point for discussion of non-parametric frontiers. Farrell illustrated the measurement of efficiency using an input-oriented approach. His argument is embodied in figure 3.1. This illustration was done by considering a firm using two inputs x_1 and x_2 to produce output y, such that the production frontier is $y = f(x_1, x_2)$ Assuming constant returns to scale , then one can write $1 = f(x_1 / y, x_2 / y)$, that is the frontier technology can be characterized by a unit isoquant and this is denoted SS' in figure 3.1. Knowledge of the unit isoquant of a fully efficient firm permits the measurement of technical efficiency. For a given firm using (x_1*, x_2*) defined by point A $(x_1*/y, x_2*/y)$ to produce a unit of output $y*$, the ratio OQ/OA measures technical efficiency and it defines the ability of a firm to maximize output from a given set of inputs. The ratio measures the proportion of (x_1, x_2) needed to produce $y*$. Technical efficiency takes a value between zero and one and therefore provides an indication of technical inefficiency. Thus, the technical inefficiency of the firm, 1-OQ/OA, measures the proportion by which (x_1*, x_2*) could be reduced (holding the input ratio x_1 / x_2 constant) without reducing output. A firm that is fully technically efficient would lie on the efficient isoquant (example, point Q) and it takes a value of 1.

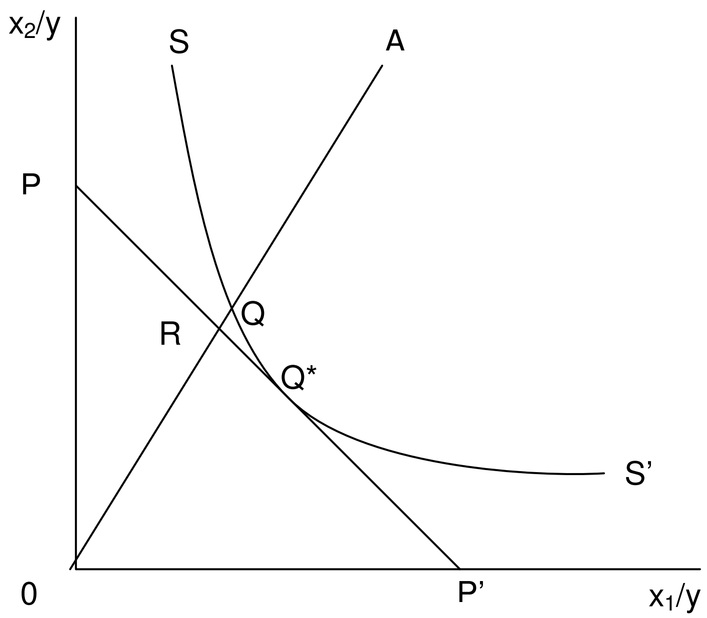

Figure 3.1: Technical, Allocative and Economic Efficiency

Further, Farrell demonstrated that the unit isoquant can provide a set of standards for measuring allocative (referred to as price efficiency by Farrell) efficiency. Let PP' represent the ratio of input prices. Then the ratio OR/OQ measures the allocative efficiency (the ability of a firm to use inputs in optimal proportions, given the respective prices at point A). Correspondingly, allocative inefficiency is 1- OR/OQ. The distance RQ is the reduction in production costs which would have been achieved had production occurred at Q*- the allocatively and technically efficient point, rather than Q- the technically efficient, but allocatively inefficient point. Finally, the ratio OR/OA measures the economic efficiency (referred to as overall efficiency by Farrell) and correspondingly 1-OR/OA measures the total inefficiency. The distance RA is the cost reduction achievable which is obtained from moving from A (the observed point) to Q* (the cost minimizing point).

In this approach, the efficient unit isoquant is not observable; it must be estimated from a sample of observations. The approach is non-parametric because Farrell simply constructs the free disposal convex hull of the observed input-output ratios by linear programming techniques which are supported by a sub-set of the sample, with the rest of the sample points lying above it.

According to Forsund et al. (1980), the major advantage of non-parametric approach is that no functional form is imposed on the data. One disadvantage of the approach is that the frontier is computed from a supporting subset of observations, and is therefore particularly susceptible to extreme observations and measurement error. A second disadvantage is that the estimated functions have no statistical properties upon which inferences can be made; however, recent developments are attempting to overcome this drawback.

Farrell's approach has been extended by Charnes et al. (1978) giving rise to what is known as data envelopment analysis (DEA). The technique envelopes observed production possibilities to obtain an empirical frontier and measures efficiency as the distance to the frontier. Efficient firms are those that produce a certain amount of or more outputs while spending a given amount of inputs, or use the same amount of or less inputs to produce a given amount of outputs, as compared with other firms in the test group. This approach generalizes Farrell's approach of computing the efficiency frontier as a piecewise-linear convex hull in the input coefficient space to multiple outputs. Charnes et al. (1978) reformulated Farrell's approach into calculating the individual input saving efficiency measures by solving a linear programming problem for each unit under the constant returns to scale (CRS) assumption while Banker et al. (1984) extended it to the case of variable returns to scale (VRS) since imperfect competition, financial constraints may cause a firm not to be operating on an optimal scale, the assumption upon which CRS is appropriate. Charnes et al. (1978) proposed a model which had an input-orientation. The DEA can be considered as a non-parametric approach to estimation of distance functions (Färe et al., 1985; 1994).

Assuming there is data on K inputs and M outputs on each of N firms. For the *i*th firm, these are represented by the vectors x_i and y_i, respectively. The K x N input matrix, X and the M x N output matrix, Y, represent the data of all N firms. The purpose of the approach is to construct a non-parametric envelopment frontier over the data points such that all observed points lie on or below the production frontier.

The input-oriented constant returns to scale DEA frontier is defined by the solution to N linear programs of the form:

$$\min_{\theta,\lambda} \theta,$$

$$\text{subject to } \quad -y_i + Y\lambda \geq 0,$$
$$\theta x_i - X\lambda \geq 0, \qquad (3.1)$$
$$\lambda \geq 0$$

where θ is a scalar and λ is an Nx1 vector of constants. The value of θ is an index of technical efficiency for the *i*th firm and will satisfy $0 \leq \theta \leq 1$, with value of 1 indicating a point on the frontier and hence a technically efficient firm, according to Farrell (1957) definition. Thus, $1-\theta$ measures how much a firm's inputs can be proportionally reduced without any loss in output.

However, the assumption of CRS is correct only as long as firms are operating at an optimal scale (Coelli et al, 2002). Using the CRS DEA model when firms are not operating at their optimal scale will cause the technical efficiency measures to be influenced by scale efficiencies and thus the measure of technical efficiency will be incorrect. The CRS linear programming problem can easily be modified to account for variable returns to scale by adding the convexity constraint: $N1'\lambda = 1$ to equation (3.1) to provide an input-oriented VRS model:

$$\min_{\theta,\lambda} \theta$$

$$\text{subject to } -y_i + Y\lambda \geq 0,$$
$$\theta x_i - X\lambda \geq 0, \qquad (3.2)$$
$$N1'\lambda = 1$$
$$\lambda \geq 0$$

where N1 is an Nx1 vector of ones. This approach forms a convex hull of intersecting planes which envelope the data points more tightly than the CRS conical hull and thus provide technical efficiency scores which are greater than or equal to those obtained using the CRS model.

The output-oriented models are very similar to their input-oriented counterparts. For instance, the output-oriented VRS model is defined by solution to N linear programs of the form:

$$\max_{\phi,\lambda} \phi$$
$$\text{subject to } -\phi y_i + Y\lambda \geq 0,$$
$$x_i - X\lambda \geq 0, \qquad (3.3)$$
$$N1'\lambda = 1$$
$$\lambda \geq 0$$

where $1 \leq \phi < \infty$, and ϕ is the proportional increase in output that could be achieved by the *i*th firm, with input held constant. $1/\phi$ defines a technical efficiency score which varies between zero and one. The CRS output-oriented model can be defined similarly by removing the convexity constraint, $N1'\lambda = 1$ from equation (3.3).

In the input-oriented models, the method sought to identify technical inefficiency as a proportional reduction in input usage. They are input-oriented because they try to find out how to improve the input characteristics of the firm concerned so as to become efficient. The output-oriented measure sought to identify technical inefficiency as a proportional increase in output production. The input and output orientations provide the same value under CRS but are unequal under the assumption of a VRS. Thus, the input- and output-oriented models will estimate exactly the same frontier and therefore, by definition, identify the same set of firms as being efficient. It is only the efficiency measures associated with the inefficient firms that may differ between the two methods. Given that linear programming cannot suffer from such statistical problems as simultaneous equation bias, the choice of an appropriate orientation is not very crucial. Essentially, one should select an orientation according to which quantities (inputs or outputs) the managers have most control over. In many instances, the choice of orientation will have only minor influences upon the scores obtained (Coelli, 1995b, Coelli and Perelman, 1999).

With availability of price information, it is possible to consider a behavioural objective, such as cost minimization or revenue maximization so that both technical and allocative efficiency can be measured. For the case of a VRS cost minimization, one would run the input-oriented DEA model set out in equation (3.2) to obtain technical efficiency (TE). One would then run the following cost minimization DEA

$$
\begin{aligned}
&\min_{\lambda, x_i*} \; w_i' x_i *, \\
&\text{subject to } \; -y_i + Y\lambda \geq 0, \\
&\qquad x_i * - X\lambda \geq 0, \qquad\qquad (3.4) \\
&\qquad N1'\lambda = 1 \\
&\qquad \lambda \geq 0
\end{aligned}
$$

where w_i is a vector of input prices for the *i*th firm and $x_i *$ is the cost minimizing vector of input quantities for the *i*th firm given the input prices w_i and the output levels y_i and this is calculated by the linear programming. The total cost efficiency (CE) or economic efficiency of the *i*th firm would be calculated as

$$CE = \frac{w_i' x_i *}{w_i' x_i} \qquad (3.5)$$

That is, the ratio of minimum cost to observed cost. One can then use equation (3.5) to calculate the allocative efficiency residually as

$$AE = \frac{CE}{TE} \tag{3.6}$$

This procedure will include any slacks into the allocative efficiency measure. This is often justified on the grounds that slack reflects an inappropriate input mix (Ferrier and Lovell, 1990).

The aim of DEA analysis is not only to determine the efficiency rate of the units reviewed, but also to find target values for inputs and outputs for an inefficient unit. After reaching these values, the unit would arrive at the threshold of efficiency. The major disadvantage of the deterministic DEA approach is that it takes no account of possible influence of measurement error and other noise in the data and as such it has been argued that it produces biased estimates in the presence of measurement error and other statistical noise. However, it has the advantage of removing the necessity to make arbitrary assumptions about the functional form of the frontier and the distributional assumption of the error term. With DEA, multiple output technologies can be examined very easily without aggregation.

As it has been stated earlier, one of the main drawbacks of non-parametric techniques is their deterministic nature. This is what traditionally has driven specialised literature on this issue to describe them as non-statistical methods. Nevertheless, recent literature has shown that it is possible to define a statistical model allowing for the determination of statistical properties of the non-parametric frontier estimators (Murillo-Zamorano, 2004). For instance, DEA models with stochastic variations have recently received attention (Banker, 1993; Land et al., 1993; Sengupter 2000a; Simar and Wilson, 1998, 2000a, 2000b; Huang and Li, 2001; Kao and Liu, 2009; Shang et al., 2009). Simar and Wilson (1998, 2000a, 2000b) for example, methodically studied statistical properties of DEA models, and developed bootstrap algorithms which can be used to examine the statistical properties of efficiency scores generated through DEA. Therefore, one might conclude that today statistical inference based on non-parametric frontier approaches to the measurement of economic efficiency is available either by using asymptotic results or by using bootstrap. However, a couple of main issues still remain to be solved, namely the high sensitivity of non-parametric approaches to extreme values and outliers, and also the way for allowing stochastic noise to be considered in a non-parametric frontier framework (Murillo-Zamorano, 2004).

3.4 Parametric Frontier Approach

The parametric approach involves a specification of a functional form for the production technology and an assumption about the distribution of the error terms. The major advantage of the parametric approach compared to the non-parametric approach is the ability to express the frontier technology in a simple mathematical form. However, the parametric approach imposes structure on the frontier that may be unwarranted. The parametric approach often imposes a limitation on the number of observations that can be technically efficient. For example, in the case of homogeneous Cobb-Douglas form, when the linear programming algorithm is used, there will in general be only as many technically efficient observations as there are parameters to be estimated (Forsund et al, 1980). This approach can be subdivided into deterministic and stochastic frontiers. The parametric deterministic approach is further subdivided into statistical and non-statistical methods.

3.4.1 Deterministic Non-Statistical Frontiers

Few people adhered to the non-parametric approach by Farrell (1957). Almost as an after thought, Farrell (1957) proposed a second approach. In this approach, Farrell proposed computing a parametric convex hull of the observed input-output ratios. He recommended the Cobb-Douglas production function for this purpose given the limited selection of functional form then. He acknowledged the undesirability of imposing a specific (and restrictive) functional form on the frontier but also noted the advantage of being able to express the frontier in a simple mathematical form. This suggestion was however not followed up by Farrell.

Aigner and Chu (1968) were the first to follow Farrell's suggestion. In order to express the frontier in a mathematical form, they specified a Cobb-Douglas production frontier, and required all observations to be on or beneath the frontier. Their model may be written as:

$$\ln y_i = \ln f(x_i;\alpha) - u_i; \qquad u \geq 0 \tag{3.7}$$

where y_i is the output of the *i*th sample firm; x_i is the inputs of the *i*th firm, u_i is a one-sided non-negative random variable associated with firm-specific factors that contribute to the *i*th firm inability to attain maximum efficiency of production. The one sided error term, u_i forces $y \leq f(x)$. The elements of the parameter vector, α, may be estimated either by linear programming (minimizing the sum of the absolute values of the residuals subject to the constraint that each residual is non-positive) or by quadratic programming (minimizing the sum of squared residuals, subject to the same constraint). Although Aigner and Chu (1968) did not do so, the technical efficiency of each observation can be computed directly from the vector of residuals, since u represents technical efficiency.

A major problem with this approach is that it produces estimates that lack statistical properties. That is, the programming procedure produces estimates without standard errors, t-ratios, etc. This is because no statistical assumptions are made about the regressors or the disturbance term in equation (3.7) and therefore inferences cannot be obtained.

3.4.2 Deterministic Statistical Frontiers

The previous models were critiqued on their lack of statistical properties. This problem can be addressed by making some assumptions about the disturbance term. The model in equation (3.7) can be written as

$$\ln y = f(x)e^{-u}, \tag{3.8}$$

or

$$\ln y = \ln[f(x) - u], \tag{3.9}$$

where $u \geq 0$, implying $0 \leq e^{-u} \leq 1$, $\ln[f(x)]$ is linear in the Cobb-Douglas case presented in equation (3.7). Some assumptions are usually made about u and x and that is, that u are independently and identically distributed (iid), with mean μ and finite variance and that x is exogenous and independent of u. Any number of distributions for u (or e^{-u}) could be specified. Aigner and Chu (1968) did not explicitly assume such a model though it seems clear it was assumed implicitly. However, the first to explicitly propose this type of model was Afriat (1972), who proposed a two-parameter beta distribution for e^{-u}, and that the model be estimated by maximum likelihood method. This amounts to gamma distribution for u, as considered further by Richmond (1974). On the other hand Schmidt (1976) has demonstrated that if u is exponential, then Aigner and Chu's linear programming procedure is maximum likelihood, while their quadratic programming procedure is maximum likelihood if u is half-normal.

In the frontier setting, there are some problems with maximum likelihood. First, maximum likelihood estimates (MLE) depend on the choice of distribution for u such that different assumptions yield different estimates. This is a problem because there are no good *a priori* arguments for choice of any particular distribution. Second, the range of the dependent variable (output) depends on the parameters to be estimated (Schmidt, 1976). This is because $y \leq f(x)$ and $f(x)$ involves the parameters which are to be estimated. For any one-sided error distribution, $y \leq f(x)$ violates one of the usual regularity conditions for consistent and asymptotic efficiency of maximum likelihood estimators (namely, that the range of the random variable should not depend on the parameters). Thus, the statistical properties of the MLE's are in general uncertain. Greene (1980a) finds sufficient conditions on the distribution of u for the MLE's to have their usual desirable asymptotic properties: (i) if g is the density of u, g(0) = 0, i.e. the density of u is zero at $u = 0$ and (ii) $g'(u) \to 0$ as $u \to 0$, i.e. the derivative of the density of u with respect to its parameters approaches zero as u approaches zero. However, as Schimdt (1986) noted, it is clearly not desirable that one's assumptions about the error term be governed by the need to satisfy such conditions.

An alternative method of estimation based on ordinary least squares was first proposed by Richmond (1974) and is called corrected OLS or COLS. Suppose equation (3.9) is assumed to be linear (Cobb-Douglas) and letting μ be the mean of u, then

$$\ln y = (\alpha_0 - \mu) + \sum_{i=1}^{n} \alpha_i \ln x_i - (u - \mu) \tag{3.10}$$

where the new error term has zero mean. Since the error term satisfies all the usual ideal conditions except normality, equation (3.10) can be estimated by OLS to obtain best linear unbiased estimates of $(\alpha_0 - \mu)$ and of α_i. If a specific distribution is assumed for u, and if the parameters of the distribution can be derived from higher-order (second, third, etc.) central moments, then these parameters can be consistently estimated from the moments of the OLS residuals. Since μ is a function of these parameters, it can also be estimated consistently, and this estimate can be used to correct the OLS constant term, which is consistent estimate of $(\alpha - \mu)$. Thus, COLS provides consistent estimates of all the parameters of the frontier. However, this technique poses some difficulties. First, some of the residuals may still have wrong signs after correcting the constant term so that these observations end up above the estimated production frontier. This makes COLS seem not to be a very good technique for computing technical efficiency of individual observations. There are two ways of resolving this problem namely, by use of stochastic frontier approach or to estimate equation (3.10) by OLS, then correct the constant term not as above, but by shifting it up until no residual is positive, and one is zero. Another difficulty with COLS technique is that the correction to the constant term is not independent of the distribution assumed for u. That is, different assumptions yields systematically different corrections for the constant term, and systematically different estimates of technical efficiency, except for the special case var (u) =1. However, this problem again can be resolved by shifting the function upward until no residual is positive, and one is zero.

3.4.3 Stochastic Frontiers

They emerged as an improvement over average functions and deterministic frontiers. In the deterministic frontiers, all variations in the firm performance are attributed solely to variation in firm efficiencies relative to the common family of frontiers, be it production, cost or profit frontiers. Thus, the idea of a deterministic frontier shared by all firms ignores the very real possibility that a firm's performance may be affected by factors that are entirely outside its control such as bad weather, input supply breakdowns etc as well as factors under its control (inefficiency). To lump these effects of exogenous shocks, both fortunate and unfortunate, together with the effects of measurement error and inefficiency into a single one-sided error term, and to label the mixture inefficiency is questionable and is a major weakness of deterministic frontiers.

Forsund et al. (1980) noted that this conclusion is reinforced if one considers also the statistical noise that every empirical relationship contains. The standard interpretation is that first, there may be measurement error on the dependent variable. Second, the equation may not be completely specified with the omitted variables individually unimportant. Both of these arguments hold just as well for production functions as for any kind of equation, and it is dubious at best not to distinguish this noise from inefficiency, or to assume that noise is one-sided. It is on this basis that the stochastic frontier (composed error) model was independently proposed by Aigner et al. (1977) and Meeusen and van den Broeck (1977). The vital idea behind the stochastic frontier model is that the error term is composed of two parts. A symmetric component permits random variation of the frontier across firms, and captures the effects of measurement error, other statistical noise, and random shocks outside the control of the firm. A one-sided component captures the effects of inefficiency relative to the stochastic frontier.

The stochastic frontier function may be defined according to Battese (1992) as:

$$y_i = f(x_i, \alpha)\exp(\varepsilon_i), \quad i = 1,.....N \qquad (3.11)$$

where $\varepsilon_i = v_i - u_i$. (3.12)

The stochastic frontier is $f(x_i, \alpha)\exp\ (v_i)$, y_i is the output of the *i*th firm and is bounded above by the stochastic quantity, x_i are the inputs of the *i*th firm. ε_i is a random variable. v_i is the random error having zero mean, and is associated with random effects of measurement errors and exogenous shocks that cause the deterministic kernel $f(x_i, \alpha)$ to vary across firms. Technical inefficiency is captured by the one-sided error component $\exp(-u_i)$, where $u_i \geq 0$ implying that all observations must lie on or beneath the stochastic production frontier.

The random errors, v_i were assumed to be independently and identically distributed as $N(0, \sigma^2{}_v)$ random variables and independent of the u_i's , which were assumed to be non-negative truncations of the half-normal distribution i.e., $|N(0, \sigma_u{}^2)|$ or exponential distribution i.e. $\mathrm{EXP}(\mu, \sigma_u{}^2)$. Aigner et al. (1977) considered half-normal and exponential distributions but Meeusen and van den Broeck (1977) considered exponential distribution only. Stevenson (1980) has shown how the half-normal and exponential distributions can be generalized to truncated normal ($N(\mu, \sigma_u{}^2)$) and gamma distributions, respectively. There was a tendency for researchers to use the half-normal and truncated normal distributions probably because of ease of estimation and interpretation and more so, as there were no standard tests for distribution selection. However, Lee (1983) proposed a Lagrange-Multiplier test to assess different distributions for the inefficiency term. Given the assumptions of the stochastic frontier model (3.11), inference about the parameters of the model can be based on the maximum likelihood estimators because the standard regularity conditions are satisfied.

Technical efficiency of an individual firm is defined in terms of the ratio of the observed output to the corresponding frontier output, conditional on the levels of inputs used by that firm. Thus, the technical efficiency of firm i in the context of the stochastic production function expressed in equations (3.11) and (3.12) is given as

$$TE_i. = \frac{y_i}{y_i^*} = \frac{y_i}{f(x_i; \alpha)\exp(v_i)^*} = \exp(-u_i) \qquad (3.13)$$

The prediction of technical efficiencies of individual firms associated with the stochastic frontier production function (3.11) was considered impossible until the appearance of Jondrow et al. (1982). Following Jondrow et al. (1982) and Battese and

Corra (1977) reparameterization, the firm specific technical efficiency can be predicted by the conditional expectation of the non-negative random variable, u_i, given that the random variable, ε_i, is observable. The technical efficiency of the *i*th firm is then given by:

$$E(u_i / \varepsilon_i) = \frac{\sigma_u \sigma_v}{\sigma}\left[\frac{f(\cdot)}{1-F(\cdot)} - \frac{\varepsilon_i}{\sigma}\left(\frac{\gamma}{1-\gamma}\right)^{1/2}\right] \qquad (3.14)$$

where ε_i are the estimated residuals for each firm, $f(\cdot)$ and $F(\cdot)$ are the values of the standard normal density function and standard normal distribution function, respectively, evaluated at $\frac{\varepsilon_i}{\sigma}\left(\frac{\gamma}{1-\gamma}\right)^{1/2}$. The parameters of the model, i.e. α, $\sigma^2 = \sigma_v{}^2 + \sigma_u{}^2$ and $\gamma = \sigma_u{}^2 / \sigma^2$ can be obtained from the maximum likelihood estimation of equation (3.11). γ is bounded between zero and one and it explains the total variation of output from the frontier which can be attributed to technical inefficiency. The estimates of v_i and u_i can be obtained by substituting the estimates of ε_i, γ, and σ. Thus, the technical efficiency of individual firms can be measured as $TE_i = \exp(-E(u_i / \varepsilon_i)$ which represents the level of technical efficiency of the *i*th firm relative to the frontier firm. However Battese and Coelli (1988) derived the best predictor of TE given as $E(-u_i / \varepsilon_i) = \left[\frac{1-F(\sigma_A + \gamma\varepsilon_i / \sigma_A)}{1-F(\gamma\varepsilon_i / \sigma_A)}\exp(\gamma\varepsilon_i + \sigma_A^2 / 2)\right]$.

One can test whether any form of stochastic frontier production is needed at all by testing the significance of the γ parameter. If the null hypothesis, that γ equals zero, is accepted, this would indicate that $\sigma_u{}^2$ is zero and hence that the u_i should be removed from the model, leaving a specification with parameters that can be consistently estimated using ordinary least squares (Coelli, 1996a).

There are two approaches to estimating the inefficiency effect models, that is, the second part of the stochastic frontier models that provides explanation for variation in efficiency of firms. These may be estimated with either a one step procedure or a two step procedure. In a one step procedure estimates of all the parameters are obtained in one step. The inefficiency effects are defined as a function of the firm specific factors (as in the two-stage approach) but they are then incorporated directly into the MLE. That is, both the production frontier and the inefficiency effect models are estimated simultaneously. For the two-step procedure, the production frontier is first estimated and the technical efficiency of each firm is derived. These are subsequently regressed against a set of variables, z, which are hypothesized to influence the firms' efficiency. The two-stage procedure has been critiqued of inconsistency in the assumptions about the distribution of the inefficiencies. This is because in the first stage, the inefficiencies are assumed to be independently and identically distributed (iid) in order to estimate their values. However, in the second stage, the estimated inefficiencies are assumed to be a function of a number of firm specific factors, and hence are not identically distributed unless all the coefficients of the factors are simultaneously equal to zero (Coelli, et al. 1998, Herrero and Pascoe, 2002). Thus, the distributional assumptions used in either step contradict each other (Coelli, et al, 2005). Kumbhakar et al. (1991) argued that the estimated technical coefficients and technical efficiency indices are biased when the determinants of technical efficiency are not included in the first step of the regression. They provided a one-step procedure which determines the influence of socioeconomic variables on technical efficiency while estimating technical coefficients of the production frontier. Kalirajan (1991), on the other hand, has defended the practice of the two-step regression on the basis that socioeconomic variables have a roundabout effect on production.

Although the two-step procedure is critiqued of producing biased results, there seems to be little evidence on the severity of this bias. For example, Caudill and Ford (1993) provide evidence on the bias of the estimated technological parameters, but not on the efficiency levels or their relationship to the explanatory variables. However, Wang and Schmidt (2002) identified two sources of bias namely, that the first step of the two-step procedure is biased for the regression parameters if the z and the inputs, x_i are correlated. Secondly, that even if z and x are independent, the estimated inefficiencies are under-dispersed when the effect of z on inefficiency is ignored. This causes the second-step estimate of the effect of z on inefficiency to be biased downward (toward zero). Therefore, they suggested that a one step procedure be employed to overcome this problem. There appear to be no consensus in the literatures on the use of either one step or two step procedure and the choice may be solely that of the analyst.

The Cobb-Douglas functional form is the commonly used in estimating the stochastic production frontier. Although its most attractive feature is simplicity, but this is associated with a number of restrictions. Most notably the returns to scale are restricted to take the same value across all firms in the sample, and elasticities of substitution are assumed equal to one. However, more flexible functional forms like the translog production function have also received attention. The translog form imposes no restriction upon returns to scale or substitution possibilities, but has the drawback of being susceptible to multicollinearity and degrees of freedom problems (Coelli, 1995b). In any case, the choice of appropriate function form can be made by conducting a likelihood ratio test between competing models.

Stochastic frontier analysis (SFA) has both advantages and disadvantages. The advantages include first, it controls for random unobserved heterogeneity among the firms. The inefficiency effect can be separated from statistical noise. With non-parametric methods, any deviation of an observation from the frontier must be attributed to inefficiency, which makes the results very sensitive to outliers or measurement errors and uncertainty. Second, by using SFA, the statistical significance of the variables determining efficiency can be verified using statistical tests, though this is also true for recent bootstrapped DEA models. Third, the firm specific inefficiency is not measured in relation to the "best" firm, as it is done in non-parametric approaches. Hence, SFA is again less sensitive to outliers in the sample. Disadvantages of the SFA approach consist of the need for distributional assumptions for the two error components as well as the assumption of independence between the error terms and the regressors. Further, implementation of the model requires the choice of an explicit functional form, the appropriateness of which raises questions.

The stochastic frontier specification has been altered and extended in a number of ways. These extensions include: consideration of panel data and time-varying technical efficiencies, the extension of the methodology to cost, revenue and profit frontiers, estimation of stochastic input and output distance functions, the estimation of systems of equations, the decomposition of the cost frontier to account for both technical and allocative efficiency. A review of most of these extensions is provided by Forsund et al. (1980), Schmidt (1986), Bauer (1990), and Coelli (1995b). However, in the subsequent sub-sections brief explanations of some these extensions are given.

3.4.3.1 Panel Data

Cross sectional data provides a snapshot of producers and their efficiency. Panel data provides more reliable evidence on their performance, because they enable one to track the performance of each producer through sequence of time periods. In the Panel data model, a time varying or time invariant inefficient effect may be specified. Also, the model may assume either a fixed or random effect. A significant advantage of panels is that given consistently large time periods, they permit consistent estimation of the efficiency of individual producers, whereas the Jondrow et al. (1982) technique does not generate consistent estimators in a cross-sectional context (Kumbhakar and Lovell, 2000). Another advantage of the panel data is that the distributional assumptions about the efficiency term upon which stochastic frontier rely is no longer necessary. Also the assumption of independence between the inefficiency term and input levels is unnecessary with panel data. Again, panel data increases degrees of freedom for estimation of parameters and it permits the simultaneous estimation of technical change and technical inefficiency changes over time. However, the dearth of panel data on farmers especially in developing country agriculture has constrained the use of panel data methodologies.

3.4.3.2 Duality Considerations and Cost System Approaches

The consideration of duality extends not only to cost minimization but also profit maximization, though cost minimization is often made in the dual frontier literatures. Thus, the discussion here is basically on cost minimization behaviour. It is very simple to change the sign of the inefficiency error component u_i and convert the stochastic production frontier model to a stochastic cost frontier model such that we have:

$$C_i = c(y_i, w_i; \beta).\exp(v_i + u_i) \quad (3.15)$$

where C_i is the cost of production of the *i*th firm, $c(y_i, w_i; \beta).\exp(v_i)$ is the stochastic cost frontier, w_i is a vector of input prices of the *i*th firm, y_i is output of the *i*th firm; β is an vector of unknown parameters; v_i are random variables which are assumed to be independently and identically distributed $N(0, \sigma_v^2)$ and independent of , u_i, which are non-negative random variables which are assumed to account for the cost of inefficiency in production, which are often assumed to be iid $|N(0, \sigma_u^2)|$. In this cost function, the u_i now defines how far the firm operates above the cost frontier. If allocative efficiency is assumed, then u_i is closely related to the cost of technical efficiency. If this assumption is not made, the interpretation of the u_i in a cost frontier is less clear, with both technical and allocative inefficiencies possibly involved (Coelli, 1996a). The Jondrow et al. (1982) technique may be used to provide an estimate of the overall cost inefficiency, but the difficult remaining problem is to decompose the estimate of u_i into estimates of the separate costs of technical and allocative inefficiency. Schmidt and Lovell (1979) accomplished the decomposition for the Cobb-Douglas case while Kopp and Diewert (1982) obtained the decomposition for the more general translog case based on deterministic frontier.

According to Coelli (1995b) there are basically three reasons for considering the alternative of dual forms of the production technology, such as the cost or profit function. First, is to reflect alternative behavioural objectives such as cost minimization. Second is to account for multiple outputs. Third, is to simultaneously predict both technical and allocative efficiency. The choice of whether to estimate a production or cost frontier may be based on exogeneity assumptions. It is more natural to estimate a production frontier if inputs are exogenous and a cost frontier if output is exogenous (Schmidt, 1986). Schmidt and Lovell (1979) suggested a maximum likelihood system estimation of their Cobb-Douglas frontier, involving the cost function and k-1 factor demand equations as this is expected to improve the precision of the parameter estimates. Such a system can be specified as follows:

$$\ln y_i = A + \sum_j \alpha_j \ln x_{ij} + v_i - u_i \qquad (3.16)$$

$$\ln x_{i1} - \ln x_{ij} = \ln p_{ij} - \ln p_{i1} + \ln \alpha_1 - \ln \alpha_j + \varepsilon_{ij}, \qquad j = 2, \ldots k \qquad (3.17)$$

$$\ln c_i = K + \frac{1}{r}\ln y_i + \sum_{j=1}^{k} \frac{\alpha_j}{r} \ln p_{ij} - \frac{1}{r}(v_i - u_i) + (E_i - \ln r) \qquad (3.18)$$

where y is output, x's inputs, p's are prices, i indexes firms and j indexes inputs. Equation (3.16) is a stochastic production frontier, while equation (3.17) is the set of first order conditions for cost minimization. Equation (3.18) is the cost function. ε_{ij} represents allocative efficiency. $r = \sum_{j=1}^{k} \alpha_j$ is the returns to scale, E_i (equation 3.19) is given as a function of ε's and the parameters. The cost of technical inefficiency is $\frac{1}{r}u_i$, while the cost of allocative inefficiency is $(E_i - Inr)$. The latter is non-negative, and zero if $\varepsilon_{ij} = 0$ for all j.

$$E_i = \sum_{j=2}^{n} \frac{\alpha_j}{r} \varepsilon_{ij} + In\left[\alpha_1 + \sum_{j=2}^{n} \alpha_j e^{-\varepsilon_{ij}}\right] \qquad (3.19)$$

This approach faces two serious draw backs. First, in some cases it may not be practical or appropriate to estimate a cost frontier. For instance, it will not be practical to estimate a cost function when input prices do not vary among firms and it will not be appropriate when there is a systematic deviation from cost-minimising behaviour in an industry. Second, Schmidt and Lovell (1979) systems estimation and the technical and allocative efficiency measurement are limited to self-dual functional forms like the Cobb-Douglas. Once one specifies a more flexible functional form like the translog forms which are not self-dual, a problem arises. The major problem with employing a translog form is associated with how to model the relationship between the allocative inefficiency error which appears in the input share equations and that which appears in the cost function (sometimes referred to as the 'Green Problem' because it was first noted by Green (1980b). Although a number of approaches have been suggested and applied in modelling the Greene problem ranging from analytic solution (e.g. Kumbhakar, 1989), approximate solution (e.g. Schmidt, 1984) to qualitative solution (e.g. Greene 1980b), debate still continues on how best to address this problem. Coelli (1995b) noted that a sound approach to take (given that the cost minimizing assumption is appropriate and suitable price data are available) is to estimate the cost function using single equation maximum likelihood method and then use the method proposed by Kopp and Diewert (1982), and refined by Zeischang (1983) for deterministic frontier case or that extended by Bravo-Ureta and Rieger (1991) for stochastic frontier case following the primal route, to decompose the cost efficiencies into their technical and allocative components. If the Cobb-Douglas functional form is considered appropriate, then the procedure involved simplify to those which are outlined in Schmidt and Lovell (1979). Berger (1993) found that efficiency estimates using no cost share equations, partially restricted share equations, and fully restricted share equations gave very similar efficiency results.

3.4.3.3 Production Frontier and Efficiency Decomposition

Given that it may not be appropriate to estimate a cost function when there is little or no variation in prices among sample firms, Bravo-Ureta and Rieger (1991) developed an alternative approach to decompose the cost efficiency into technical and allocative efficiencies. They followed a primal route in their methodology. The methodology involved using the level of output of each firm adjusted for statistical noise, the observed input ratio and the parameters of the stochastic frontier production function (SFPF) to decompose economic efficiency into technical and allocative efficiency. Then the cost function is analytically derived from the parameters of the SFPF. To illustrate the approach, a stochastic frontier production function is given as:

$$Y_i = f(X_i;\beta) + \varepsilon_i \qquad (3.20)$$

$$\varepsilon_i = v_i - u_i \qquad (3.21)$$

where ε_i is the composed error term. The two components v_i and u_i are assumed to be independent of each other, where v_i is the two-sided, normally distributed random error and u_i is the one-sided efficiency component with a half normal distribution. Y_i is the observed output of the *i*th firm, X_i is the input vectors of *i*th firm and β is unknown parameters to be estimated. The parameters of the SFPF were estimated using the maximum likelihood method. Subtracting v_i from both sides of the equation (3.20) results in

$$Y_i^* = Y_i - v_i = f(X_i;\beta) - u_i \tag{3.22}$$

where Y_i^* is the observed output of the ith firm adjusted for statistical noise captured by v_i. From equation (3.22), the technically efficient input vector, X_i^T, for a given level of Y_i^* is derived by solving simultaneously equation (3.22) and the input ratios, $X_1 / X_k = \rho_k (k > 1)$, where ρ_k is the ratio of the observed inputs.

Assuming the production function is self-dual function like the Cobb-Douglas production function, the corresponding dual cost frontier can be derived and written in a general form as:

$$C_i = h(W_i, Y_i^*; \delta) \tag{3.23}$$

where C_i is the minimum cost of the ith firm associated with output Y_i^*; W_i is a vector of input prices of the ith firm; and δ is a vector of parameters which are functions of the parameters in the production function.

The economically efficient (cost minimizing) input vector, X_i^E, is derived by using Shephard's Lemma and then substituting the firm's input prices and adjusted output quantity into the system of demand equations:

$$\frac{\partial C_i}{\partial W_i} = X_i^E (W_i, Y_i^*; \delta) \tag{3.24}$$

For a given level of output, the corresponding technically efficient, economically efficient and actual costs of production are equal to $W_i X_i^T$, $W_i X_i^E$ and $W_i X_i$, respectively. These three cost measures are then used as the basis for calculating the technical and economic (cost) efficiency indices for the *i*th firm :

$$TE_i = \frac{W_i X_i^T}{W_i X_i} \quad (3.25)$$

and

$$EE_i = \frac{W_i X_i^E}{W_i X_i} \quad (3.26)$$

Following Farrel (1957), allocative efficiency can be calculated by dividing economic efficiency (EE) by technical efficiency (TE):

$$AE_i = \frac{W_i X_i^E}{W_i X_i^T} \quad (3.27)$$

3.4.3.4 Distance Functions and Efficiency Decomposition

The production, cost, profit and perhaps revenue functions are well known alternative methods of describing a production technology. These functions have been used by economists to measure efficiencies. Of recent the application of distance functions is growing. The majority of recent distance function studies have been motivated by a desire to calculate technical efficiencies or shadow prices. The principle advantage of the distance function representation is that it allows the possibility of specifying a multiple-input, multiple-output technology when price information is not available or alternatively when price information is available but cost, profit or revenue function representations are precluded because of violations of the required behavioural assumptions (Coelli and Perelman 2000). The distance function contains the same information about technology as does the cost function but may have some advantages econometrically over the cost function if, for example, input prices are the same for firms, but input quantities vary across firms (Bauer, 1990).

The output distance function measures how close a particular level of output is to the maximum attainable level of output that could be obtained from the same level of inputs if production is technically efficient. In other words, it represents how close a particular output vector is to the production frontier given a particular input vector (Mawson et al., 2003). The definition of an output-distance function starts with a definition of the production technology of the firm using the output set, $P(x)$, which represents the set of all output vectors, $y \in R_{+}^{M}$, which can be produced using the input vector, $x \in R_{+}^{K}$. That is,

$$P(x) = \{ y \in R_{+}^{M} : x \text{ can produce } y \} \tag{3.28}$$

The output-distance function is then defined on the output set, $P(x)$, as

$$D_O(x, y) = \min\{\theta : (y/\theta) \in P(x)\} \tag{3.29}$$

$D_O(x, y)$ is non-decreasing, positively linearly homogeneous and convex in y, and decreasing in x (Lovell et al., 1994). The distance function, $D_O(x, y)$, will take the value which is less than or equal to one if the output vector, y, is an element of the feasible production set, $P(x)$. That is, $D_O(x, y) \leq 1$ if $y \in P(x)$. Furthermore, the distance function will take the value of unity if y is located on the outer boundary of the production possibility set. That is,

$$D_O(x, y) = 1 \text{ if } y \in \text{Isoq } P(x)$$
$$= \{ y : y \in P(x), \omega y \notin P(x), \omega > 1 \}; \tag{3.30}$$

A Stochastic Output Distance Function (SODF) is not the same as a Stochastic Frontier Production Function (SFPF). Both consider the maximum feasible output from a given set of inputs. The difference is that SODF is defined in a set theoretic framework which involves vector of outputs and inputs and can only be implemented empirically by normalizing using one of the outputs whereas SFPF is simply defined for the case of one output or aggregated outputs and does not require normalization.

An input-distance function is defined in a similar manner as the output distance function. However, rather than looking at how the output vector may be proportionally expanded with the input vector held fixed, it considers by how much the input vector may be proportionally contracted with the output vector held fixed. The input-distance function may be defined on the input set, $L(y)$, as

$$D_I(x, y) = \max\{\rho : (x / p) \in L(y)\} \tag{3.31}$$

where the input set, $L(y)$, represents the set of all input vectors, $x \in R_+^K$, which can produce the output vector, $y \in R_+^M$. That is,

$$L(y) = \{\ x \in R_+^K :\ x \text{ can produce y}\} \tag{3.32}$$

$D_I(x, y)$ is non-decreasing, positively linearly homogenous and concave in x, and increasing in y. The distance function, $D_I(x, y)$, will take a value which is greater than or equal to one if the input vector, x, is an element of the feasible input set, $L(y)$. That is, $D_I(x, y) \geq 1$ if $x \in L(y)$. Furthermore, the distance function will take a value of unity if x is located on the inner boundary of the input set.

Under the assumption of constant returns to scale (CRS), the input distance function is equivalent to the inverse of the output distance function (i.e., $D_O = 1/D_I$) (Färe et al. 1993, 1994). That is, the proportion by which one is able to radially expand output (with input held fixed), will be exactly equal to the proportion by which one is able to radially reduce input usage (with output held constant). However, under variable returns to scale (VRS) this condition need not hold.

The distance function can be illustrated graphically. For instance, the input distance function as exemplified in Coelli et al. (2003) is shown in figure 3.2. Here two inputs, x_1 and x_2, are used to produce output y. The isoquant SS', is the inner boundary of the input set, reflecting the minimum input combinations that may be used to produce a given output vector. In this case, the value of the distance function for a firm producing output y, using the input vector defined by point P, is equal to the ratio, OP/OQ.

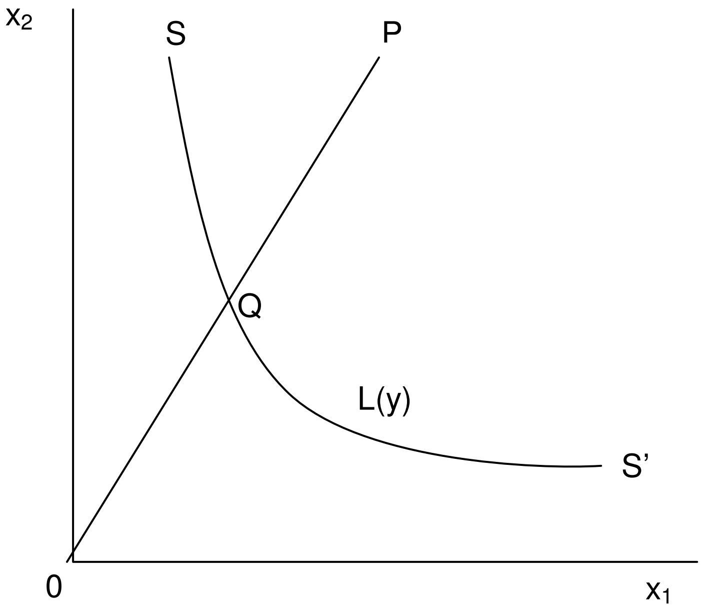

Figure 3.2: The input distance function and the input set

In empirical literatures on efficiency measurement involving distance functions, different methods have been employed to estimate the function. These include the construction of parametric frontier using linear programming methods (Färe et al., 1994; Coelli and Perelman, 1999; Alene and Manfred, 2005); the construction of non-parametric piece-wise linear frontier using the linear programming method known as data envelopment analysis (DEA) (e.g. Färe et al., 1989; Färe et al., 1994; Coelli and Perelman, 1999; Alene and Manfred, 2005); estimation of parametric frontier using corrected ordinary least square (COLS) (e.g. Lovell et al., 1994; Grosskopf et al., 1997; Coelli and Perelman, 1999) and maximum likelihood estimation (MLE) of a parametric stochastic distance frontier (e.g. Coelli et al., 2003; Irz and Thirtle, 2004; Solis et al., 2009). However all of these studies have basically focused on analysing technical efficiency except that of Coelli et al. (2003) that applied the cost decomposition approach to estimate both technical and allocative efficiency.

Decomposition of cost efficiency in a single equation stochastic input distance frontiers framework was first developed by Coelli et al. (2003) to overcome the problems that arise when one either tries to estimate a cost frontier and then use duality to derive the implicit production frontier as in Schmidt and Lovell (1979) or alternatively estimating a primal production technology, and then derive the implicit cost frontier as in Bravo-Ureta and Rieger (1991). The input distance function approach avoids all of these problems because first it does not require price information to vary among firms. Second, it is robust to systematic deviations from cost minimising behaviour. Third, it does not suffer from simultaneous equations bias when firms are cost minimisers or shadow cost minimisers (Coelli, 2000; Coelli et al., 2003). Finally, the approach has an added advantage over production function in that it can easily accommodate multiple outputs without aggregation as in production function.

A general framework of the decomposition approach is described below using the parametric input distance function. It is noted that the value of the distance function is not observed so that imposition of a functional form for $D_I(x, y)$ does not permit its direct estimation. A convenient way of handling this problem was suggested by Lovell et al. (1994) who exploit the property of linear homogeneity of the input distance function. Given a general form of a parametric input distance function as:

$$D_I = f(x, y) \qquad (3.33)$$

where f is a known functional form such as Cobb-Douglas or translog. Linear homogeneity implies:

$$\lambda D_I = \lambda f(x, y) \qquad \forall \lambda > 0 \qquad (3.34)$$

Assuming x is a vector of K inputs and setting $\lambda = 1/x_1$, where x_1 is its (arbitrarily chosen) first component, then equation (3.34) can be expressed in a logarithmic form as:

$$\ln(D_I / x_1) = \ln f(x / x_1, y) \qquad (3.35)$$

or

$$\ln(D_I) - \ln(x_1) = \ln f(x / x_1, y) \qquad (3.36)$$

and hence

$$-\ln(x_1) = \ln f(x/x_1, y) - \ln(D_I) \qquad (3.37)$$

where $-\ln(D_I)$ is defined as $\varepsilon = v - u$ to indicate that the distance term may be interpreted as a traditional stochastic frontier analysis disturbance term. That is, the distances in a distance function (which are radial distances between the data points and the frontier) could be due to either noise (v) or technical inefficiency (u) which is the standard SFA error structure (Coelli et al., 2003). Therefore equation (3.37) can be rewritten as:

$$-\ln(x_1) = \ln f(x/x_1, y) + v - u \qquad (3.38)$$

The random errors, v are assumed to be independently and identically distributed as $N(0, \sigma^2{}_v)$ random variables and independent of the u's , which are assumed to either be a half-normal distribution i.e., $|N(0, \sigma_u{}^2)|$ or exponential distribution i.e. EXP$(\mu, \sigma_u{}^2)$ or truncated normal (($N(\mu, \sigma_u{}^2)$) or gamma distributions. The predicted radial input-oriented measure of TE for an *i*th firm is given as:

$$T\hat{E}_i = 1/\hat{D}_I = E[\exp(u_i)|v_i - u_i] \qquad (3.39)$$

In other words, $1 - T\hat{E}_i$ measures the proportion by which costs would be reduced by improving technical efficiency, without reducing output. A value greater than one for the input distance function ($\hat{D}_I$) indicates that the observed input-output vector is technically inefficient. When the producer is operating on the technically efficient frontier or the isoquant, the parametric input distance function attains a value of one. The technically efficient input quantities can be predicted as follows:

$$\hat{x}_{ji}^T = x_{ji} \times T\hat{E}_i; \qquad j = 1,2...K \qquad (3.40)$$

Using the first order condition for cost minimisation, the duality between the cost and input distance function can be derived and expressed in a general form as:

$$C_i(w_i, y_i) = \underset{x}{Min}\{w_i x_i : D_I(x_i, y_i) \geq 1\} \tag{3.41}$$

where C is the cost of production and w denotes a vector of input prices. From this minimisation problem, it is possible to relate the derivatives of the input distance function to the cost function and by making use of Shephard's Lemma, allocative efficiency and cost efficiency can then be computed.

The current study makes a comparison of the production function and distance function frontier results and proposes an integrated efficiency model for resolution of model selection problems in efficiency studies and agricultural policy analysis.

3.5 Empirical Studies on Efficiency Measurement

A number of empirical studies both in agricultural and non-agricultural sectors have applied the frontier models since the pioneering work of Farrell (1957). However, given the large volume of theoretical and empirical literature in the field of efficiency measurement, a general review of comparative studies in agriculture and other sectors is provided. The review of comparative studies in other sectors is limited to those involving the use of distance functions since the application of distance functions is not vast yet. Finally, to place this section in the Nigerian context, a review of some of the efficiency studies in Nigeria that used either one or more of the frontier approaches is provided.

3.5.1 Empirical Comparative Studies in Agriculture

Ferrier and Lovell (1990) compared two techniques for estimating production economies and efficiencies with each having both advantages and disadvantages. One approach involved the econometric estimation of a cost frontier; the second was a series of linear programs which calculate a production frontier. Their results showed that the two different techniques yielded very similar results regarding cost economies, and dissimilar results regarding cost efficiencies.

Kalaitzandonakes and Dunn (1995) in their study on the relationship between technical efficiency and education calculated technical efficiency with three alternative frontier methods for a sample of Guatemalan corn farms namely, a deterministic statistical frontier (COLS), a stochastic production frontier estimated by MLE technique and a non-parametric DEA. The three alternative frontier methods resulted in significant differences both in the average technical efficiency of the sample and the efficiency rankings of individual farms. Furthermore, following two-step procedures where technical efficiency is regressed against a set of explanatory variables, it was shown that the choice of efficiency measurement technique can alter the importance of education as a contributing factor to increased technical efficiency. The study therefore recommended that inferences based on efficiency studies should be cautious as technical efficiency may not be dependable when difficulties in the empirical measurement of conceptual variables and other measurements errors are not explicitly accounted for. Hence, an alternative approach was therefore presented for investigating the relationship between education and efficiency while accounting for difficulties in the measurement of conceptual variables and measurement errors.

Sharma et al. (1997) compared the performance of stochastic and DEA production frontiers in predicting technical efficiencies for a sample of Hawaii swine producers. Under the stochastic method, the efficiency measures were estimated under the specifications of the Cobb-Douglas production frontier for which the inefficiency effects have the truncated-normal distribution. In the DEA analyses, the output-oriented frontiers were estimated under the specifications of constant and variable returns to scale. The estimated mean technical efficiency in the stochastic frontier is larger than those obtained from the DEA analyses. The correlation between the technical efficiency rankings of the two approaches was positive and highly significant.

Sharma et al. (1999) analyzed technical, allocative and economic efficiency measures derived for a sample of swine producers in Hawaii using the parametric stochastic efficiency decomposition technique and nonparametric data envelopment analysis. The results from both approaches revealed considerable inefficiencies in swine production in Hawaii. The estimated mean technical and economic efficiencies obtained from the parametric technique were higher than those from DEA for CRS models but quite similar for VRS models, while allocative efficiencies were generally higher in DEA. However, the efficiency rankings of the sample producers based on the two approaches were highly correlated, with the highest correlation being achieved for the technical efficiency rankings under CRS. Based on mean comparison and rank correlation analyses, the return to scale assumption was found to be crucial in assessing the similarities or differences in inefficiency measures obtained from the two approaches. Analysis of the role of various firm-specific factors on productive efficiency shows that farm size had strong positive effects on efficiency levels. Similarly, farms producing market hogs were more efficient than those producing feeder pigs.

Mbaga et al. (2000) measured the technical efficiency of two groups of dairy farms in Quebec. While the actual production technology was unknown, they checked three commonly used functional form (Cobb-Douglas, translog, and generalized Leontief) along with three alternative potential inefficiency distributions (half-normal, truncated-normal, and exponential). To gain information about the robustness of the obtained technical efficiency, they also estimated a production frontier using data envelopment analysis (DEA) as an alternative methodology. The authors obtained cross-sectional data on 1143 farms that specialized in dairy production in 1996. They divided these farms into two groups (non-maize and maize regions) as proxies for differences in climate and soil quality. Their results indicated that all the correlation coefficients, as well as the rank correlation coefficients between the DEA scores and those of the parametric models, were relatively low. The average efficiency scores obtained from the DEA approach were 0.9215 for the non-maize region and 0.95 for the maize region. For the maize region, the average DEA score was similar to those generated by the generalized Leontief (GL) function, but scores were somewhat lower for the non-maize region. The DEA model showed that about 66 percent of the farms were classified as being over 90 percent efficient, while more than 93 percent of the farms fell in this category with the GL function, irrespective of the efficiency distribution.

Wadud and White (2000) compared DEA and stochastic frontiers production function (SFPF) measures of the efficiency of 150 rice farmers in two villages in Bangladesh. For the stochastic frontier model both the one-stage and two-stage procedures were implemented. The technical efficiency estimates SFPF from was lower than that from CRS DEA but greater than that of the VRS DEA. Efficiency rankings were however positive and significant. Results from both approaches indicate that technical efficiency is significantly influenced by factors measuring environmental degradation and irrigation infrastructure.

Wadud (2003) assessed estimates of technical, allocative and economic efficiency of farms using farm- level survey data for rice farmers in Bangladesh. Results from the stochastic production efficiency decomposition technique and Data Envelopment Analysis were compared. Inefficiency effects were modelled as a function of farm specific human capital variables, irrigation infrastructure and environmental factors. The results from both approaches showed that there was substantial technical, allocative and economic inefficiency in production and that analysis of technical, allocative and economic inefficiency in terms of land fragmentation, irrigation infrastructure and environmental factor were robust.

Premanchandra (2002) evaluated the extent to which alternative methods of estimation vary from one another in measuring technical efficiency. Using data from the New Zealand dairy industry for the year 1993, the paper calculated farm-specific technical efficiency estimates and mean technical efficiency estimates for each estimation method. The methods adopted include the stochastic frontier production function, corrected ordinary least squares regression (COLS) and Data Envelopment Analysis. The results derived show that the mean technical efficiency of an industry is sensitive to the choice of the production frontier method. In general, the SFPF and DEA frontiers resulted in higher mean technical efficiency estimates compared to the COLS production frontier. The resulting mean TE estimate from the SFPF production frontier was significantly higher than that of DEA, except under the variable returns to scale DEA model. The results from the DEA and SFP frontiers also indicate that New Zealand dairy farmers were operating nearer to or at the efficiency frontier. All three methods are consistent in ranking individual production units in terms of technical efficiency.

Haghiri (2003) used a stochastic nonparametric frontier regression analysis to estimate and compare the technical efficiency of a large set of dairy producers in

Canada with their counterparts in the U.S. Using a panel data set, an iterative procedure called a smoothing process was used to estimate the mean response function and its parameters constructed in a generalized additive model (GAM). Using the method of locally scoring smoothing, the parameters of the regression function were estimated by employing two separate nonparametric techniques: locally weighted scatter plot smoothing (LOWESS), and spline smoothing. After estimating the response function and its parameters, the technical efficiency scores were computed. These efficiency indices were also compared with the one obtained from conducting a stochastic parametric (translog) frontier function using both the maximum likelihood estimation (assuming a half-normal distribution) and the COLS methods. The results show that the overall mean technical efficiency obtained from translog function for all regions is higher than that of the corresponding values obtained from the nonparametric approaches. Both parametric and nonparametric methodologies indicated evidence of differences between the mean technical efficiency of dairy farms in all regions meaning that various policies implemented in the two countries significantly impacted the performance of dairy producers.

Jaforullah and Premanchandra (2004) estimated technical efficiency for the New Zealand dairy industry using three different estimation techniques under both constant returns to scale and variable returns to scale in production. The approaches used were the econometric stochastic production frontier (SPF), corrected ordinary least squares (COLS) and data envelopment analysis (DEA). Mean technical efficiency of the industry was found to be sensitive to the choice of estimation technique. In general, the SPF and DEA frontiers resulted in higher mean technical efficiency estimates than the COLS production frontier.

Alene and Manfred (2005) compared the performances of the parametric deterministic distance functions (PDF) and DEA with applications to adopters of improved cereal technology in Eastern Ethiopia. Although they found positive and significant correlations between the two approaches, the result from PDF was more robust when analysis was subjected to sensitivity to possible outliers. The results from the preferred PDF approach revealed that adopters of improved technology have average technical efficiencies of 79 percent, implying that they could potentially raise their food crop production by an average 21 percent through full exploitation of the potentials of improved varieties and mineral fertilizer.

Herrero (2005) compared four different approaches data envelopment analysis, stochastic production frontier, panel data, and distance function to estimation of technical efficiency of the Spanish Trawl Fishery that was operated in Moroccan water. Their findings show that the efficiency estimates were similar and highly correlated. Thus, they conclude that none of the methodologies can be said to be better than the rest; rather, the most appropriate methodology depends on the characteristics of the production process, the degree of stochasticity, number of outputs and possibility of aggregation.

Johansson (2005) estimated technical, allocative and economic efficiency scores for an unbalanced panel of Swedish dairy farms, using data envelopment analysis and the stochastic production frontier approach. The mean technical, allocative and economic efficiency indices for the entire period were 0.55, 0.75, and 0.41, respectively in the SFPF model. However, when the data envelopment analysis was applied, the technical, allocative and economic efficiency indices were 0.74, 0.61, and 0.45, respectively. Thus, the mean technical and economic efficiency indices were higher under DEA than under SFPF whereas the reverse was the case for allocative efficiency. A paired t-test results showed that the measures of technical and economic efficiency were significantly higher under the DEA approach while allocative efficiency was higher under SFPF approach. However, both SFPF and DEA provided similar rankings. Further results showed a positive relationship between size and efficiency. Finally it was concluded that the main challenge facing the Swedish dairy farms is to enhance their cost minimizing skills.

Tingley et al. (2005) calculated technical efficiency for segments of the English Channel fisheries using the econometric stochastic production frontier (SPF) and the non-stochastic, linear-programming data envelopment analysis (DEA) methodologies. The influence of factors most affecting technical efficiency was analysed using an SPF inefficiency model and tobit regression of DEA-derived scores. While the overall DEA technical efficiency scores were affected by random error and thus lower that those of SPF, the results demonstrated that both techniques were able to produce reasonable models of factors that affect efficiency. With only one exception, the analysis of the efficiency scores using the two methods (DEA and SPF) was consistent, at least in terms of direction of the effect. They concluded that based on the explanatory power of the models and the number, sign and consistency of significant variables between models, the tobit regression of DEA-derived scores are generally as robust as those of the comparative SPF inefficiency model and therefore, tobit regression of DEA-derived technical efficiency scores can be used as an alternative method to explain inefficiency where SPF model specification is problematic.

Alene et al. (2006) analysed efficiency of intercropping annual and perennial crops in Southern Ethiopia by comparing technical efficiency predictions from parametric stochastic frontier production function (SFPF), parametric deterministic distance functions (PDF) and non-parametric DEA using different orientations. The mean technical efficiency from SFPF (72 percent) were lower than that obtained from PDF (89-93 percent) and DEA (92-94 percent). Further, SFPF gave higher technical efficiency variation across farms but efficiency rankings were similar for the three approaches. They concluded that whether stochastic or deterministic frontiers yield higher or lower estimates cannot be determined a priori. Testing the stability of technical efficiency estimates from the three approaches, they found that PDF and DEA are more robust than SFPF. Based on similarity of results from DEA and PDF, the final efficiency scores were obtained from their geometric mean.

Bojnec and Latruffe (2007) investigated the determinants of technical efficiency of Slovenian farms by comparing results from parametric stochastic frontier production function and the non-parametric data envelopment analysis. They obtained consistent results for all the included variables except for land where the two methods produced contradicting result both in terms of sign and significance. They thus concluded that the influence of land is undetermined.

Odeck (2007) compared data envelopment analysis and stochastic frontier analysis to assess efficiency and productivity growth of Norwegian grain producers. He found consistency between the approaches to the extent that there were potentials for efficiency improvements, but the magnitudes depend on the model applied and by segmentation of the data set. However, he warned that policy-makers should not be indifferent with respect to the approach used for efficiency and productivity measurement at least with respect to the magnitudes of potential for efficiency improvements and productivity growth since each approach may give different results.

3.5.2 Empirical Comparative Studies in other Sectors involving Distance Functions

Coelli and Perelman (1999) investigated technical efficiency in European railways. They compared the results obtained from three alternative methods of estimating multi-output distance functions. Specifically they considered the construction of a parametric frontier using linear programming (PLP); data envelopment analysis (DEA) and corrected ordinary least squares (COLS). Input-orientated, output-orientated and constant returns to scale (CRS) distance functions were estimated and results from these were compared. Their results indicated a strong degree of correlation between the input- and output-orientated results for each of the three methods. Significant correlations were also observed between the results obtained using the alternative estimation methods. The strongest correlations were observed between the parametric linear programming and the COLS methods. Based on similarity of results, they used the geometrical mean of efficiency scores from all model results for final ranking.

Coelli and Perelman (2000) compared results from three specifications of distance functions estimated by COLS and two specifications of single output production frontiers. The study focused on the use of technical efficiency as a measure of performance of the European railways. The results obtained indicate substantial differences in parameter estimates and technical efficiency rankings, casting significant doubt upon the reliability of the single-output models. Therefore, their final preferred model was the (unrestricted) input distance function with a mean technical efficiency level of 0.863 and mean values for individual companies that range from 0.784 for Italy to 0.980 for the Netherlands.

Jamasb and Pollitt (2003) compared 63 regional electricity distribution utilities in the six European countries. To calculate technical efficiency and to consider the effects of choosing the variables and methods, they used six DEA, two COLS, and two SFA techniques of estimating input distance functions. Their results show a strong correlation between the non-parametric base model DEA-CRS and the parametric COLS and SFA models. However, they found that the mean and minimum efficiency scores in DEA-CRS base model were significantly lower than the other two models. They also found that the DEA-CRS base model efficiency scores were significantly lower than those of corresponding DEA-VRS and that the VRS model exhibited a somewhat weaker correlation with the latter model than with COLS and SFA models.

Estache et al. (2004) applied DEA and econometric methods for performance assessment and ranking of South American electricity units. Specifically they estimated two parametric distance models (an input distance function and an input requirement function) and four deterministic nonparametric DEA models (two input distance functions, one with variable returns to scale and another with constant returns to scale, and two input requirement functions, one with variable returns to scale and another with constant returns to scale). Testing the internal consistency of results obtained from all approaches, first they found that efficiency levels from different approaches were significantly different. Secondly, they found high correlation between different econometrics as well as DEA models. However, there was low correlation between DEA and econometrics models. Thirdly, they found that the best and worst performers were identified reasonably well by all the DEA models but the selection of a particular SFA model was not a trial choice. They also tested the external consistency of different approaches by determining the year-to year stability of DEA and SFA efficiency estimates over time. The results suggest that the efficiency scores were stable over time.

Cuesta et al. (2009) compared the performance of parametric stochastic hyperbolic distance functions with DEA in the analysis of environmental efficiency of U.S. electricity generating units and found that although the means and distributions of the models were significantly different, the ranking of the units by each model is similar.

3.5.3 Recent Empirical Efficiency Studies in Nigerian Agriculture

Ajibefun (2002) analysed the determinants of technical efficiency of small scale farmers in Nigeria and the effect of policy changes on technical efficiency, using a Cobb-Douglas stochastic frontier production function. The result showed a wide variation in the estimated technical efficiencies, ranging between 0.18 and 0.91, and a mean value of 0.63, indicating a wide room for improvement in the technical efficiency. The results of simulation of policy variables showed that the level of technical efficiency significantly increased with rising level of education and farming experience.

Ogunyinka and Ajibefun (2004) analysed the determinants of technical inefficiency among the farmers that are participating in the Ondo State chapter of the National Directorate of Employment program in Nigeria. They obtained an average efficiency score of 61 percent which translates to average inefficiency of 39 percent. Employing a second stage tobit regression analysis, it was found that extension visits, higher education, land input and membership of farm association were significant factors influencing technical efficiency with only extension visit having a negative influence, while others had the expected positive influence. The study concluded that sound education, efficient inputs supply strategy and public awareness of efficient technology are key factors necessary for policy consideration.

Ogundele and Okoruwa (2004) examined technical efficiency differentials between farmers who planted traditional rice varieties and those who planted improved varieties in Nigeria using stochastic production frontier. Results showed that significant increase recorded in output of rice in the country could be traced mainly to area expansion. Other variables that contributed to technical efficiency were; hired labour, herbicides and seeds. The average technical efficiency was 90 and 91 percent for traditional and improved rice variety farmers, respectively. Further analysis showed that farmers in both categories were operating at a point of increasing return to scale. The test of hypothesis on the differentials in technical efficiency between the two groups of farmers showed that there was no absolute differential in technical efficiency between them.

Amaza and Maurice (2005) investigated factors that influence technical efficiency in rice-based production systems among fadama farmers in Adamawa State, Nigeria. A Cobb-Douglas stochastic frontier production function, which incorporates technical inefficiency model, was estimated using the maximum likelihood estimation (MLE) technique. Technical efficiencies vary widely among farms, ranging between 0.26 and 0.97 and a mean technical efficiency of 0.80 implying that efficiency in rice production among fadama farmers in Adamawa State could be increased by 20 percent through better use of available resources, given the current state of technology. The inefficiency model reveals that farming experience and education significantly affect farmers efficiency levels.

Umeh and Asogwa (2005) analyzed the effect of some government policy packages on the technical efficiency of cassava farmers in Benue State, Nigeria. The study used the Cobb-Douglas frontier production function and assumed a truncated normal distribution for the inefficiency term. Cross-sectional data was used. The parameters of the model were estimated by the maximum likelihood estimation method. Their results show that majority (63.6 percent) of the cassava farmers operated close to the frontier production function. The estimated technical efficiency scores varied between 31 percent and 100 percent with a mean score of 89 percent. The findings showed that cassava production in the state can be improved by increasing farmers' access to policy packages such as extension services, market access, improved cassava variety and processing technology.

Ogundari (2006) employed a stochastic frontier profit function to analyse determinants of profit efficiency among scale rice farmers in Nigeria. The obtained mean profit efficiency of 60 percent. The results also showed age education, farming experience and household size has positive and significant effect on profit efficiency.

Ogundari and Ojo (2006) examined the production efficiency of cassava farms in Osun state of Nigeria using farm level data. The stochastic frontier production and cost function model were used to predict the farm level technical and economic efficiencies, respectively. Their results shows that mean TE, EE and AE of 0.903, 0.89 and 0.807 were obtained from the analysis respectively meaning that TE appears to be more significant than AE as a source of gain in EE.

Okoruwa et al. (2006) analysed technical, allocative and economic efficiency of upland and lowland rice producers in Niger State Nigeria using a stochastic production function efficiency decomposition methodology. They obtained an average technical efficiency of 81.6 percent for upland rice and of 76.9 percent for lowland rice. The analysis of variance (ANOVA) was used to investigate the association between EE, TE and AE, and seven socioeconomic characteristics. They found that experience, household size, farm size, sex and improved rice variety has significant impact on rice farmers. Their results showed that farmers could increase output and household income through better use of available resources given the state of technology in terms of improved varieties of rice seeds.

Ogundari et al. (2006) estimated a Cobb-Douglas cost frontier function in order to examine economies of scale and cost efficiencies of small scale maize farmers in Nigeria using a cross-sectional data on 200 farms. The maximum likelihood estimates of the frontier cost function and the inefficiency model were obtained simultaneously in a one-stage procedure. They obtained mean cost efficiency of 1.16 implying that an average maize farm in the area has costs that are 16 percent above the minimum defined by the frontier. About 83 percent of the farms included in the sample operated close to the frontier level. Farming experience and age were found to have significant effect on the cost efficiency of the farmers.

Okoye et al. (2006) employed stochastic frontier translog cost and production functions to measure the level of allocative efficiency and it's determinants in small-holder cocoyam production in Anambra state, Nigeria. The parameters of the stochastic frontier cost function were estimated using the maximum likelihood method. The result of the analysis shows that individual farm level allocative efficiency was about 65 percent. The study found age and education to be negatively and significantly related to allocative efficiency. Farm size coefficient also had a negative relationship with allocative efficiency and was significant. Fertilizer use, credit access and farm experience was significant and directly related to allocative efficiency.

Amos (2007) estimated a stochastic frontier by maximum likelihood method to examine the productivity and technical efficiency of Crustacean production in

Nigeria. A Cobb-Douglas stochastic frontier production function was estimated using primary data. Two models were tested for the presence of technical inefficiency effects using the log likelihood ratio (LR) test. The model without the inefficiency term was dropped. The technical efficiency of producers ranged between 0.45 and 0.98 with a mean of 0.70. The result showed that age and level of education were an increasing function of technical inefficiency while family size and leadership role were decreasing functions of technical inefficiency. Although the sign of the education variable was contrary to the a priori expectation, the explanation given for this is that probably the more educated the producers are, the less time they devote to Crustacean production and the more time they devote to other activities such as politics and merchandising as a form of income diversification. This study also found that cost of fishing equipments and other production costs had significant influence on Crustacean production in Nigeria. The study therefore recommended that producers be encouraged to use better fishing nets and motorized outboard engines to increase their production. It appears that productivity and efficiency were treated as same in this study as there was no evidence of measuring productivity as a separate variable.

Idiong (2007) employed a stochastic frontier production function that incorporated inefficiency factors to provide estimates of technical efficiency and its determinants using data obtained from 112 small scale swamp rice farmers in Cross River State. The results indicated that, the rice farmers were not fully technically efficient. The mean efficiency obtained was 77 percent indicating a 23 percent allowance for improving efficiency. The result also shows that, farmers' educational level, membership of cooperative/farmer association and access to credit significantly influenced the farmers' efficiency positively.

Adewumi and Adebayo (2008) used a cross-sectional data from 152 sweet potato farmers from Kwara State, Nigeria to measure the profitability and technical efficiency of these farmers. For estimation of technical efficiency, they assumed a Cobb-Douglas stochastic frontier production function and estimated the model using maximum likelihood method. A mean technical efficiency score of 0.44 was obtained showing there is considerable inefficiency among the sweet potato farmers. Farm size, education, access to credit, contact with extension agents were found to have significant influence on technical efficiency of the farmers thus improving these variables could increase their technical efficiency.

Ajibefun (2008) assessed the sensitivity of technical efficiency predictions to the choice of estimation method by comparing results from parametric SFPF and non-parametric DEA. The SFPF mean technical efficiency (0.68) was somewhat higher than that from DEA (0.65) and this was explained by the fact that the DEA model being non-stochastic reports noise as inefficiency hence its lower mean technical efficiency. The study also observed dissimilar distributions of efficiency distribution. The study did not indicate if these differences were statistically significant. The study however found that both methods produced similar result for age and education variable with respect to the sign and significance of their impact on efficiency.

Kareem et al. (2008) applied the stochastic frontiers production analysis to estimate the technical, allocative and economic efficiency among the fish farmers using concrete and earthen pond systems in Ogun State. Mean technical efficiency in the concrete pond system was 88percent while earthen pond system was 89 percent. Similarly, the allocative efficiency results revealed that concrete pond system was 79 percent while earthen pond had 85 percent. The results of economic efficiency also revealed an average of 76 percent in concrete pond system while it was 84 percent in the earthen pond system. Further analysis revealed that pond area, quantity of lime used, and number of labour used were significant factors that contributed to the technical efficiency of concrete pond system while pond, quantity of feed and labour are the significant factors in earthen pond system.

Oyekale and Idjesa (2009) employed the stochastic production function to analyse adoption of improved maize seeds and technical efficiency of maize farmers in Rivers State Nigeria. Their results show that use of hybrid seeds, experience, crop rotation, minimum tillage, fertilization and age significantly reduces inefficiency. This study however did not provide estimates of technical efficiency of maize farmers.

Okoruwa et al. (2009) examined the relative economic efficiency of small and large rice farms in North Central, Nigeria. They found that the use of modern rice varieties significantly increases profits. Significant difference in economic efficiency between small and large farms was also discovered. Therefore, it is suggested that, to improve technical efficiency of rice farms, an accelerated program to provide modern rice varieties, fertilizer and land availability is needed. The paper provided support to eliminate bias distribution of production inputs to large rice farms.

Ojo et al. 2009 examined the implication of resource productivity and farm level technical inefficiency in yam production on food security in Niger state, Nigeria using a stochastic frontier production function. Their findings showed the return to scale of 1.686 indicating an increasing return to scale. The study also showed that the levels of technical efficiency ranged from 31.72 percent to 95.10 percent with mean of 75.64 percent which suggests that average yam output falls 24.46 percent short of the maximum possible level. Their result further showed that, farmers' educational level, years of farming experience and access to extension service had significant and positive impact on farmers' efficiency. Thus, it was recommended that relevant policies that would enhance the technical skill of the farmers and access to extension services should be evolved by the stakeholders.

Okoye et al. (2009) employed a Cobb-Douglas stochastic frontier production function to examine the relationship between farm size and technical efficiency in small holder cassava production in Ideato LGA of Imo state using data from a 2008 farm-level survey of 90 rural households. The study showed a strong inverse relationship between farm size and technical efficiency. They concluded that policies of de-emphasizing cassava production in the estate sector while encouraging it in smallholdings will foster equity and efficiency. Therefore, the study recommended land redistribution policies targeted towards giving lands to the small-holder farmers.

To conclude on the Nigerian studies, a detailed review of a meta analysis of technical efficiency in Nigerian agriculture by Ogundari (2009) is provided. A variety of sources were explored to compile the list of papers cited in the study. The analysis was performed with a truncated regression on a total of sixty four studies covering the period 1999-2008. Only studies with the application of primal- stochastic frontier production model were used because studies based on dual representations of the technology frontier as well as non-parametric (e.g., DEA) models in Nigerian agriculture obtained were insignificant in number. None of the studies used panel data showing the dearth of panel survey in Nigeria. The study showed that 63 percent of technical efficiency studies in Nigeria were conducted on food crops showing the dominant position of this sub-sector in Nigerian agriculture. Sixty (69) percent of the studies used single output while 31 percent used aggregate output. Of the studies that employed a single output approach, only one was on maize despite the importance of maize in Nigeria. Cobb-douglas functional form was employed by 88 percent of the studies while only 12 percent employed translog form. Whereas 49 percent of the studies were conducted in the Southeast zone, only 12 percent of such study was conducted in the Northcentral zone (the intended study area for this current study). The results showed that mean technical efficiency (MTE) in Nigerian agriculture increased significantly over the years. The overall average MTE computed from all the studies was 0.739 which is significantly not different from 0.737 obtained by Bravo-Ureta et al. (2007) for African countries and 0.68 obtained by Thiam et al. (2001) for developing countries. This finding, however, suggests that, there is a large potential for improvement in Nigerian agricultural production systems, as about 26 percent of the agricultural output in the country could be expanded without any additional use of inputs in comparison to what could be achieved under full technical efficiency. The findings further showed that studies in the Southwest region of the country produced higher MTE with average of 0.842 whereas the average is 0.720 for Northcentral zone implying that improving efficiency and productivity in Nigerian agriculture might require regional specific-policy responses. Regarding the unconditional effect of the choice of functional form, the study observed an average MTE of 0.79 for studies with Cobb-Douglas, and 0.69 for translog. In contrast, Thiam et al. (2001) and Bravo-Ureta et al. (2007) reported higher average MTE for studies with translog compared to Cobb-Douglas. The study however, found no statistical difference between the MTE of Cobb-Douglas and translog in this study. Study specific-characteristics such as sample size, number of inputs used as well as studies with focus on crop and livestock production were found to significantly impact MTE. Within the sample, seventy one observations contain quantitative results on sources of technical efficiency differences usually incorporating socio-economic variables. Based on this, fifty three percent identified educations as a significant determinant of technical efficiency while thirty eight percent showed that experience is important. Extension was shown to be an important determinant by twenty three percent of the observations while nineteen percent identified age as significant determinant of technical efficiency in Nigerian agriculture over the years.

All the above studies that compared distance function and other approaches limited their analysis to technical or environmental efficiency only. This is not surprising given the methodological complexity involved in decomposing cost efficiency into its technical and allocative components. Further, with exception of the Herrero (2005) and Cuesta et al. (2009) studies, all others considered parametric deterministic distance functions, thus the possibility of stochastic noise in the data was ignored. Given that the focus of this study is on agriculture which is well known to be affected by factors such as weather and macro economic factors that are beyond the control of farmers, the neglect of random factors may have serious implications on the study conclusions. Thus, the current study intends to fill these gaps by making a comparison of parametric stochastic input distance functions (SIDF), non-parametric data envelopment analysis (DEA) and conventional parametric stochastic frontier production frontier (SFPF) approaches to analysis of technical, allocative and cost efficiency and their determinants in the Nigerian maize sector. Based on the result of the comparative analysis an integrated model is developed for resolution of model selection difficulties.

CHAPTER 4

ANALYTICAL FRAMEWORK AND EMPIRICAL SPECIFICATIONS

4.1 Introduction

Production efficiency has been measured using parametric and non-parametric approaches. Parametric methods include econometric estimation of production or cost functions. They represent single-output technologies and estimate the production frontier or curve which traces out the maximum feasible output for different input levels conditional on the technology in use. Transformations can be applied to multiple-output technology such that production and transformation functions yield optimal output given technology and resources (Andreu, 2008). These functions need to be estimated econometrically and can take several functional forms, ranging from the restrictive Cobb-Douglas to more flexible forms such the translog. Other functions related to production that can be econometrically estimated are cost functions, profit functions, and revenue functions. All of these can be formulated to account for multiple inputs and/or outputs. As in the case of production functions, these latter functions need to conform to certain properties in order to satisfy the economic concept they represent. In a set theory orientation, any production technology can be represented by output and input sets which need to satisfy some mathematical and economic properties to be an accurate representation of the production possibility frontier or curve. This approach is used in efficiency because of the relationship between technical efficiency and distance function. Distance functions are alternative representations of production technology that model multiple-input and multiple-output technological relationships. A disadvantage of the parametric approach is the imposition of an explicit functional form and a distributional assumption on the error terms.

In contrast, the non-parametric approach does not impose parametric restrictions on the underlying technology and therefore is less prone to misspecification. Data Envelopment Analysis (DEA) is the most common non-parametric approach. The choice between these approaches has been an issue of debate with some preferring the parametric approach while others prefer the non-parametric approach. Even within the class of parametric approaches, an interest is usually set on one approach against the other due to one limitation or the other. Given the different strengths and weaknesses of these approaches, it is of interest to compare their empirical performance using the same data set. In this study results from parametric stochastic input distance function is compared to those from non-parametric input distance frontier, the data envelopment analysis and parametric stochastic frontier production function. In the next section, the analytical framework of each approach is presented. The empirical models for this study are specified and described in section three.

4.2 Analytical Framework

4.2.1 The Production Frontier and Efficiency Decomposition

The production function is one of the conventional methods of representing the production technology. The use of production frontiers for decomposition of cost efficiency into its technical and allocative components was developed by Bravo-Ureta and Rieger (1991) to solve the problem of estimating a cost function directly when there is little or no variation in prices among sample firms. They followed a primal route in their methodology. The methodology involves using the level of output of each firm adjusted for statistical noise, the observed input ratio and the parameters of the stochastic frontier production function (SFPF) to decompose economic efficiency into technical and allocative efficiency. Then the cost function is analytically derived from the parameters of the SFPF. To illustrate the approach, a stochastic frontier production function is given as:

$$Y_i = f(X_i;\beta) + \varepsilon_i \tag{4.1}$$

$$\varepsilon_i = v_i - u_i \tag{4.2}$$

where ε_i is the composed error term. The two components v_i and u_i are assumed to be independent of each other, where v_i is the two-sided, normally distributed random error and u_i is the one-sided efficiency component with a half normal distribution. Y_i is the observed output of the ith firm, X_i is the input vector of ith firm and β is unknown parameters to be estimated.

The composed error (ε_i) is obtained by subtracting predicted output from the observed output:

$$\varepsilon_i = Y_i - \hat{Y}_i \tag{4.3}$$

The parameters of the SFPF were estimated using the maximum likelihood method. Subtracting v_i from both sides of the equation (4.2) results in

$$Y_i^* = Y_i - v_i = f(X_i;\beta) - u_i \tag{4.4}$$

where Y_i^* is the observed output of the *i*th firm adjusted for statistical noise captured by v_i. From equation (4.4), the technically efficient input vector, X_i^T, for a given level of Y_i^* is derived by solving simultaneously equation (4.4) and the input ratios, $X_1 / X_k = \rho_k (k > 1)$, where ρ_k is the ratio of the observed inputs.

Assuming the production function is self-dual function like the Cobb-Douglas production function , the corresponding dual cost frontier can be derived and written in a general form as:

$$C_i = h(W_i, Y_i^*;\delta) \tag{4.5}$$

where C_i is the minimum cost of the *i*th firm associated with output Y_i^*; W_i is a vector of input prices of the *i*th firm; and δ is a vector of parameters which are functions of the parameters in the production function.

The economically efficient (cost minimising) input vector, X_i^E, is derived by using Shephard's Lemma and then substituting the firm's input prices and adjusted output quantity into the system of demand equations:

$$\frac{\partial C_i}{\partial W_i} = X_i^E (W_i, Y_i^*;\delta) \tag{4.6}$$

For a given level of output, the corresponding technically efficient, economically efficient and actual costs of production are equal to $W_iX_i^T$, $W_iX_i^E$ and W_iX_i, respectively. These three cost measures are then used as the basis for calculating the technical and economic efficiency indices for the *i*th firm :

$$TE_i = \frac{W_iX_i^T}{W_iX_i} \tag{4.7}$$

and

$$EE_i = \frac{W_iX_i^E}{W_iX_i} \tag{4.8}$$

Following Farrel (1957), allocative efficiency can be calculated by dividing economic efficiency (EE) by technical efficiency (TE):

$$AE_i = \frac{W_iX_i^E}{W_iX_i^T} \tag{4.9}$$

Although, Bravo-Ureta and Rieger (1991) method was an attempt to resolve the problem of estimating a cost frontier directly, their methodology faced criticism because the parameters of the frontier are estimated using an output-oriented approach but technical efficiency is derived by imposing an input-oriented approach implied by the simultaneous solution of adjusted outputs and the observed input ratios to yield the technically efficient input vectors. This method will give technical efficiency scores that are very different from those obtained from the maximum likelihood estimation of the SFPF in equation (4.1) which is output-oriented unless the firms are operating under constant returns to scale. Even if the hypothesis of constant returns to scale is not rejected, consistent estimates cannot be obtained as long as the function coefficient is numerically different from unity (Alene, 2003; Alene and Hassan, 2005). Thus the estimates may suffer simultaneous equations bias because the production function was estimated when input quantities were clearly assumed to be the decision variables. That is, the endogenous input variables appear as regressors in the production function (Coelli et al., 2003).

4.2.2 Distance Function Approach to Efficiency Decomposition

Given the weaknesses in the cost decomposition using the stochastic frontier production function methodology, an alternative approach which avoids the simultaneous equation bias was proposed by Coelli et al. (2003). This methodology involves the use of distance functions. The notion of distance function was first introduced by Shephard (1953). The distance function can have either an output or input orientation. The output distance function measures how close a particular level of output is to the maximum attainable level of output that could be obtained from the same level of inputs if production is technically efficient. In other words, it represents how close a particular output vector is to the production frontier given a particular input vector (Mawson et al., 2003). An input-distance function is defined in a similar manner. However, rather than looking at how the output vector may be proportionally expanded with the input vector held fixed, it considers by how much the input vector may be proportionally contracted with the output vector held fixed. They are input-oriented because they try to find out how to improve the input characteristics of the firm concerned so as to become efficient. In most empirical studies, the selection of orientation is justified based on exogeneity/endogeniety argument for inputs and outputs. However, (Coelli, 1995b, Coelli and Perelman, 1999) observed that in many instances, the choice of orientation will have only minor influences upon the efficiency scores obtained. Based on this, the study employs the input orientation and therefore the discussion is limited to input distance functions.

The input distance function may be defined on the input set, $L(y)$, as

$$D_I(x, y) = \max\{\rho : (x / p) \in L(y)\} \tag{4.10}$$

where the input set $L(y)$ represents the set of all input vectors, $x \in R_+^K$, which can produce the output vector, $y \in R_+^M$. That is,

$$L(y) = \{\, x \in R_+^K : x \text{ can produce y}\} \tag{4.11}$$

$D_I(x, y)$ is non-decreasing, positively linearly homogenous and concave in x, and non-increasing in y. The distance function, $D_I(x, y)$, will take a value which is greater than or equal to one if the input vector, x, is an element of the feasible input set, $L(y)$. That is, $D_I(x, y) \geq 1$ if $x \in L(y)$. Furthermore, the distance function will take a value of unity if x is located on the inner boundary of the input set.

The distance function has been estimated by different methods. These include the construction of parametric frontier using linear programming methods (Färe et al., 1994; Coelli and Perelman, 1999; Alene and Manfred, 2005); the construction of non-parametric piece-wise linear frontier using the linear programming method known as data envelopment analysis (DEA) (e.g. Färe et al., 1985, 1989, 1994; Coelli and Perelman, 1999; Alene and Manfred, 2005); estimation of parametric frontier using corrected ordinary least square (COLS) (e.g. Lovell et al., 1994; Grosskopf et al., 1997; Coelli and Perelman, 1999) and maximum likelihood estimation (MLE) of a parametric stochastic distance frontier (e.g. Coelli et al., 2003; Irz and Thirtle, 2004; Solis et al., 2009). ML of the parametric frontiers is preferred to COLS because of large mean square error advantages when γ^* is greater than 50 percent (Coelli, 1995). This study employs both the parametric stochastic input distance function (SIDF) and non-parametric input distance function, DEA approaches with the intent to make comparison of results. Results from the distance functions are further compared with those from conventional production frontiers.

4.2.2.1 The Parametric Stochastic Input Distance Function

The value of the distance function is not observed so that imposition of a functional form for $D_I(x, y)$ does not permit its direct estimation. A convenient way of handling this problem was suggested by Lovell et al. (1994) who exploit the property of linear homogeneity of the input distance function. Given a general form of an input distance function as:

$$D_I = f(x, y) \tag{4.12}$$

where f is a known functional form such as Cobb-Douglas or translog. Linear homogeneity implies:

$$\lambda D_I = f(\lambda x, y) \qquad \forall \lambda > 0 \tag{4.13}$$

Assuming x is a vector of K inputs and setting $\lambda = 1/x_1$, where x_1 is its (arbitrarily chosen) first component, then equation (4.13) can be expressed in a logarithmic form as:

$$\ln(D_I / x_1) = \ln f(x/x_1, y) \tag{4.14}$$

or

$$\ln(D_I) - \ln(x_1) = \ln f(x/x_1, y) \tag{4.15}$$

and hence

$$-\ln(x_1) = \ln f(x/x_1, y) - \ln(D_I) \tag{4.16}$$

where $-\ln(D_I)$ is defined as $\varepsilon = v - u$ to indicate that the distance term may be interpreted as a traditional stochastic frontier analysis disturbance term. That is, the distances in a distance function (which are radial distances between the data points and the frontier) could be due to either noise (v) or technical inefficiency (u) which is the standard SFA error structure (Coelli et al., 2003). Therefore equation (4.16) can be rewritten as:

$$-\ln(x_1) = \ln f(x/x_1, y) + v - u \tag{4.17}$$

The random errors, v are assumed to be independently and identically distributed as $N(0, \sigma^2{}_v)$ random variables and independent of the u's , which are assumed to be either a half-normal distribution i.e., $\left|N(0, \sigma_u{}^2)\right|$ or exponential distribution i.e. EXP$(\mu, \sigma_u{}^2)$ or truncated normal (($N(\mu, \sigma_u{}^2)$) or gamma distributions. The predicted radial input-oriented measure of TE for an ith firm is given as:

$$T\hat{E}_i = 1/\hat{D}_I = E[\exp(u_i) \left| v_i - u_i \right.] \tag{4.18}$$

In other words, $1-T\hat{E}_i$ measures the proportion by which costs would be reduced by improving technical efficiency, without reducing output. A value greater than one for the input distance function ($\hat{D}_I$) indicates that the observed input-output vector is technically inefficient. When the producer is operating on the technically efficient frontier or the isoquant, the parametric input distance function attains a value of one.

The technically efficient input quantities can be predicted as follows:

$$\hat{x}^T_{ji} = x_{ji} \times T\hat{E}_i; \qquad j = 1,2...K \tag{4.19}$$

Using the first order condition for cost minimisation, the duality between the cost and input distance function can be derived (see Coelli et al. 2003 for derivation and explicit specification). The general form of the cost function is given as :

$$C_i(w_i, y_i) = \underset{x}{Min}\{w_i x_i : D_I(x_i, y_i) \geq 1\} \tag{4.20}$$

where C is the cost of production and w denotes a vector of input prices. From this minimisation problem, it is possible to relate the derivatives of the input distance function to the cost function and by making use of Shephard's Lemma, cost and allocative efficiency can be computed as in equations 4.34 and 4.35.

4.2.1.2 The Non-Parametric Input Distance Function

The input distance function can also be estimated through non-parametric techniques, such as Data Envelopment Analysis (DEA) and they are the reciprocal of the Debreu-Farrell technical efficiency measure (Lovell, 1993; Färe et al, 1994; Estache, et al., 2004). The original distance function by Shephard (1953) takes the (multiple) outputs as given and seeks to locate feasible contraction in the input vector, thus providing a complete characterization of an efficient production technology and a reciprocal measure of the distance of each producer to the efficient frontier (Färe et al., 1994).

Each DEA model tries to determine which firms form an envelopment (piecewise linear) of the technological set (the efficient frontier). Then DEA provides a methodology for the analysis of individual firms' efficiency relative to this (best-practice) frontier. Consequently, the selection of a particular DEA model involves a decision about the shape of the efficient frontier and another one about the distance concept used (Estache, et al., 2004). Thus, the purpose of the approach is to construct a non-parametric envelopment frontier over the data points such that all observed points lie on or below the production frontier. The DEA can either assume constant returns to scale (CRS) or variable returns to scale (VRS). The theoretical specification of an input distance function in a DEA framework consists of an optimization problem subject to certain constraints. Assuming there is data on K inputs and M outputs on each of N firms. For *i*th firm, these are represented by the vectors x_i and y_i, respectively. The K x N input matrix, X and the M x N output matrix, Y, represent the data of all N firms. The input-oriented constant returns to scale DEA frontier is defined by the solution to N linear programs of the form:

$$\min_{\theta,\lambda} \theta,$$

$$\begin{aligned} \text{subject to } \; & -y_i + Y\lambda \geq 0, \\ & \theta x_i - X\lambda \geq 0, \qquad\qquad (4.21) \\ & \lambda \geq 0 \end{aligned}$$

where θ is the technical efficiency score for the *i*th firm and will satisfy $0 \leq \theta \leq 1$, with value of 1 indicating a point on the frontier and hence a technically efficient firm. θ is therefore the proportion by which the observed inputs of the analysed firm could be contracted if the firm were efficient and therefore provides the input distance measure. λ is a Nx1 vector of intensity parameters that allows for convex combination of the observed inputs and outputs (in order to build the envelopment surface).

The input-oriented VRS model is solved by N linear programs of the form:

$$\min_{\theta,\lambda} \theta,$$

$$
\begin{aligned}
\text{subject to } & -y_i + Y\lambda \geq 0, \\
& \theta x_i - X\lambda \geq 0, \\
& \lambda \geq 0 \\
& N1'\lambda = 1
\end{aligned}
\tag{4.22}
$$

where $N1'\lambda = 1$ is the convexity constraint which ensures that an inefficient farm is only benchmarked against farms of similar size and it is this additional constraint that makes equation (4.22) a VRS DEA. $N1'$ is an Nx1 vector of ones.

With availability of price information, both technical and allocative efficiencies can be measured. For the case of a CRS cost minimisation, one would run the input-oriented CRS DEA model set out in equation (4.21) to obtain technical efficiency scores. One would then run the following cost minimisation DEA

$$
\begin{aligned}
& \min_{\lambda, x_i^*} \; w_i' x_i^*, \\
\text{subject to } & -y_i + Y\lambda \geq 0, \\
& x_i^* - X\lambda \geq 0, \\
& \lambda \geq 0
\end{aligned}
\tag{4.23}
$$

where w_i is a vector of input prices for the *i*th firm and x_i^* is the cost minimising vector of input quantities for the *i*th firm given the input prices w_i and the output levels y_i and this is calculated by the model. The overall or cost efficiency of the *i*th firm is then calculated as

$$
CE = \frac{w_i' x_i^*}{w_i' x_i} \tag{4.24}
$$

Allocative efficiency is calculated as

$$
AE = \frac{CE}{TE} \tag{4.25}
$$

For a VRS cost-minimisation, equation (4.23) is altered by adding the convexity constraint, $N1'\lambda = 1$. The procedure for obtaining the allocative and cost efficiency under variable returns to scale is similar to that of the CRS DEA cost-minimisation problem.

4.3 Empirical Models

This section presents the empirical models employed for the study which are established based on the above framework. The specification begins with the distance functions followed by that of the conventional approach.

4.3.1 Parametric Stochastic Input Distance Function (SIDF)

The Cobb-Douglas (CD) parametric stochastic input distance function is assumed for this study. The specification is admittedly restrictive in terms of the maintained properties of the underlying production technology. However, a likelihood ratio test was conducted to test the hypothesis that the CD functional form is not an adequate representation of the data for maize farmers in Benue State given the specification of the more flexible Translog (TL) form. This hypothesis could not be rejected at 5% level of significance. More over, a t-test was also conducted to test the hypothesis that efficiency scores from CD functional form are not statistically different from those from TL form. Again this hypothesis could not be rejected at 5% level of significance. Therefore CD was preferred based on these tests results and given TL's susceptibility to multicollinearity (Coelli, 1995b; Seymoun et al., 1998; Hassine-Belghith, 2009). Moreover, the main advantage of TL is its flexibility, but at the same time its main disadvantage is that it does not easily permit the decomposition of and identification of allocative efficiency as the CD does. For the case of single output, K inputs, N farms, the empirical model is specified as:

$$\ln D_i = \delta + \alpha \ln Y_i + \sum_{j=1}^{4} \beta_j \ln X_{ji}, \quad i = 1, \ldots 240, \tag{4.26}$$

where Y_i is the observed maize output for the ith farmer and X_{ji} is the jth input quantity for the ith farmer, namely land, labour, inorganic fertilizer and Fisher index of other inputs (seed, pesticide and herbicides). ln represents the natural logarithm of the associated variables, and δ, α and β_j are unknown parameters to be estimated.

Equation (4.26) is transformed by imposing the restriction for homogeneity of degree +1 in inputs:

$$\sum_{j=1}^{4} \beta_j = 1, \qquad (4.27)$$

gives:

$$-\ln X_{ki} = \delta + \alpha \ln Y_i + \sum_{j=1}^{4-1} \beta_j \ln\left(X_{ji} / X_{ki}\right) - \ln D_i, \qquad (4.28)$$

The unobservable distance term "$-\ln \mathrm{D_i}$" represents a random term and can be interpreted as the traditional stochastic frontier analysis (SFA) composed disturbance term, ε_i. Thus equation (4.28) can be rewritten as:

$$-\ln X_{ki} = \delta + \alpha \ln Y_i + \sum_{j=1}^{4-1} \beta_j \ln\left(X_{ji} / X_{ki}\right) + v_i - u_i, \qquad (4.29)$$

The statistical noise (v_i) is assumed to be iid $N(0, \sigma_v{}^2)$ and independent of u_i. The selection of the distribution of u_i requires a statistical test. A likelihood ratio test was conducted to test the hypothesis that u_i is half-normally distributed $\left|N(0, \sigma_v{}^2)\right|$ against the alternative that it has a truncated normal distribution. The test could not reject the hypothesis of half-normal distribution at 5% level of significance.

The input-orientated TE scores are predicted using the conditional expectation predictor:

$$T\hat{E}_i = E[\exp(-u_i)|\varepsilon_i)], \qquad (4.30)$$

From the parameters of the Cobb-Douglas input distance function, the corresponding parameters of the dual cost function are analytically derived (Coelli et al., 2003) and defined as:

$$\ln C_i = b_0 + \sum_{j=1}^{4} b_j \ln W_{ji} + \phi \ln Y_i \tag{4.31}$$

where C_i is the cost of production of maize for the ith farmer, W_{ji} is the jth input price vector which includes the price of land, price of labour, price of inorganic fertilizer and implicit price index for other inputs. b_0, b_j and ϕ are unknown parameters which are derived from the primal function. Using the first order condition for cost minimisation, it can be shown that the parameters of the cost and input distance function are related as follows (Coelli et al., 2003):

$b_j = \hat{\beta}_j$, $\phi = -\hat{\alpha}$, and $b_0 = -\hat{\delta} - \sum_{j=1}^{4} \hat{\beta}_j \ln(\hat{\beta}_j)$

The technically efficient input quantities are predicted as follows:

$$\hat{X}_{ji}^{T} = X_{ji} \times T\hat{E}_i, \qquad \text{j = 1, 2, 3, 4} \tag{4.32}$$

The cost-efficient input quantities are predicted by making use of Shephard's Lemma, which states that they will equal the first partial derivatives of the cost function:

$$\hat{X}_{ji}^{C} = \frac{\partial C_i}{\partial W_{ji}} = \frac{\hat{C}_i b_j}{W_{ji}}, \quad \text{j=1, 2, 3, 4} \tag{4.33}$$

where $\hat{C}_i$ is the cost prediction obtained by substituting the estimated parameters into (the exponent) of equation (4.31). Thus, for a given level of output, the minimum cost of production is $\hat{X}_i^C \cdot W_i$, while the observed cost of production of the ith farmer is $X_i \cdot W_i$. These two cost measures are then used to calculate the CE scores for the ith farmer:

$$C\hat{E}_i = \frac{\hat{X}_i^C \cdot W_i}{X_i \cdot W_i}, \tag{4.34}$$

AE is calculated residually as:

$$A\hat{E}_i = \frac{C\hat{E}_i}{T\hat{E}_i}, \tag{4.35}$$

Each of these three efficiency measures takes a value between zero and one, with a value of one, indicating full efficiency. The model is estimated using the computer program, FRONTIER version 4.1 (Coelli, 1996a). The program gives the maximum likelihood estimates for the parameters of the model as well as the technical efficiency scores whereas a programme was written and implemented in STATA version 10.0 to compute the allocative and cost efficiency scores.

4.3.2 Non-parametric Input Distance Function

The first decision to make here is that of assumption concerning returns to scale. The VRS model permits the construction of production frontier to have increasing, constant or decreasing returns to scale and would be a desirable choice. However, the constant returns to scale model is also computed because in variable returns to scale models, the smallest and least-productive units (in terms of partial productivities) often show up as fully efficient simply because they lack peers to be compared with (Estache et al. 2004).

The DEA input-oriented CRS and VRS models are used to obtain the technical efficiency scores. The DEA model for this study is developed for the case of a single output and multiple inputs. For N farms which produce maize using K (land, labour, fertilizer and other) inputs and for the *i*th farm who produces y_i units of maize by applying x_{ji} units of kth input, the KxN input matrix, X, and the 1xN output matrix, Y, represent the data for all N farms in the sample. The input-oriented CRS DEA model is specified as:

$$\min_{\theta,\lambda} \theta,$$

$$\text{st} \quad -y_i + Y\lambda \geq 0,$$
$$\theta x_{ji} - X\lambda \geq 0, \quad (4.36)$$
$$\lambda \geq 0,$$

where θ is the input oriented technical efficiency measure having a value $0 \leq \theta \leq 1$. The resultant efficiency measure depicts the distance of each farm unit from the frontier. If the score is equal to one, it implies that the farmer is on the frontier. The vector λ is an Nx1 vector of weights which defines the linear combination of the peers of the *i*th farmer. $X\lambda$ and $Y\lambda$ are efficient projections on the frontier. The linear programming problem is solved N times, providing a value for each farmer in the sample.

The DEA problem in equation (4.36) has an intuitive interpretation. The problem takes the *i*th farm and then seeks to radially contract the input vector, x_i, as much as possible, while remaining within the feasible input set. The radial contraction of the input vector, x_i , produces a projected point, ($X\lambda$, $Y\lambda$), on the surface of the production technology. This projected point is a linear combination of these observed data points. The constraints in equation (4.36) ensure that this projected point cannot lie outside the feasible set.

The input-oriented VRS DEA model is specified as:

$$\min_{\theta,\lambda} \theta,$$
$$\text{st} \quad -y_i + Y\lambda \geq 0,$$
$$\theta x_{ji} - X\lambda \geq 0, \quad (4.37)$$
$$N1' \times \lambda = 1$$
$$\lambda \geq 0,$$

where $N1'$ is an Nx1 vector of ones and $N1' \times \lambda = 1$ is the convexity constraint which makes the model a VRS model and it ensures that an inefficient farm is only benchmarked against farms of similar size. The linear programming problem is also solved N times, providing a value for each farmer in the sample.

The cost and allocative efficiencies are obtained by solving the following additional cost minimisation DEA problem. The cost minimising vector of input quantities for the *i*th farmer is calculated using the cost minimising CRS DEA. The model is specified as:

$$\begin{aligned} &\min_{\lambda, x_{ji}^C,}\ x_{ji}^C w_{ji} \\ &\text{st} \quad -y_i + Y\lambda \geq 0, \\ &\qquad x_{ji}^C - X\lambda \geq 0, \\ &\qquad \lambda \geq 0, \end{aligned} \tag{4.38}$$

where w_{ji} is the *j*th input price vector which includes the price of land, price of labour, price of inorganic fertilizer and price index for other inputs for the *i*th farmer and x_i^C is the cost-minimising vector of input quantities for the *i*th farmer.

Cost efficiency is calculated by dividing minimum cost by observed cost.

$$CE = \frac{w_i x_i^C}{w_i x_i} \tag{4.39}$$

Allocative efficiency is calculated by dividing cost efficiency by technical efficiency.

$$AE = \frac{CE}{TE} \tag{4.40}$$

where TE is the θ obtained from equation (4.36).

Under the VRS cost minimisation problem, the model in 4.38 is modified by adding the convexity constraint, $N1'\lambda = 1$ and similar procedures laid out under CRS problem are followed for computing allocative and cost efficiency.

The model is implemented using Data Envelopment Analysis Program (DEAP) version 2.1 by Coelli (1996b). The program computes all the three efficiency estimates.

4.3.3 Parametric Stochastic Frontier Production Function (SFPF)

The Cobb-Douglas model for this study is specified as:

$$\ln Y_i = \delta + \sum_{j=1}^{4} \beta_j \ln X_{ji,} + v_i - u_i \qquad (4.41)$$

All variables are as defined for the SIDF model. δ and $\beta's$ are parameters to be estimated.

Given the vector of input prices for the *i*th farm (W_{ji}), parameter estimates of the stochastic frontier production function ($\hat{\beta}$) in equation (4.41), and the input oriented adjusted output level Y_i^* in equation (4.4), the corresponding Cobb-Douglas dual cost frontier is derived and written as

$$\ln C_i = b_0 + \sum_{j=1}^{4} b_j \ln W_{ji} + \phi \ln Y_i^* \qquad (4.42)$$

where $\phi = \left(\sum_{j=1}^{4} \hat{\beta}_j \right)^{-1}$, $b_j = \phi \hat{\beta}_j$, $b_0 = \frac{1}{\phi} \left(\hat{\delta} \prod \hat{\beta}_j^{\hat{\beta}_j} \right)^{-\phi}$

By using Shephard's Lemma, the cost minimising (economically efficient) input vector, X_i^C, is derived by substituting the firm's input prices and adjusted output quantity into the system of demand equations which is given as:

$$\frac{\partial C_i}{\partial W_i} = b_j W_j^{-1} C_i = X_i^C \qquad (4.43)$$

For a given level of output, the corresponding technically efficient, cost efficient and actual costs of production are equal to $W_i X_i^T$, $W_i X_i^C$ and $W_i X_i$, respectively. These three cost measures are then used as the basis for calculating the technical and cost efficiency indices for the *i*th farm:

$$TE_i = \frac{W_i X_i^T}{W_i X_i} \tag{4.44}$$

and

$$CE_i = \frac{W_i X_i^C}{W_i X_i} \tag{4.45}$$

Following Farrel (1957), allocative efficiency can be calculated by dividing economic efficiency (CE) by technical efficiency (TE):

$$AE_i = \frac{W_i X_i^C}{W_i X_i^T} \tag{4.46}$$

The model is estimated using the computer program, FRONTIER version 4.1 (Coelli, 1996a). The program gives the maximum likelihood estimates for the parameters of the model as well as the technical efficiency scores whereas a programme was written and implemented in STATA version 10.0 to compute the allocative and cost efficiency scores.

4.3.4 Technology and Policy Impact on Efficiency

To analyse the impact of technological innovation (hybrid seed, inorganic fertilizer, herbicides and conservation practices) and other policy and socioeconomic variables (gender, age, education, household size, land, off-farm work, membership in a farmer group, access to extension, credit and market) on efficiency, a second stage procedure is used whereby the efficiency scores obtained from the first stage are regressed on the selected explanatory variables using a double-bounded Tobit model. The two stage procedure is well accepted in the case of non-parametric DEA models. However, a one stage procedure would have been preferable in the case of technical efficiency in the parametric approach since the stochastic frontier is estimated under the assumption that the technical inefficiency effects are identically distributed (Battese and Coelli, 1995). However, cost and allocative efficiency in the parametric models are derived not estimated hence, a one stage procedure cannot be implemented for them. Therefore, the two stage procedure is followed in this study to ensure uniformity and consistency in the interpretation of results from all the different models. The Tobit model is implemented in STATA version 10.0. The model is specified as:

$$Y_i^* = \beta_0 + \sum_{\substack{n=1\\=0}}^{10} \beta_n X_{in} + \sum_{\substack{m=1\\=0}}^{4} \beta_m T_{im} + u_i \quad \text{if}$$

$$\left. L_i < \beta_0 + \sum_{\substack{n=1\\=0}}^{10} \beta_n X_{in} + \sum_{\substack{m=1\\=0}}^{4} \beta_m T_{im} + u_i < U_i \right\} \qquad (4.47)$$

where Y_i^* is a latent variable representing the efficiency measure for each farm household, X_i is a $nx1$ vector of explanatory variables for the ith farm, T_i is an $mx1$ vector of technology variables for the ith farm, β_n and β_m is a $kx1$ and $mx1$ vectors of unknown parameters to be estimated, u_i are residuals that are independently and normally distributed, with mean zero and a constant variance σ^2, and L_i and U_i are the distribution's lower and upper censoring points, respectively. Denoting Y_i as the observed dependent variable, $Y_i = 0$ if $Y_i^* \leq 0$; $Y_i = Y_i^*$ if $0 < Y_i^* < 1$; and $Y_i = 1$ if $Y_i^* \geq 1$.

The inclusion of technology adoption variables in an efficiency model presents the problem of potential endogeneity and self selectivity. This is because technology adoption is a decision variable and is not randomly assigned but farmers self-select themselves into it depending on a number of factors which may also have an impact on farm efficiency hence resulting in the errors in the efficiency and technology adoption models been correlated. The exogeneity of these variables were tested using the instrumental variable approach as proposed by Smith and Blundell (1986). This methodology follows two steps. In the first step, each potential endogenous variable is estimated with ordinary least squares over a set of instruments and the exogenous variables of the Tobit model. In this study, instruments are chosen according to literature on determinants of the respective technology adoption (Solis et al., 2009; Langyintuo and Mekuria 2008; Fufa and Hassan 2006; Adesina and Baidu-Forson, 1995; Adesina and Zinnah, 1993; Pike et al., 1991). The two vital features of a valid instrument are that it must be strongly related to the endogenous explanatory variable-technological innovations in our case-while at the same time it must be unrelated to the error term of the technical, allocative and cost efficiency equations. These features were put into consideration in making the choice. It is a common practice to have same instrument for all potential endogenous variables. However, for this study two instruments were found for each technology as this takes care of the specific characteristics of each technology though some instruments may also apply to more than one technology.

In the second step, the predicted residual from the OLS regression is included as an additional explanatory variable and the revised Tobit model is estimated. If the coefficient of the predicted residual is found not to be statistically significant (i.e. has no explanatory power), then the potential endogenous variable can be treated as exogenous. However, if the null hypothesis of exogeniety is rejected, then the potential endogenous variable is truly endogenous and an alternative method has to be used to correct for endogeneity. This test is related to an auxiliary regression test for exogeneity in a regression context, which in turn is a convenient alternative to the commonly employed Hausman test. To correct for endogeneity, the study follows a two step approach, in which each endogenous technology variable is estimated in a first stage and their predicted values are included in a second step as additional explanatory variables which yields unbiased estimates of impact of technological innovation on efficiency.

CHAPTER 5

STUDY AREA, SURVEY DESIGN AND SOCIO-ECONOMIC CHARACTERISTICS OF THE SAMPLE HOUSEHOLDS

5.1 Introduction

This chapter describes the study area, the research design and socioeconomic characteristics of the sample households. The next section provides the description of geographical location and agro-ecological characteristics of the study area. The description of survey design and sampling procedure is provided in section three. Section four presents data types, sources and collection. The last section provides a description of variables used for estimation of the various models and of socio-economic characteristics of sample households.

5.2 The Study Area

The study was conducted in Benue State Nigeria. Benue State whose capital city is Makurdi lies within the lower river Benue trough in the middle belt (Northcentral zone) region of Nigeria. The location of the state capital is marked with red outlined oval in figure 5.1. Its geographic coordinates are longitude 7° 47’ and 10° 0’ East. Latitude 6° 25’ and 8° 8’ North; and shares boundaries with five other states namely: Nassarawa to the north, Taraba to the east, Cross-River to the south, Enugu to the south-west and Kogi to the west. The state also shares a common boundary with the Republic of Cameroun on the south-east. Benue has a population of 4,780,389 (National Population Commission (NPC), 2006) and occupies a landmass of 32,518 square kilometers (Benue State Government, 2007).

The State is made up of 23 Local Government Areas and these are clearly shown in figure 5.1. The state comprised of several ethnic groups: Tiv, Idoma, Igede, Etulo, Abakpa, Jukun, Hausa, Akweya and Nyifon. The Tiv are the dominant ethnic group, occupying 14 local government areas, while the Idoma and Igede occupy the remaining nine local government areas. There are three agricultural zones (zones A, B, and C) in the state. Zone A Consists of Kastina-Ala, Kwande, Ukum, Vandeikya,

Figure 4.1: Map of Nigeria showing the capital cities of each State

Source: Adapted from 1992 MAGELLAN Goegraphix

Ushongo, Konshisha and Logo. Zone B consists of Gboko, Gwer East, Gwer West, Makurdi, Buruku, Guma and Tarka. Zone C consists of Ado, Oju, Agatu, Apa, Obi, Ogbadibo, Ohimini, Otukpo and Okpokwu.

Benue State experiences two distinct seasons, the wet/rainy season and the dry/summer season. The rainy season lasts from April to October with annual rainfall in the range of 100-200mm. The dry season begins in November and ends in March. Temperatures fluctuate between 23 - 37 degrees Celsius in the year. The south-eastern part of the state adjoining the Obudu-Cameroun mountain range, however, has a cooler climate similar to that of the Jos Plateau (Benue State Government, 2007).

Agriculture is the mainstay of the economy, engaging over 75 percent of the state working population. Benue State is the nations acclaimed food basket because of its rich agricultural produce which includes major crops such as yams, rice, cassava, sweet potatoes, maize, soyabeans, groundnut, sorghum, millet, beniseed and cocoyam. The state accounts for over 70 percent of Nigeria's soyabean production (Benue State Government, 2007). The major vegetation types and land use in Benue State showed that 85.6 percent of her land use is under agriculture while the remaining 10.6 percent is under forestry (Agbeja and Opii, 2005). The production and productivity trend of some of the major crops planted in Benue State is provided in table 5.1. It can be clearly observed from this table that maize productivity is very low and has remained almost static over the period. Other crops planted in the state include sugar cane, ginger, melon and beans. The state also produces large quantities of tree crops such as oil palm, cashew, coconut, oranges, banana, plantain, coffee and cola nut. Vegetables which include tomatoes, pepper, pumpkin, okro, spinach and pineapples are also produced in abundance. Benue State also possesses a great deal of livestock resources, which include goats, sheep, pigs, poultry and cattle.

Table 5.1: Production and productivity trends of major crops in Benue State

	Maize		Rice		Sorghum		Cassava		Yam	
	Output		Output		Output		Output		Output	
Year	(‘000MT)	Yield	(‘000MT)	Yield	(‘000MT)	Yield	(‘000MT)	Yield	(‘000MT)	Yield
2000	146.37	1.33	275.10	1.99	193.01	1.75	3526.00	13.20	2868.00	12.70
2001	148.31	1.36	275.72	2.00	191.87	1.74	3554.00	13.31	2875.00	12.72
2002	148.32	1.35	276.08	2.00	193.04	1.75	3547.00	13.28	2872.00	12.71
2003	146.42	1.34	275.90	2.00	191.52	1.74	3545.00	13.26	2871.00	12.70
2004	148.41	1.36	272.08	2.00	190.68	1.73	3548.00	13.28	2854.00	12.68
2005	148.48	1.36	274.69	2.00	191.75	1.74	3547.00	13.27	2866.00	12.70
2006	152.78	1.39	294.45	2.07	191.70	1.74	3595.61	13.29	2874.34	12.72
2007	151.05	1.38	296.15	2.07	192.94	1.75	3571.48	13.17	2872.21	12.71

Sources: Federal Ministry of Agriculture and Water resources (2008); Benue State Agricultural and Rural Development Agency (2005, 2008)

The farms are generally small and fragmented, ranging from less than one hectare to more than six hectares. Bush fallow using simple tools is the dominant system though mechanization and plantation agriculture/agroforestry are gradually creeping in. A tractor hiring unit, which specialises in land clearing and ploughing, has been established in Makurdi, the State capital. In addition, some local governments own tractors which can be hired by farmers.

The use of farm inputs, such as fertilizers, improved seed, insecticides and herbicides is on the increase through the activities of the Ministry of Agriculture, Benue State Agricultural and Rural Development Agency (BNARDA), the National Agricultural Land Development Authority (NALDA) and their network of extension workers. For instance, a total of 12563.38 metric tonnes of inorganic fertilizer, 26734.89 litres of agrochemicals and 2774.50 metric tonnes of improved seeds were used by farmers in Benue State in the 2007 agricultural production year (BNARDA, 2008). However, availability of fertiliser at affordable prices at the right time of the year and in sufficient quantity is still a big problem.

The State also boasts of one of the longest stretches of river systems in the country with great potential for a viable fishing industry, dry season farming through irrigation and for an inland water highway. The abundant agricultural potential of the state has created opportunities for investment in areas which include the following: large scale mechanized farming; post harvest processing and packaging of agricultural produce for local and external markets; vegetable oil processing; sugar processing industry; livestock farming, meat processing and marketing; fruit juice production; starch and glue production; livestock/animal feeds production; production of organic and inorganic fertilizers.

5.3 Survey Design and Sampling Procedure

Due to scarcity of resources which makes it difficult to undertake a census of all maize farmers, a sample survey was employed in this study. In drawing the sample, the laws of statistical theory of probability was followed in order to draw valid inferences from the sample and to ascertain the degree of accuracy of the results. The appropriateness of a sampling method depends on how it meets the objectives of the study successfully. A multistage sampling procedure was employed in selecting the respondents in this study.

The first stage involved a random selection of two agricultural zones since maize is produced in all the three agricultural zones in Benue State. In this stage, Zones B and C were selected. In the second stage, two Local Government Areas were purposefully selected from each zone based on the adequate representation of distinct maize production in these local government areas for the analysis of efficiency of maize production. The statistics for this selection was provided by BNARDA. Thus, in the second stage, Buruku and Gwer East were selected from Zone B while Oju and Otukpo were selected from Zone C. The third stage involved a random selection of maize farm households from the selected local government areas based on a sampling frame from Benue State Agricultural and Rural Development Agency. In each of the selected farm households, the household head who makes the day-to-day decisions on farm activities, input use and technology adoption was used as the sampling unit for this study.

Sample size determination in any study is usually a difficult task. Theoretically, the sample size is determined by the pre-assigned level of accuracy of the estimates of the mean of the parameters. Thus, knowledge of the variability of a large number of parameters is required because all have different degrees of variability. Unfortunately, this knowledge hardly exists prior to the study. Therefore, in practice sample size determination is based on consideration of financial constraints, and availability and adequacy of other resources such as time and trained manpower (Assefa, 1995 cited in Alene, 2003). However, this situation can be enhanced by stratifying the population into as many sub-population as possible based on one or more classification variables. Taking these issues into account and given that theoretically a sample size of 30 and above is considered asymptotically normal, sixty (60) maize farm households were randomly selected from each local government area, making a total of 240 farm households for the study.

5.4 Data Collection

Data was collected on all aspects that are relevant to the study. This study made use of both primary and secondary data. Given the unavailability of neither farm records by smallholders from experience nor adequate disaggregated household survey data in Benue State, a field survey method of obtaining information is adopted in this study for collecting the needed primary data. The data was collected using structured questionnaires designed for a single visit given the time and financial constraints. The questionnaire was designed in such a way that they provide adequate input-and output data and household characteristics to enable the assessment of the production efficiency of smallholder maize farmers and probable sources of any inefficiency.

To realize objectives 1 and 2, data was collected on the quantities and prices of inputs and maize output. The inputs for which data was needed for both quantities and prices were maize seeds, inorganic fertilizer, land planted to maize, family and hired labour. To realize objectives 3 and 4, data was collected on socioeconomic factors such as education, farmer experience, age, household labour force and farm size; institutional factors such as access to extension services, access to credit, access to market and membership in farmer associations; technology policy variables such as use of hybrid seeds, use of inorganic fertilizer, use of herbicides and conservation practices. In addition data was collected on farmers' perception of the attributes of the technology packages as this was needed as instruments in the preliminary analysis.

The primary data was collected with the assistance of trained enumerators. These enumerators were sourced from among the extension staff at the Benue State Agricultural and Rural Development Agency. The enumerators were trained on the survey instrument by going through the entire questions one after the other and ensuring that the intended meaning of each question is well understood. The questionnaire was pre-tested through a preliminary survey. Based on the results of the pilot survey and the trainees' field experiences, the questionnaire was modified before actual data collection was done. Further, the questionnaire was designed such that majority of the questions were closed and therefore little or no enumerator and or respondent bias is expected.

Secondary data was also obtained to supplement the primary data. Data on maize crop area, production, yield and prices were sourced from the Federal Ministry of Agriculture and Water resources, Central Bank of Nigeria, National Bureau of Statistics, State Ministry of Agriculture, and BNARDA. Also information on dissemination and use of improved maize seeds were sourced from BNARDA while information on fertilizer procurement, supply and marketing was sourced from both

BNARDA and MOA. The secondary data was essentially needed to beef up the literature on maize production trends in Nigeria in general and Benue State in particular.

5.5 Variable Description

In this section the description of all variables used for analysis is provided. The means and standard deviations of all variables used in estimation of frontier models which include the output quantity and input quantities and their respective prices are also given.

The output variable, PROD is the quantity of maize produced during 2008/2009 agricultural season by a farm household and is measured in kilograms. LAND is measured as the area of land in hectares cultivated with maize by a farm household in the relevant period. LABOUR is measured as the amount of both family and hired labour in man-days used by the farm household. The labour force was disaggregated by age and gender and conversion factors for adult and man equivalents were applied to arrive at the final labour used. FERT is the amount of inorganic fertilizer in kilograms used by the farm household. OTHER is the Fisher quantity index of seed, herbicides and pesticides used by the farm household. Information on inputs and output quantities in kilograms were elicited using the prevailing local measure in the study area which is a 25kg basin. For instance a farmer was asked to recall how many basins of maize he/she harvested during the last planting season and the given figures were converted to standard metrics. Likewise all area measurement was captured using the local counting in lines of crops planted. Hundred (100) lines is equivalent to a hectare. Observed average price per unit of inputs used were used in the analysis. W_{LAND} is rental price of a hectare of farm land. W_{LABOUR} is price of labour per day. W_{FERT} is price of inorganic fertilizer per kilogram. W_{OTHER} is an implicit price index of seed, herbicides and pesticides derived by dividing the cost of other inputs by OTHER following Coelli et al. 2005. All prices were in local currency, Naira.

Table 5.2 provides the summary statistics of the inputs and output used in estimation of the frontier functions and hence technical efficiency, and of input prices used in computing cost and allocative efficiency. The average production of maize is

1320.38kg. The farm size ranged between 0.4 and 2.52 with a mean of 1.2 hectares. This shows that farmers sampled for this study were actually smallholder farmers. It can easily be seen that these farmers are yet to utilize production and technology resources to a point where maximum output can be achieved and therefore is an indication of inefficiency. On average, maize farmers applied only 115.19kg of fertilizer which translates to about 95.39kg/ha. The use of fertilizer is low compared to about 400kg/ha and 600kg/ha recommended for local and hybrid maize production in the area (USAID/ICS, 2002). Labour is usually distributed between the various farm operations ranging from land preparation to harvesting. The farmers used an average of 111 man-days on their maize farms. This average includes both family and hired labour.

Table 5.2: Summary statistics of variables in the frontier functions

Variables	Mean	Standard deviation	Minimum	Maximum
Quantities				
PROD (kg)	1320.38	656.308	300.000	3780.000
LAND (ha)	1.208	0.490	0.400	2.520
LABOUR (man-days)	111.195	101.891	23.000	720.000
FERT (kg)	115.185	69.207	0.000	360.000
OTHER (index)	56.343	49.035	1.865	310.020
Prices				
WLAND (Naira)	4989.167	1726.209	3000.000	8500.000
WLABOUR (Naira)	89.808	33.675	50.000	200.000
WFERT (Naira	57.899	17.981	0.000	84.000
WOTHER (Naira)	68.638	29.938	25.537	187.696

Four variables indexing technological innovation included in second stage procedure, that is in the Tobit efficiency model are HYV, AFERT, HERB and PRACTICES. Each technology policy variable was represented by two instruments for the first stage of endogeneity-corrected Tobit model. These are YIELD and PALATABILITY for HYV. AVAILABILITY and RAINRISK for AFERT. NEED and ENVTRISK for HERB. SLOPE and DEGRADATION for PRACTICES. Other variables include AGE, GENDER, EDU, HHS, OFFWORK, MFG, EXT, CREDIT and MARKET.
The variable descriptions are given in table 5.3.

Table 5.3: Description of variables used in the second stage Tobit regression

Variable name	Description
AGE	Age of the household head in years
GENDER	1 = the household head is a male; 0 otherwise
EDU	Number of years of formal education completed by the household head
HHS	Number of persons in the household
LAND	Area of land in hectares cultivated with maize
OFFWORK	1 = engagement in off-farm work; 0 otherwise
MFG	1 = the household head is a member of any farmer organization; 0 otherwise
EXT	Number of extension visits during the cropping period
CREDIT	1 = if farmer had access to credit; 0 otherwise
MARKET	Distance to the nearest market in km
HYV	Area of maize farm (ha) cultivated with hybrid seed variety
AFERT	Area of maize farm (ha) applied with inorganic fertilizer
HERB	Area of maize farm (ha) subjected to herbicide application
PRACTICES	Number of conservation practices adopted by a farmer on his or her maize farm
YIELD	1= farmer perceives hybrid seed produces more than local variety
PALATABILITY	1= farmer perceives hybrid maize is sweeter than local maize
AVAILABILITY	1= farmer perceives fertilizer is readily available
RAINRISK	1 = farmer's perception of poor rainfall years is low; 0 otherwise
NEED	1 = farmer perceives a need for weed control in his maize farm
ENVTRISK	1 = farmer's perceives negative environmental effects of herbicide use
SLOPE	1 = the farmers maize farm is on a non-flat plane; 0 otherwise
DEGRADATION	1 = farmer perceives soil erosion as a problem in his or her farm.

5.6 Household and Farm Characteristics of Study Sample

Various household and farm characteristics of the farmers hypothesized to influence technical, allocative and cost efficiency of the farm households are discussed here. These include sex of the household head, age, level of formal education of the household head, household size, land holding dedicated to maize production, engagement in non-farm income generating activities, membership in a solidarity group, access to credit, access to market and access to extension services. The distribution of household and farm characteristics is presented in table 5.4.

Two hundred and thirteen (213) representing about 89 percent out of 240 household were male headed while 27 (11percent) were female headed. This is not too different from the national figure where about 83 percent of households were male headed

Table 5.4: Household and farm characteristics of the sample households

Item	Frequency	Percentage
Gender of household head:		
Male	213	88.75
Female	27	11.25
Household size (count):		
2-5	30	12.50
6-10	98	40.83
11-15	71	29.58
>15	41	17.08
Mean household size	11.742	
Age (years):		
≤30	31	12.92
31-40	51	21.25
41-50	59	24.58
51-60	58	24.17
>60	41	17.08
Mean age	47.167	
Education (years):		
No formal education	82	34.17
1- 6	14	5.83
7-12	75	31.25
>12	69	28.75
Mean education	8.433	
Land (ha):		
<0.5	9	3.75
0.5-0.99	75	31.25
1-1.49	93	38.75
1.5-1.99	49	20.42
≥2	14	5.83
Mean land	1.208	
Non-farm income activities:		
None	78	32.50
Public service	40	16.67
Trading	110	45.83
Others	12	5.00
Access to credit:		
No	207	86.25
Yes	33	13.75
Membership of farmer group:		
No	131	54.58
Yes	109	45.42
Extension contact (count):		
None	120	50.00
1-3	48	20
>3	72	30
Mean	2.546	
Distance to market (km)		
1-5	156	65.55
6-10	30	12.61
>10	52	21.84
Mean distance	6.278	

Source: Survey data

while only 17 percent were female headed (NPC, 2004). The average household size in the study area is 12 persons. Large family members are considered important asset as source of farm labour in the study area. The average age of farmers is 47 years showing that majority of the farmers are still in their productive years.

Education is considered important in determining the efficiency with which farmers use production resources because it improves the skill and entrepreneurial ability of the farmer to organize inputs for the maximum efficiency. Education level in the study area is low with an average of eight (8) years of schooling. This implies that most farmers were only able to complete their primary school. The median number of years of schooling in Nigeria was 0.2 and 3.6 for females and males, respectively as at 2003 (NPC, 2004). Land and labour usually accounts for largest share of agricultural inputs in Nigeria. Land serves as a means of survival for most rural populace. Although, Benue state is known to have vast area of land, the area cultivated with maize is very small with an average of 1.2 hectares. This may be due to fragmentation of land holdings into a wide range of crops usually cultivated by farmers in Benue State. Only 14 percent of farm households own a farm size of 2 hectares and above.

Engagement in non-farm activities is an important determinant of efficiency. While on one hand it increases the income base of the farm household thus helping them to overcome credit and insurance constraints and increase their use of industrial inputs. On the other hand, it reduces the labour available for agricultural production which may have a negative effect on efficiency. About 33 percent of farmers surveyed did not engage in any non-farm activity while the remaining 67 percent were involved in one form of non-farm activity or the other. About 86 percent of farmers had no access to production credit while only 14 percent had access to credit. This situation is very common and has been serious constraint to increased agricultural productivity in Nigeria as farmers are unable to purchase the necessary inputs at the right time and quantity. Membership in a farmer group indexes social capital and affords the farmers opportunity of sharing information on modern maize practices by interacting with others as well as provides farmers with bargaining power in the input, output and credit markets. In Benue State, about 45 percent of sampled farmers were a member of one form of farmer organization or cooperative or the other while 55 percent did not belong to any farmer group.

Access to extension services enhances farmers' access to information and improved technological packages and is therefore postulated to be an important determinant of efficiency. The mean number of contacts with extension agents is about three times per year with half of the sampled farmers having no access to extension services. This is somewhat startling given the wide spread of Benue State Agricultural and Rural Development Agency operations in the State. Access to market serves as a proxy for the development of road and market infrastructures in any area. On average the farmers are located about 6.3 kilometres from the nearest market.

Table 5.5: Distribution of households by use of improved technology

Technology	Frequency	Percent
Hybrid seed	190	79.17
Fertilizer	225	93.75
Herbicides	153	63.75
Conservation practices	153	63.75

The distribution of farmers by use of technological innovations is presented in table 5.5. Hybrid seeds were used by 79.17 percent of farm households. Fertilizer was used by 93.75 percent of farm households. Herbicides and conservation practices were adopted by 63.75 farm households. It was however observed that the quantities used of these technologies are suboptimal as demonstrated in the case of fertilizer which therefore constrained the intended impacts.

CHAPTER 6

COMPARISON OF RESULTS FROM ALTERNATIVE APPROACHES

6.1 Introduction

This chapter is concerned with the discussion of results from the different approaches employed in this study. The next section presents the frontier estimates and efficiency scores from the parametric stochastic input distance function (SIDF). In the third section, results of the frontier estimates and efficiency scores from the parametric stochastic production function (SFPF) are discussed. The efficiency scores from the non-parametric input distance function are presented in section four. A visual comparison of efficiency scores from the different frontier models are presented in section five. Formal tests are conducted and results of sensitivity of efficiency scores to estimation approaches are discussed in section six. In section seven, input usage ratio which depicts the nature of allocative efficiency is presented. In section eight, results of technology and policy impacts on efficiency from the various approaches are discussed and compared. The last section concludes on the chapter.

6.2 Parameter Estimates and Efficiency Scores from the SIDF Model

The maximum likelihood (ML) and the ordinary least square (OLS) estimates of the Cobb-Douglas SIDF are presented in table 6.1. A well behaved input distance function is non-decreasing in inputs and non-increasing in outputs, linearly homogeneous and concave in inputs (Coelli et al. 2005). Result shows that the estimated input distance function is well behaved with all input coefficients positive and output coefficient negative. All variables are significant at 1 percent. The estimated coefficient of output is less than one in absolute terms indicating increasing returns to scale which for the parametric stochastic input distance function is computed as the inverse of the negative of this value, which is 1.351 (Estache et al., 2004; Coelli et al., 2005). The partial output elasticity of land is 0.67 and is the largest among the inputs thereby depicting the importance of land in the household production. It implies that a 10 percent increase in land size would increase output by

6.7 percent. This finding confirms the observation of this study that the share of expenditure on land in the cost of production of sampled farmers is higher than those of other inputs. Land is the scarcest input and the high marginal returns to land are a reflection of the very small size of plot many farmers are constrained to cultivate. The second largest contributor to household production is labour with an elasticity of 0.23 implying that a 10 percent increase in labour supply will raise output by 2.3 percent. This is followed by the partial elasticity of other inputs (0.06) and fertilizer (0.04) implying that a 10 percent increase in other inputs and fertilizer will lead to 0.6 and 0.4 percent increase in output respectively.

Table 6.1: The OLS and maximum likelihood estimates of the SIDF

Variable	Mean	Parameter	OLS estimates	ML estimates
INTERCEPT		δ	3.718*** (0.200)	3.883*** (0.216)
PROD	1320.38	α	-0.729*** (0.021)	-0.740*** (0.021)
LAND	1.208	β_1	0.679*** (0.022)	0.667*** (0.024)
LAB	111.195	β_2	0.219*** (0.021)	0.233*** (0.023)
FERT	115.185	β_3	0.036*** (0.003)	0.038*** (0.003)
OTHER	56.343	β_4	0.067	0.061 [a]
SIGMA-SQUARED		$\sigma^2 = \sigma_u^2 + \sigma_v^2$		0.043*** (0.006)
GAMMA		$\gamma = \sigma_u^2 / \sigma^2$		0.825*** (0.060)
LLF			125.479	132.274

***Significant at 1% level. Standard errors are shown in parenthesis. [a] The estimate of β_4 is computed by the homogeneity condition

The estimate of the variance parameter, γ, is 0.83 and is significant at 1 percent implying that 83 percent of the total variation in output is due to inefficiency, that is, the technical inefficiency effects are significant in the stochastic input distance function. This result is confirmed by conducting a likelihood ratio test to test the hypothesis of OLS model versus input distance frontier model. LR test statistic is 13.23 and this was significant when compared with mixed chi-square value of 5.412 at one degree of freedom, thus rejecting the adequacy of the OLS model in representing the data.

Based on the estimated parameters of the stochastic input distance function, the parameters of the corresponding dual cost function were derived as specified in equation (4.42) and this formed the basis of computing the cost and allocative efficiency. The dual cost frontier is given as:

$$\ln C_i = -2.977 + 0.667 \ln W_{Land} + 0.233 \ln W_{Labour} + 0.038 W_{Fert} + 0.061 \ln W_{Other} + 0.740 \ln PROD_i \tag{5.1}$$

where C is the cost of production for the *i*th farmer. W_{Land} is the rental price of land per hectare estimated at ₦4989.17 . W_{Labour} is the price of labour per day estimated at ₦ 89.81. W_{Fert} is the price of inorganic NPK fertilizer per kg estimated at. ₦57.9. W_{Other} is implicit price index of other inputs estimated at ₦68.64 per kg. The derived cost function is equally well behaved.

The results of efficiency distributions and some descriptive statistics from the parametric stochastic input distance function are present in table 6.2. The results presented in this section are for the entire sample. Technical efficiency (TE) ranges from 64.3 to 97.1 with a mean of 86.7 percent. This implies that if farm households will operate on the frontier, they will achieve a cost savings of 13.3 percent without reducing output. On the other hand, if the average farm household in the sample was to achieve the TE level of its most efficient counterpart, then the average farm household could realize a 10.7 percent cost savings (i.e., 1–[86.7/97.1]). A similar calculation for the most technically inefficiency farm household reveals cost saving of 33.7 percent (i.e., 1– [64.3/97.1]).

The average allocative efficiency (AE) from the SIDF model is 57.8 percent with a low of 23 percent and a high of 88.8 percent. This implies that there is room to improve allocative efficiency of the farm households by 42.2 percent, if they operate on the frontier. It also suggests that if the average farm household was to achieve the AE level of its most efficient farm household, then the average farm household could achieve a cost saving of 34.9 percent while the least efficient farm household would achieve a cost saving of 74 percent.

Cost efficiency (CE) from the SIDF model ranges from 19.6 to 85.9 with a mean of 50.3 percent giving room for cost efficiency improvement by 49.7 percent, if farm households were to operate on the frontier and also suggests a gain economic efficiency of 41.5 percent for the average farm household and 77.2 percent for the least efficient farm household.

Table 6.2: Frequency distribution of efficiency estimates from SIDF model

Efficiency level (%)	TE		AE		CE	
	Number	**Percent**	**Number**	**Percent**	**Number**	**Percent**
≤ 40	0	0.00	21	8.75	55	22.92
41-50	0	0.00	37	15.42	59	24.58
51-60	0	0.00	68	28.33	73	30.42
61-70	14	5.83	84	35.00	44	18.33
71-80	29	12.08	28	11.67	8	3.33
81-90	111	46.25	2	0.83	1	0.42
91-100	86	35.83	0	0.00	0	0.00
Mean	86.7		57.8		50.3	
Min	64.3		23		19.6	
Max	97.1		88.8		85.9	
SD	7.6		11.9		12	
CV	8.8		20.5		23.9	

CV = coefficient of variation; Min = Minimum; Max = Maximum; SD = Standard deviation

6.3 Parameter Estimates and Efficiency Scores from the SFPF Model

The maximum likelihood (ML) and the ordinary least square (OLS) estimates of the Cobb-Douglas SFPF are presented in table 6.3. All the input coefficients in both models are positive as expected and statistically significant at 1 percent level implying that they contribute to increased output. The sum of the input coefficients is 1.136 indicating increasing returns to scale. This further implies that farmers are operating in the irrational stage of production. The partial output elasticity of land is 0.82 and is the largest among the inputs thereby depicting the importance of land in the household production. It implies that a 10 percent increase in land size would increase output by 8.2 percent. This finding confirms the observation of this study that the share of expenditure on land in the cost of production of sampled farmers is higher than those of other inputs. Land is the scarcest input and the high marginal returns to land are a reflection of the very small size of plot many farmers are constrained to cultivate. The contribution of land in the SFPF model is more than its contribution in the SIDF model. The second largest contributor to household production is labour with an elasticity of 0.19 implying that a 10 percent increase in labour supply will raise output by 1.9 percent. This contribution is low when compared to that of the SIDF model. The partial elasticity of other inputs (0.06) and fertilizer (0.05) are the least and these values are similar to the results from the SIDF model.

Table 6.3: The OLS and maximum likelihood estimates of the SFPF

Variable	Mean	Parameter	OLS estimates	MLE estimates
INTERCEPT		δ	5.623***	5.908***
			(0.140)	(0.145)
LAND	1.208	β_1	0.820***	0.838***
			(0.031)	(0.027)
LAB	111.195	β_2	0.216***	0.192***
			(0.029)	(0.029)
FERT	115.185	β_3	0.048***	0.050***
			(0.004)	(0.004)
OTHER	56.343	β_4	0.056***	0.056***
			(0.011)	(0.010)
SIGMA-SQUARED		$\sigma^2 = \sigma_u^2 + \sigma_v^2$		0.067***
				(0.009)
GAMMA		$\gamma = \sigma_u^2 / \sigma^2$		0.837***
				(0.051)
LLF			72.044	81.100

***Significant at 1% level. Standard errors are shown in parenthesis.

The value of the parameter, γ, is 0.84 and is significant at 1 percent level implying that 84 percent of variation in output is due to inefficiency that is, the technical inefficiency effects are significant in the stochastic frontier production function. This result is confirmed by conducting a likelihood ratio test to test the hypothesis of OLS model versus production frontier model. LR test statistic is 18.11 and this was significant when compared with mixed chi-square value of 5.412 at one degree of freedom. Therefore, the traditional production function, with no technical inefficiency effects, that is the OLS model is not an adequate representation of the data.

Based on the estimated parameters of the stochastic frontier production function, the input ratios, and the adjusted observed output levels, the parameters of the corresponding dual cost function were derived and this formed the basis of computing the cost and allocative efficiency. The dual cost frontier is given as:

$$\ln C_i = -4.390 + 0.738 \ln W_{Land} + 0.169 \ln W_{Labour} + 0.044 W_{Fert} + 0.049 \ln W_{Other} + 0.740 \ln PROD_i \quad (5.2)$$

where C is the cost of production for the *i*th farmer. W_{Land} is the rental price of land per hectare estimated at ₦4989.17 . W_{Labour} is the price of labour per day estimated at ₦ 89.81. W_{Fert} is the price of inorganic NPK fertilizer per kg estimated at. ₦57.9. W_{Other} is implicit price index of other inputs estimated at ₦68.64 per kg. The derived cost function is well behaved.

The efficiency scores from the SFPF model is presented in table 6.4. Technical efficiency ranges from 43.3 to 99.7 with a mean of 85.3 percent. The presence of technical inefficiency indicates potential output gains without increasing input use. This implies that if farm households were to operate on the frontier, they will achieve a cost savings of 14.7 percent. On the other hand, if the average farm household in the sample was to achieve the TE level of its most efficient counterpart, then the average farm household could realize a 14.4 percent cost savings (i.e., 1–[85.3/99.7]). A similar calculation for the most technically inefficiency farm household reveals cost saving of 56.6 percent (i.e., 1– [43.3/99.7]).

The average allocative efficiency from the SFPF model is 52.6 percent with a low of 22.9 percent and a high of 79.9 percent. This implies that there is room to improve allocative efficiency of the farm households by 47.4 percent, if they operate on the frontier. It also suggests that if the average farm household was to achieve the AE level of its most efficient farm household, then the average farm household could achieve a cost saving of 34.2 percent while the least efficient farm household would achieve a cost saving of 71.3 percent.

Cost efficiency from the SFPF model ranges from 15.8 to 69.6 with a mean of 44.6 percent giving room for cost efficiency improvement by 55.4 percent, if farm households were to operate on the frontier and also suggests a gain economic efficiency of 35.9 percent for the average farm household and 77.3 percent for the least efficient farm household.

Table 6.4: Frequency distribution of efficiency estimates from SFPF model

Efficiency level (%)	TE		AE		CE	
	Number	Percent	Number	Percent	Number	Percent
≤ 40	0	0.00	34	14.17	88	36.67
41-50	1	0.42	77	32.08	72	30.00
51-60	2	0.83	67	27.92	70	29.17
61-70	27	11.25	48	20.00	10	4.17
71-80	51	21.25	14	5.83	0	0.00
81-90	73	30.42	0	0.00	0	0.00
91-100	86	35.83	0	0.00	0	0.00
Mean	85.3		52.6		44.6	
Min	43.3		22.9		15.8	
Max	99.7		79.9		69.6	
SD	10.7		11.9		10.8	
CV	12.5		22.6		24.2	

CV = coefficient of variation; Min = Minimum; Max = Maximum; SD = Standard deviation

6.4 Efficiency Scores from the Non-parametric Input Distance Models

The efficiency scores from the VRS DEA model are presented in table 6.5. Technical efficiency ranges from 51.5 to 100 with a mean of 85.5 percent. Thus, the most technically efficient farm household is operating on the frontier in this model. Therefore, if the average farm household in the sample was to achieve the TE level of its most efficient counterpart, then the average farm household could realize a 14.5 percent cost savings (i.e., 1–[85.5/100]) without reducing outputs. A similar calculation for the most technically inefficiency farm household reveals cost saving of 48.5 percent (i.e., 1– [51.5/100]).

The average allocative efficiency from the VRS DEA model is 73.8 percent with a low of 28.8 percent and a high of 100 percent. Again, the most allocatively efficient farm household is operating on the frontier. It suggests that if the average farm household was to achieve the AE level of its most efficient farm household, then the average farm household could achieve a cost saving of 26.2 percent while the least efficient farm household would achieve a cost saving of 71.2 percent.

Cost efficiency from the VRS DEA model ranges from 28.8 to 100 with a mean of 62.3 percent giving room for cost efficiency improvement by 37.7 percent on average and also suggests a gain economic efficiency of 71.2 percent for the least efficient farm household.

Table 6.5: Frequency distribution of efficiency estimates from VRS DEA model

Efficiency level (%)	TE		AE		CE	
	Number	Percent	Number	Percent	Number	Percent
≤ 40	0	0.00	13	5.42	21	8.75
41-50	0	0.00	11	4.58	34	14.17
51-60	11	4.58	24	10.00	46	19.17
61-70	22	9.17	45	18.75	72	30.00
71-80	58	24.17	50	20.83	46	19.17
81-90	51	21.25	60	25.00	16	6.67
91-100	98	40.83	37	15.42	5	2.08
Mean	85.5		73.8		62.3	
Min	51.5		28.8		28.8	
Max	100.0		100.0		100.0	
SD	12.9		16.7		14.6	
CV	15.1		22.6		23.4	

CV = coefficient of variation; Min = Minimum; Max = Maximum; SD = Standard deviation

The efficiency scores from the CRS DEA model are presented in table 6.6. Technical efficiency ranges from 37.5 to 100 with a mean of 80.1 percent. Thus, the most technically efficient farm household is operating on the frontier in this model. Therefore, if the average farm household in the sample was to achieve the TE level of its most efficient counterpart, then the average farm household could realize a 19.9 percent cost savings (i.e., 1–[80.1/100]) without reducing output. A similar calculation for the most technically inefficiency farm household reveals cost saving of 62.5 percent (i.e., 1– [37.5/100]).

The average allocative efficiency from the CRS DEA model is 65.9 percent with a low of 22.4 percent and a high of 100 percent. Again, the most allocatively efficient farm household is operating on the frontier. It suggests that if the average farm household was to achieve the AE level of its most efficient farm household, then the average farm household could achieve a cost saving of 34.1 percent while the least efficient farm household would achieve a cost saving of 77.6 percent.

Cost efficiency from the CRS DEA model ranges from 14.9 to 100 with a mean of 51.6 percent giving room for cost efficiency improvement by 48.4 percent on average and also suggests a gain economic efficiency of 85.1 percent for the least efficient farm household.

Table 6.6: Frequency distribution of efficiency estimates from CRS DEA model

Efficiency level (%)	TE		AE		CE	
	Number	Percent	Number	Percent	Number	Percent
≤ 40	1	0.42	28	11.67	68	28.33
41-50	20	8.33	37	15.42	57	23.75
51-60	7	2.92	28	11.67	37	15.42
61-70	42	17.50	34	14.17	58	24.17
71-80	49	20.42	46	19.17	12	5.00
81-90	49	20.42	49	20.42	5	2.08
91-100	72	30.00	18	7.50	3	1.25
Mean	80.1		65.9		51.6	
Min	37.5		22.4		14.9	
Max	100.0		100.0		100.0	
SD	15.8		19.2		15.6	
CV	19.7		29.1		30.2	

CV = coefficient of variation; Min = Minimum; Max = Maximum; SD = Standard deviation

6.5 A Visual Comparison of Efficiency Estimates from Different Frontier Models

From tables 6.3 to 6.6, maize farmers in Benue State operate with considerable inefficiency dominated by cost inefficiency as depicted by all approaches thereby providing an avenue for policy interventions that would help reduce inefficiency. It is observed that the estimated the technical, allocative and cost efficiency measures from the distance frontiers are greater than those from the production frontiers. In terms of technical efficiency, results from the parametric stochastic distance functions is better than those of other models, but in terms of allocative and cost efficiency , results from the non-parametric distance function is better. Similar results were obtained by Herrero (2005) for technical efficiency. No previous study has made comparison of allocative and cost efficiency from either parametric or non-parametric distance functions or from distance functions and production frontiers. In terms of variability, the efficiency scores from the parametric approach are less variable than those from the non-parametric approach. Specifically, the efficiency scores from the SIDF model are less variable than those from SFPF and DEA models whereas DEA models especially the CRS DEA model exhibited the greatest variability. The only similarity observed in terms of variability is in the allocative efficiency from VRS DEA and SFPF models. Results also show that no farm is one hundred percent efficient in the SIDF and SFPF models (ie. at the efficient frontier). This is due to the stochastic nature of the frontier; it allows for the possibility that part of the deviation of the observed output from the frontier may be due to noise or measurement errors. Results appear to imply that the best and worst performers can be identified reasonably well by any of the four models with respect to technical efficiency but the selection of a particular model with respect to allocative efficiency is not a trivial choice as the results are mixed.

Further, the comparison efficiency scores from different frontier models can be shown in their scatter plots. In this study, the scatter plot is used for two purposes namely: to show the correlation (if any) between and equality of any two set of efficiency scores. The scatter plot of technical efficiency estimates from SIDF and SFPF models is presented in figure 6.1. It can be deduced from the scatter plot that the TE values from these two models are not correlated and this is confirmed by the trend line which neither sloped upwards nor downwards. Similar results were obtained between VRS DEA and SFPF and between CRS DEA and SFPF TE scores as depicted in figures 6.4 and 6.5, respectively. TE scores from SIDF and the DEA models are positively correlated. Similar positive correlation is observed between TE scores from VRS DEA and CRS DEA models. Scatter plots of allocative and cost efficiency from different models are presented in figures 6.7 to 6.18. In all cases, positive correlation is observed though the degree varies between different models.

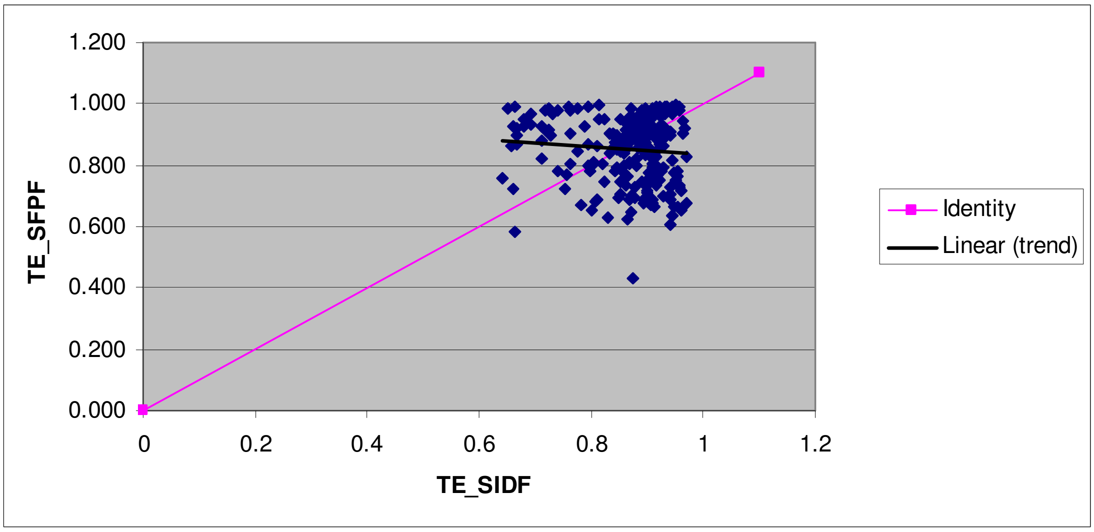

Figure 6.1: Scatter plot of technical efficiency from SIDF and SFPF models

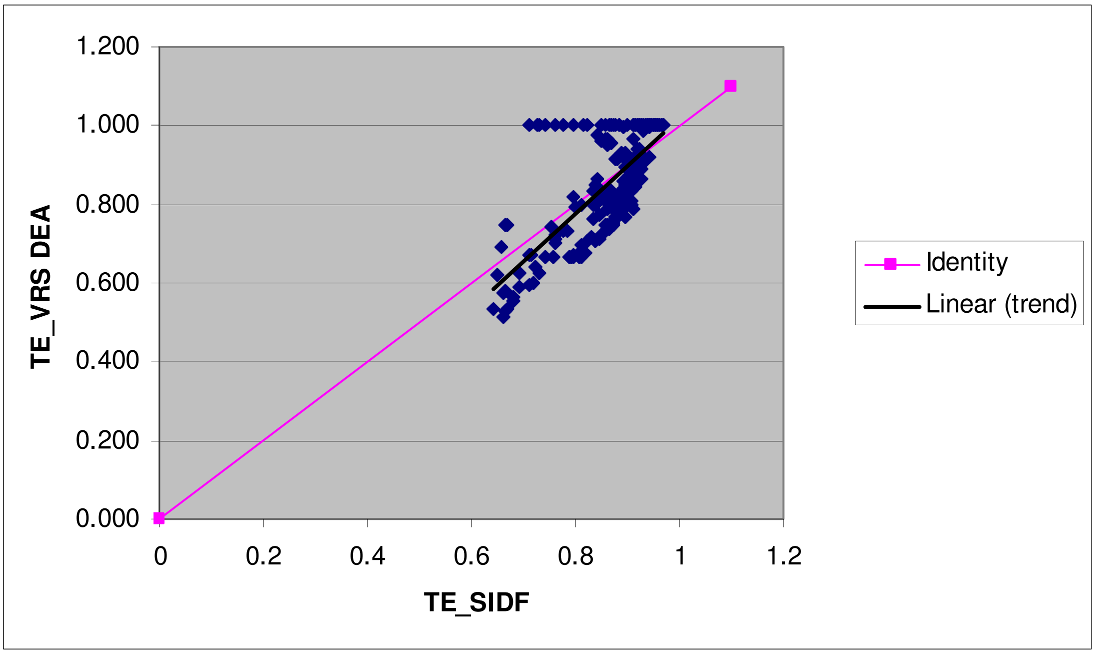

Figure 6.2: Scatter plot of TE from SIDF and VRS DEA models

In a scatter plot, an identity line, which is a 45^{o} line with the abscissa, is an easy means of showing the equality of two sets of data. The more the two data sets agree, the more the scatters tend to concentrate in the vicinity of the identity line; if the two data sets are numerically identical, the scatters fall on the identity line exactly. In all the scatter plots, no two sets of efficiency score scatters fall exactly on the identity line implying that no two frontier models produce identical results. However, figures 6.14 and 6.16 show a clear difference between the numerical values of cost efficiency scores from the two parametric approaches (SIDF and SFPF) and the non-parametric VRS DEA models.

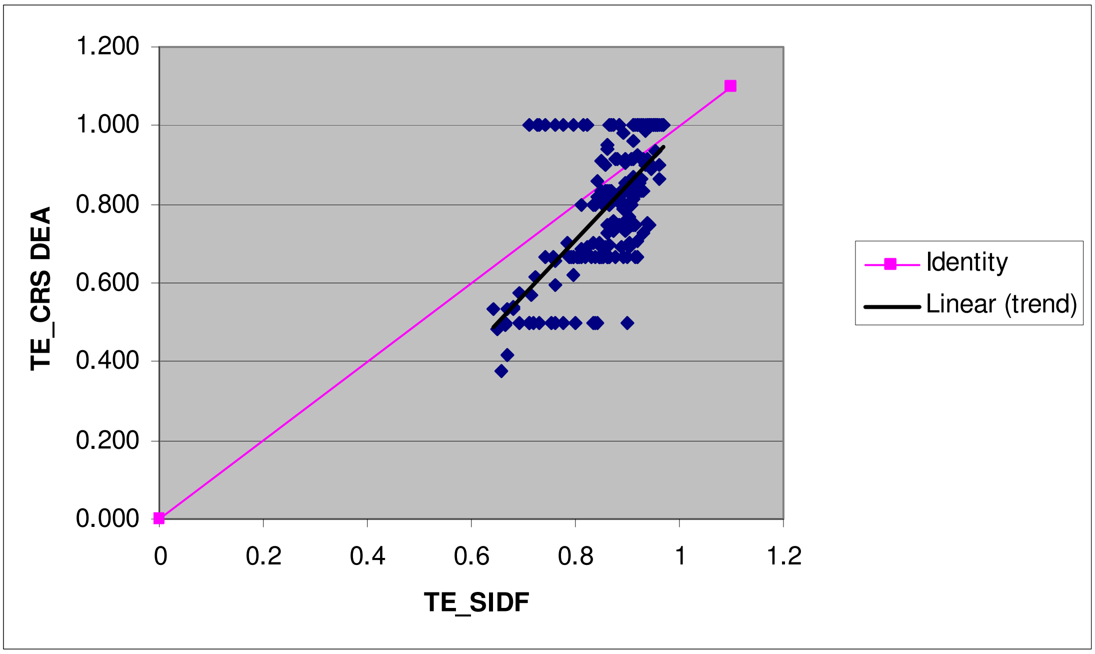

Figure 6.3: Scatter plot of TE from SIDF and CRS DEA models

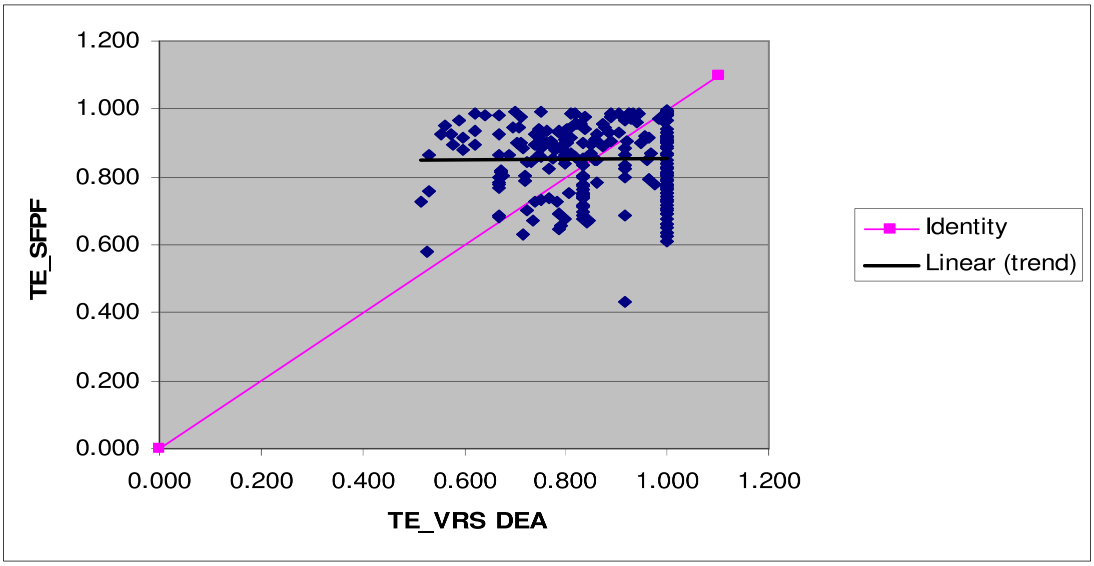

Figure 6.4: Scatter plot of TE from VRS DEA and SFPF models

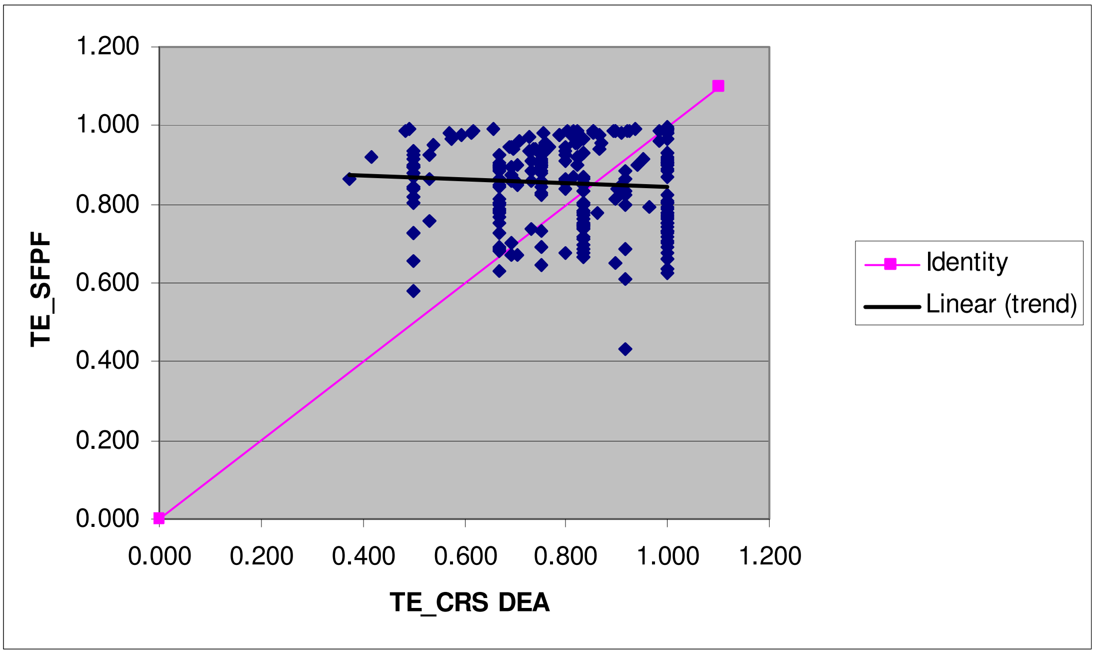

Figure 6.5: Scatter plot of TE from CRS DEA and SFPF models

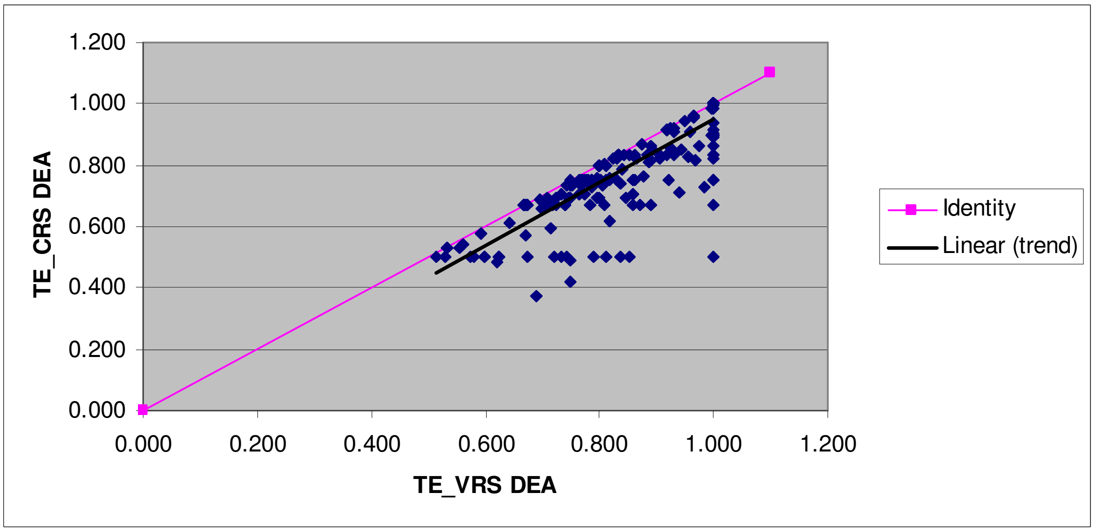

Figure 6.6: Scatter plot of TE from VRS and CRS DEA models

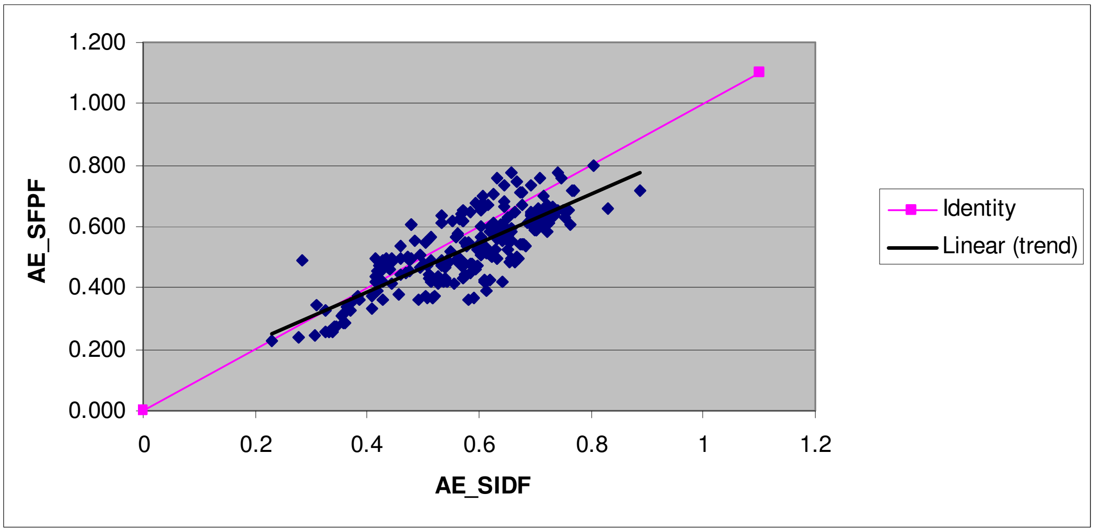

Figure 6.7: Scatter plot of allocative efficiency from SIDF and SFPF models

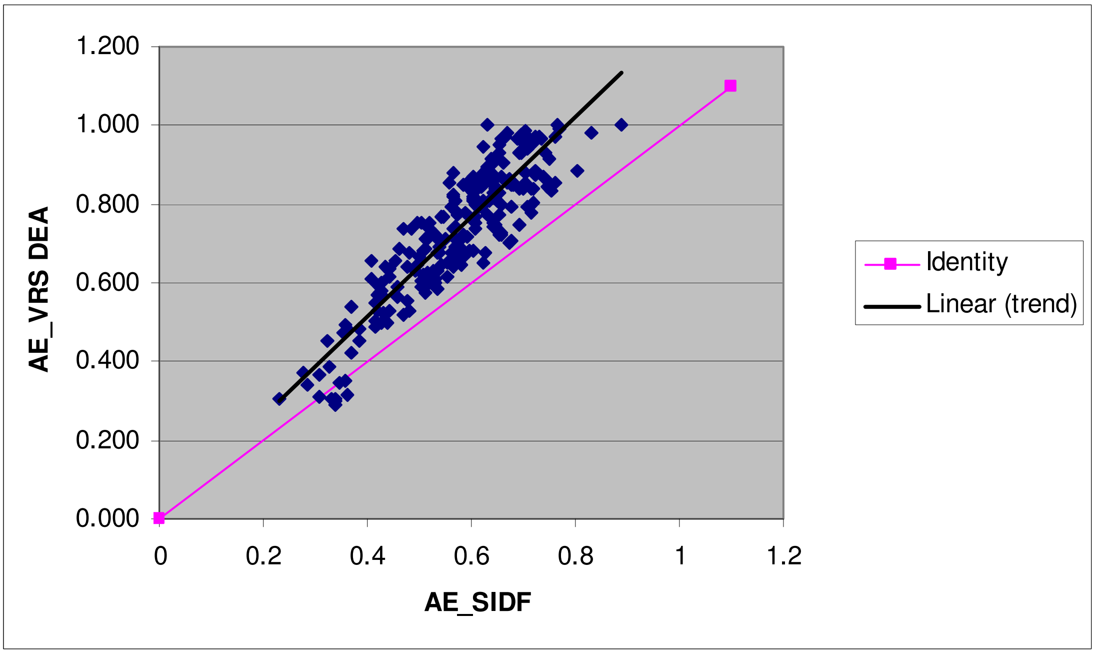

Figure 6.8: Scatter plot of AE from SIDF and VRS DEA models

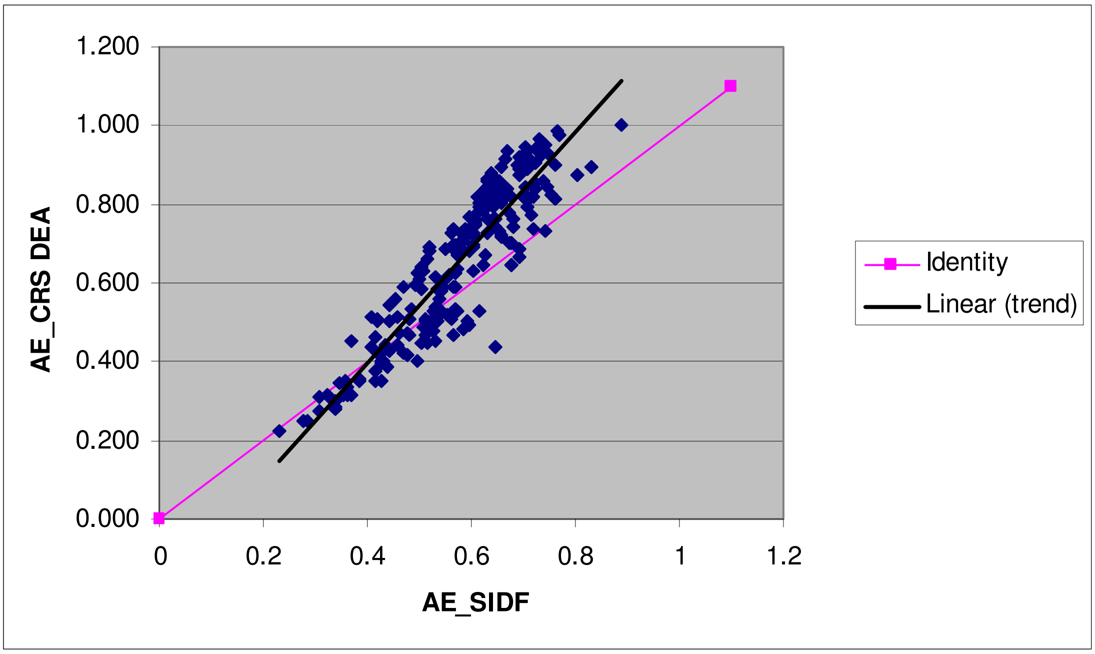

Figure 6.9: Scatter plot of AE from SIDF and CRS DEA models

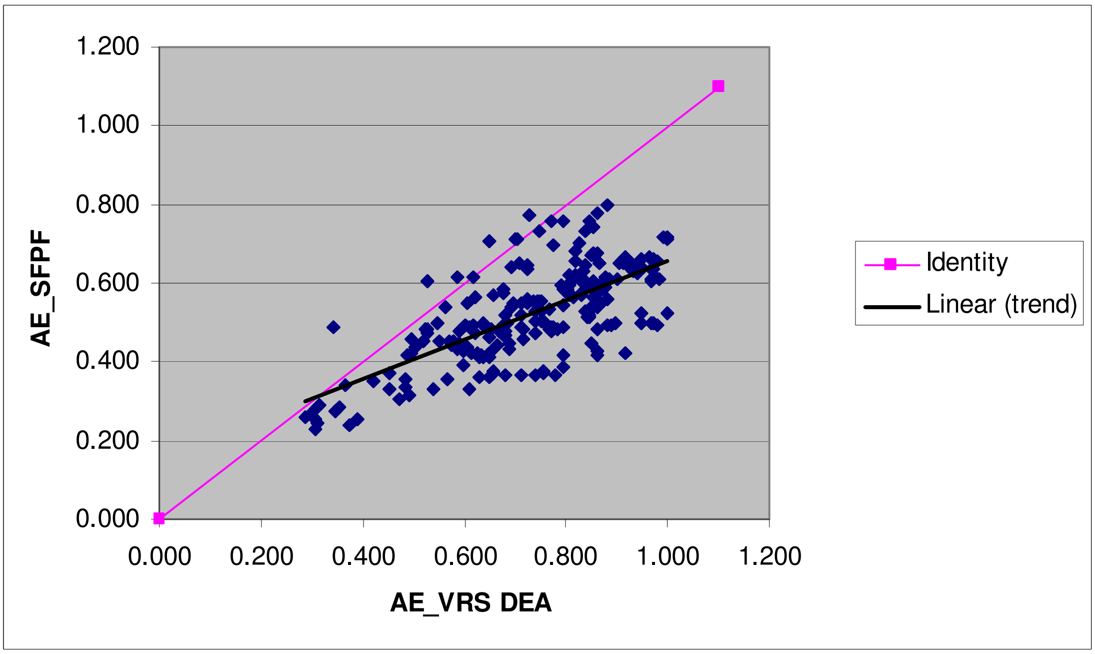

Figure 6.10: Scatter plot of AE from VRS DEA and SFPF models

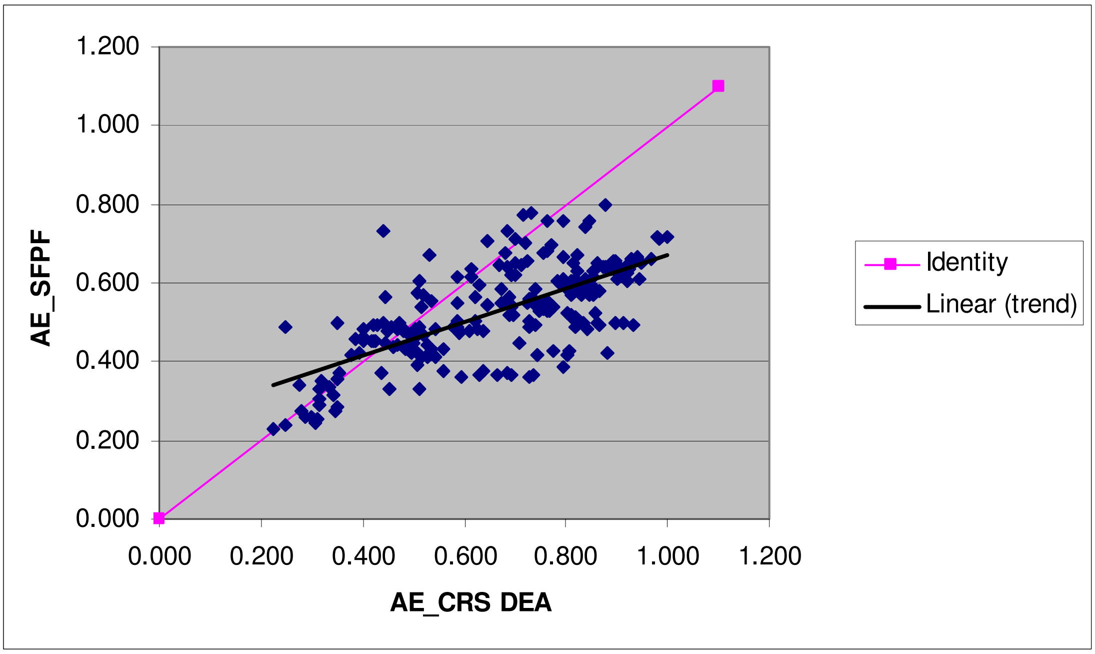

Figure 6.11: Scatter plot of AE from CRS DEA and SFPF models

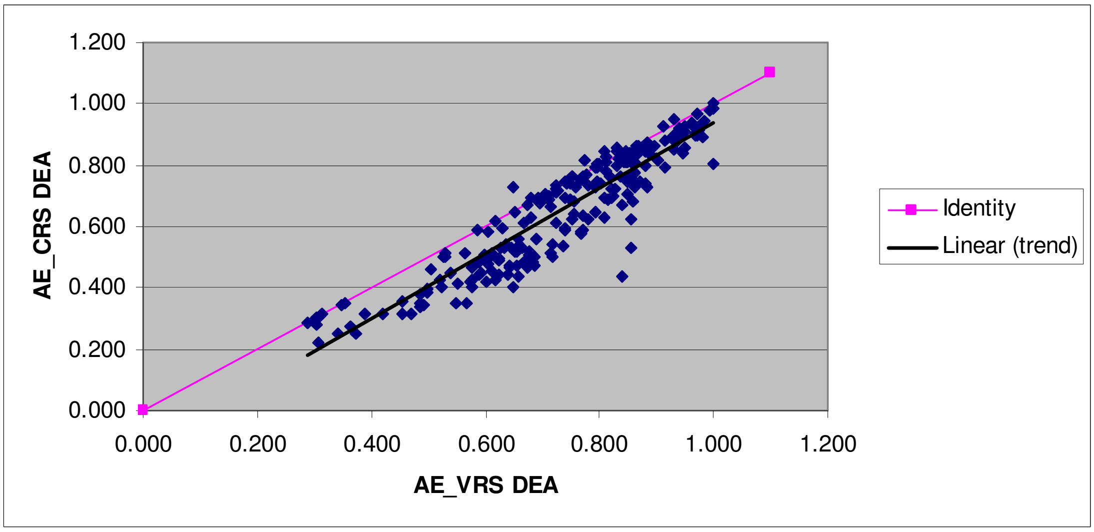

Figure 6.12: Scatter plot of AE from VRS and CRS DEA models

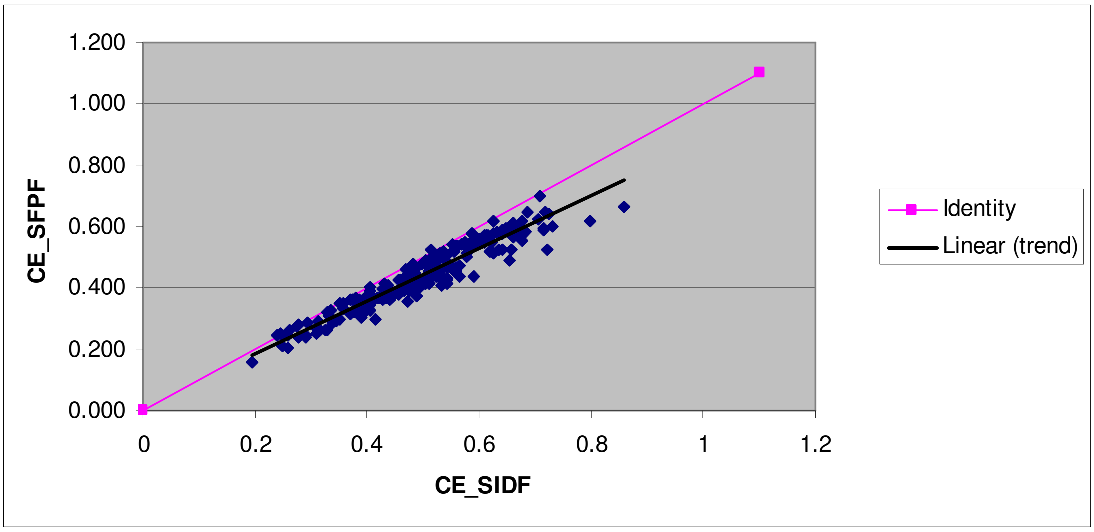

Figure 6.13: Scatter plot of cost efficiency from SIDF and SFPF models

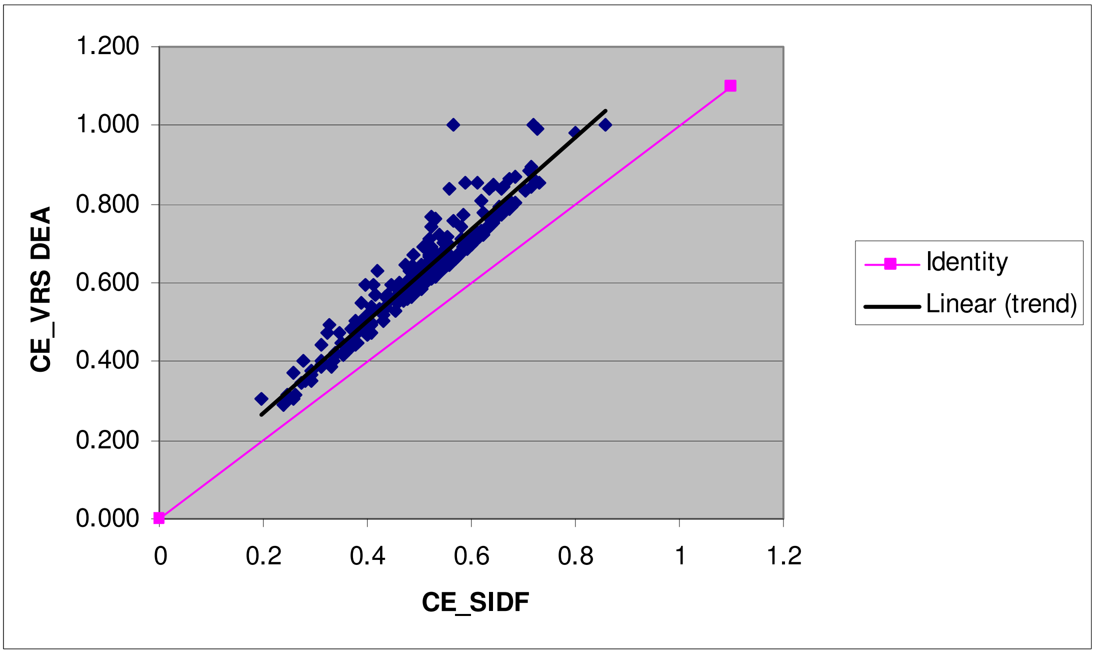

Figure 6.14: Scatter plot of CE from SIDF and VRS DEA models

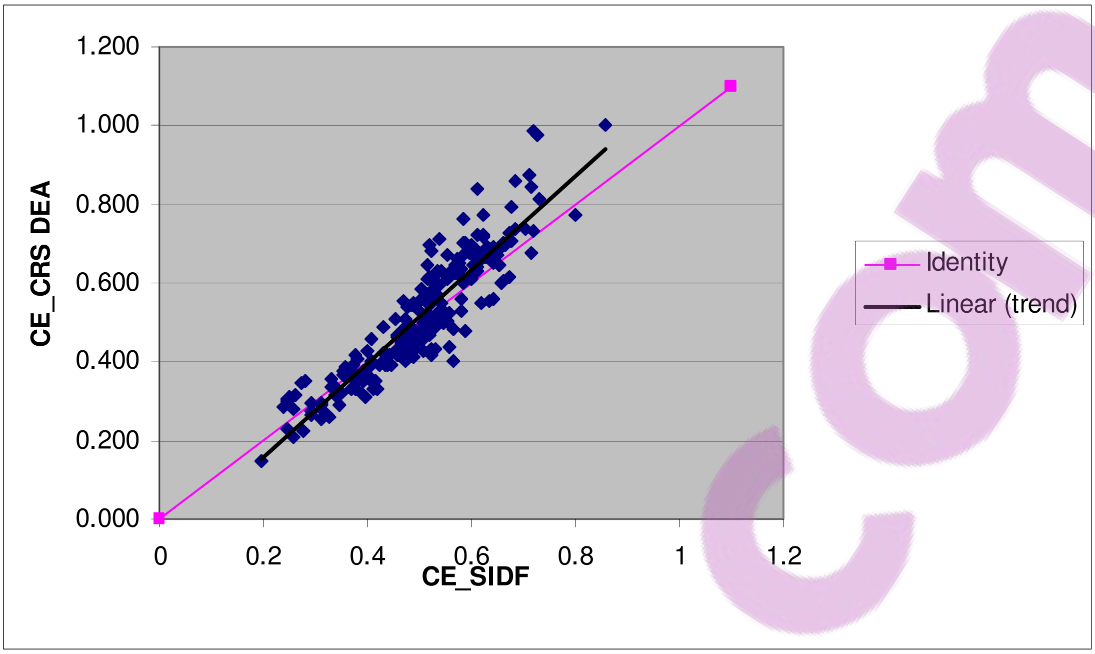

Figure 6.15: Scatter plot of CE from SIDF and CRS DEA models

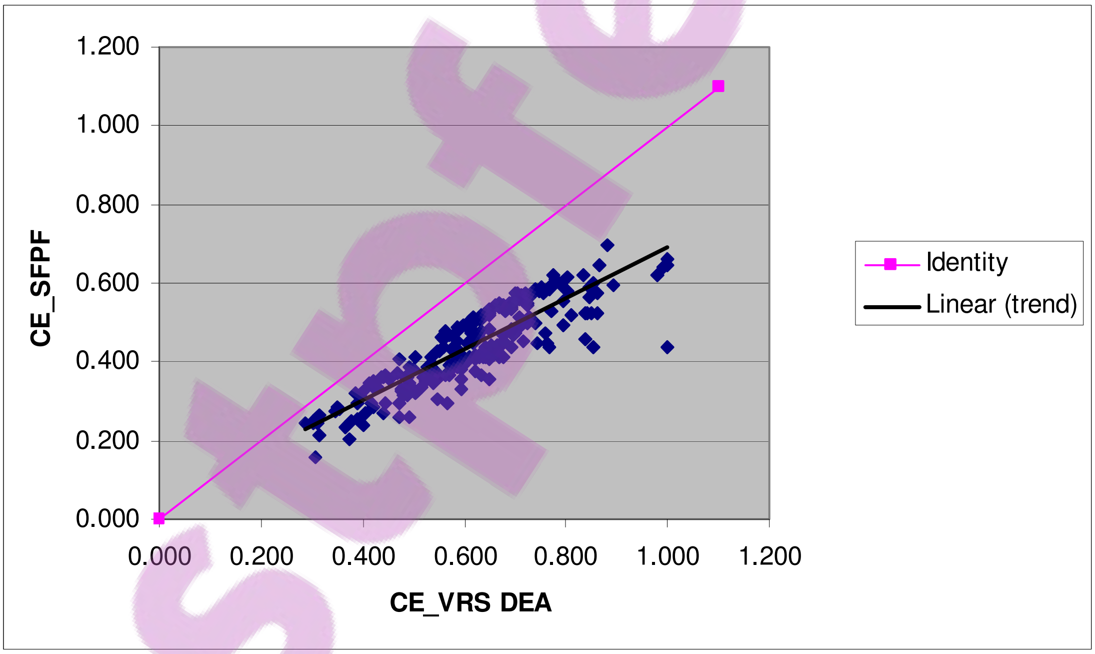

Figure 6.16: Scatter plot of CE from VRS DEA and SFPF models

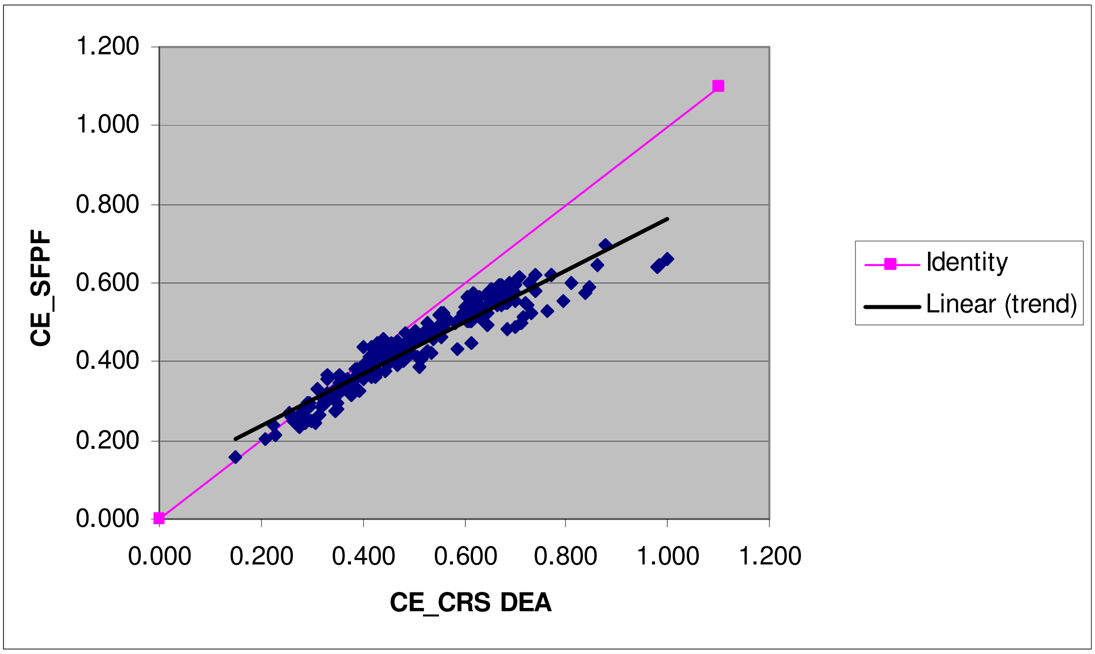

Figure 6.17: Scatter plot of CE from CRS DEA and SFPF models

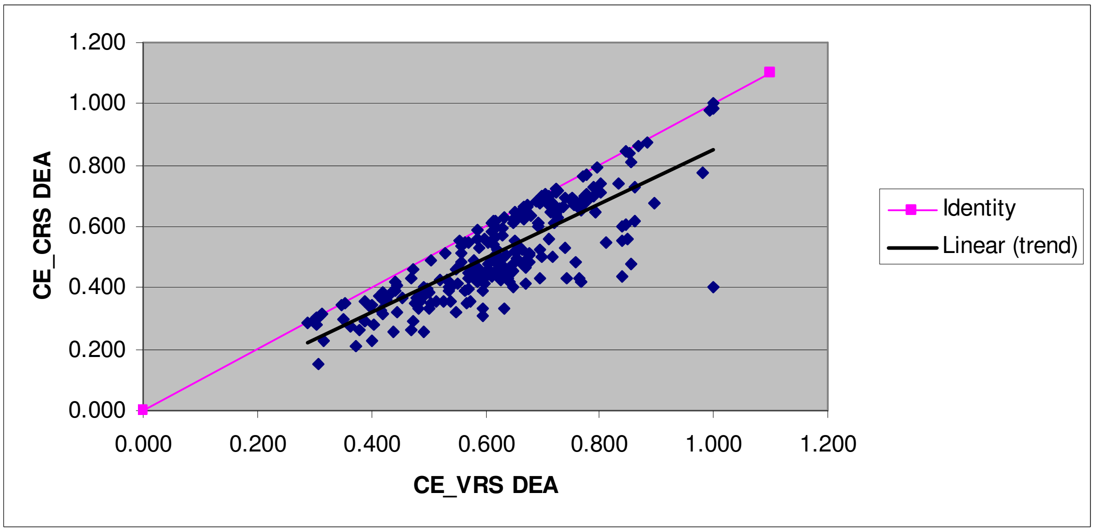

Figure 6.18: Scatter plot of CE from VRS and CRS DEA models

6.6 Sensitivity of Efficiency Scores to Estimation Approaches: Formal Tests

A problem faced by policy analysts to apply frontier studies is the variety of options at hand. The problem is particularly acute when the different approaches yield inconsistent results. Bauer et al. (1998) proposed a set of consistency conditions that if met, would make the choice of a particular approach trivial. The efficiency measures generated by the different techniques should show internal and external consistency: they should be consistent in their efficiency levels, rankings and identification of the best and worst performers and they should demonstrate reasonable stability. In the previous section a presentation of efficiency scores from different approaches was made without any test of hypothesis. However, to make a more concrete conclusion of this comparative study, formal tests of hypotheses are necessary. In this section, an evaluation of the statistical significance of the difference in efficiency scores generated by the different approaches is conducted. This is achieved by testing different complementary hypotheses relative to: (i) the equality of means (t-test), (ii) the equality of distributions (Wilcoxon signed rank-test), and (iii) the independence of the results with regard to their rank (Spearman's correlation test) which provides the evidence of overall consistency of results from different approaches.

The results of the t-test and Wilcoxon signed rank-test are presented in table 6.7 concluding that in the case of the t-tests, the differences between the technical, allocative and cost efficiency scores generated by SIDF and each of the DEA are statistically significant with a confidence of 95 percent. Also the difference between the SIDF and SFPF allocative and cost efficiency scores are statistically significant with a confidence of 95 percent but only marginally significant with respect to technically efficiency.

Table 6.7: Tests of hypothesis of the difference between efficiency means

Test	**t-test[a] t-statistic**			**Wilcoxon test[b] Z-statistic**		
	TE	**AE**	**CE**	**TE**	**AE**	**CE**
SIDF vs VRS DEA	2.133	-31.406	-39.925	2.936	-13.386	-13.431
	(0.034)	(0.000)	(0.000)	(0.003)	(0.000)	(0.000)
SIDF vs CRS DEA	8.606	-13.045	-3.044	7.900	-9.842	-2.356
	(0.000)	(0.000	(0.003)	(0.000)	(0.000)	(0.019)
SIDF vs SFPF	1.623	10.640	23.842	1.164	8.929	13.393
	(0.106)	(0.000)	(0.000)	(0.245)	(0.000)	(0.000)
VRS DEA vs SFPF	0.152	27.876	37.224	- 0.158	13.255	13.430
	(0.871)	(0.000)	(0.000)	(0.874)	(0.000)	(0.000)
CRS DEA vs SFPF	-4.125	14.905	16.941	-3.997	10.958	12.950
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

[a] H0 is the equality of means; [b] H0 is that both distributions are the same ; p-values in parenthesis

Further, the differences between the each of the DEA and SFPF technical, allocative and cost efficiency scores are statistically significant with a confidence of 95 percent with exception of the difference between technical efficiency scores from VRS DEA and SFPF which is not significant at any reasonable level. The Wilcoxon test further reinforces these results by indicating that the distributions of technical, allocative and cost efficiency estimates within the bilateral pairs of results are also statistically different with exception of technical efficiency results generated by SIDF and SFPF and VRS DEA and SFPF.

In addition to the test of differences in means, ANOVA was also conducted in order to test the hypothesis that variances of the efficiency scores generated by the four models (SIDF, SFPF, VRS DEA and CRS DEA) are the same against the alternative that at least two of them differ from one another. As the ANOVA test is parametric and therefore requires the population variances to be equal in the four models, the results derived from this test alone may not be valid. Therefore, the Kruskal-Wallis test which is non-parametric was also carried out. It does not require any assumptions regarding the normality or variances of the populations. These results are reported in table 6.8. At the 5 percent level of significance, these tests reject the null hypothesis in favour of the alternative. These results further strengthen the findings from table 6.7.

Table 6.8: Tests of hypothesis of the difference between efficiency variances

Test	TE	AE	CE
ANOVA (F-statistic)	14.19	90.13	72.44
	(0.000)	(0.000)	(0.000)
Kruskal-Wallis (χ^2 statistic)	21.749	216.118	171.837
	(0.000)	(0.000)	(0.000)

Note: p-values in parenthesis

Although, the different approaches produced efficiency measures that are quantitatively different from each other with exception of the technical efficiency results from VRS DEA and SFPF, it is still possible to achieve consistency of results with respect to ranking of individual farm households which in many policy analysis may be more important than the quantitative estimates of efficiency. Therefore, to assess the overall consistency of the three methods in ranking individual farms in terms of efficiency, the coefficient of Spearman rank-order correlation was calculated for each efficiency measure. Results are presented in table 6.9. The Spearman's rank correlation coefficients for allocative and cost efficiency from all the four models are positive and highly significant suggesting that the different farm household rank similarly when they are ordered according to either their parametric and non-parametric allocative and cost efficiency scores. Similar result is obtained for technical efficiency scores from both the parametric and non-parametric distance functions, suggesting that the different farm household rank similarly when they are ordered according to either their parametric and nonparametric distance function technical efficiency scores. The findings with respect to technical efficiency are consistent with that of Cuesta et al. (2009). However, the Spearman's rank correlation results between technical efficiency scores from the distance frontiers and production frontiers are very low and not statistically significant.

Table 6.9 Spearman's rank correlations among efficiency scores

		Technical Efficiency		
	SIDF	VRS DEA	CRS DEA	SFPF
SIDF	1.000	0.705 ***	0.654***	-0.020
VRS DEA		1.000	0.871***	0.023
CRS DEA			1.000	-0.040
SFPF				1.000
		Allocative Efficiency		
	SIDF	VRS DEA	CRS DEA	SFPF
SIDF	1.000	0.872***	0.902***	0.772***
VRS DEA		1.000	0.929***	0.669***
CRS DEA			1.000	0.674***
SFPF				1.000
		Cost Efficiency		
	SIDF	VRS DEA	CRS DEA	SFPF
SIDF	1.000	0.963***	0.927***	0.957***
VRS DEA		1.000	0.836***	0.883***
CRS DEA			1.000	0.960***
SFPF				1.000

*** Significantly different from zero at 5% level

6.7 Input Usage Ratios

The mean allocative efficiency reported for each of the models indicates that some inputs are being used in incorrect proportions. To check for over-utilization or under-utilization of the production inputs by farmers, the ratio of technically efficient input quantity over the cost-efficient input quantity (for each observation) is calculated from each of the frontier models. The means of these ratios are presented in table 6.10. The results show that given the respective market prices of the various inputs, fertilizer is consistently under-utilized, labour is consistently over-utilized, land is under-utilized in most cases whereas results of other inputs are mixed. Therefore, for the farmers to operate efficiently, the use of fertilizer and land needs to be increased whereas the use of labour needs to be contracted.

Table 6:10: Input usage ratios of maize farmers in Benue State

Models	Land	Labour	Fertilizer	Other inputs
SIDF	0.61	2.86	0.46	4.71
SFPF	0.72	5.20	0.63	0.10
VRS	0.98	1.34	0.40	1.61
CRS DEA	1.21	1.81	0.98	0.88

6.8 Technological Innovation and Efficiency: Comparison of Alternative Models

A major goal of this section is to evaluate the impact of technological innovation on farm efficiency. Two approaches are followed here. First, a t-test of difference in means of technical, allocative and cost efficiency generated from each model for adopters and non-adopters of each technology was conducted. Second, an empirical evidence of the direction and magnitude of the impact of technological innovations and other policy variables on farm efficiency is provided in a second stage Tobit regression after testing and correcting for endogeniety. The test of difference in the mean technical efficiency for improved and traditional maize farm households are presented in table 6.11. Results show that for the hybrid seed, the null hypothesis of equality in average technical efficiency were rejected at 5 percent level in all the four models implying that farm households who adopted hybrid seed were more technically efficient than those who did not and this conclusion is robust to different approaches employed for the analysis. This is reasonable as use of hybrid seed is expected to enhance yield thus bringing the farmers closer to the frontier. Farm households who used fertilizer were significantly less efficient than those who did not as shown by the non-parametric models. One could have taught that it may be the case that the farmers either applied the fertilizer wrongly or below recommended rates but since these may apply to all farmers, the only explanation could be as a result of algorithm used in estimating the technical efficiency. In most cases, households who used herbicides for weed control on their maize farms were significantly more technically efficient than those who did not use. Results further show that farm households who adopted conservation practices on their maize farms were consistently and significantly more technically efficient in all the distance frontier models.

Table 6.11: Technical efficiency estimates and test of difference in means for traditional versus improved maize farmers

	HYV			
Improved:	SIDF	VRS DEA	CRS DEA	SFPF
Mean	0.887	0.874	0.822	0.885
Min.	0.650	0.556	0.483	0.433
Max.	0.971	1.000	1.000	0.997
SD	0.058	0.111	0.144	0.091
Traditional:				
Mean	0.794	0.782	0.721	0.845
Min.	0.643	0.515	0.375	0.581
Max.	0.958	1.000	1.000	0.994
SD	0.092	0.166	0.182	0.109
t-ratio	8.816	4.643	4.179	2.381
	AFERT			
Improved:	SIDF	VRS DEA	CRS DEA	SFPF
Mean	0.866	0.847	0.793	0.851
Min.	0.643	0.515	0.375	0.433
Max.	0.971	1.000	1.000	0.997
SD	0.078	0.129	0.159	0.108
Traditional:				
Mean	0.888	0.972	0.912	0.888
Min.	0.843	0.864	0.816	0.663
Max.	0.950	1.000	1.000	0.992
SD	0.040	0.037	0.077	0.092
t-ratio	-1.111	-3.718	-2.873	-1.313
	HERB			
Improved:	SIDF	VRS DEA	CRS DEA	SFPF
Mean	0.884	0.869	0.827	0.819
Min.	0.643	0.515	0.500	0.433
Max.	0.971	1.000	1.000	0.994
SD	0.068	0.124	0.142	0.111
Traditional:				
Mean	0.838	0.829	0.754	0.913
Min.	0.650	0.556	0.375	0.693
Max.	0.963	1.000	1.000	0.997
SD	0.081	0.135	0.173	0.065
t-ratio	4.721	2.302	3.515	-7.282
	PRACTICES			
Improved:	SIDF	VRS DEA	CRS DEA	SFPF
Mean	0.899	0.890	0.839	0.867
Min.	0.712	0.597	0.500	0.608
Max.	0.971	1.000	1.000	0.994
SD	0.047	0.105	0.132	0.104
Traditional:				
Mean	0.812	0.792	0.734	0.845
Min.	0.643	0.515	0.375	0.433
Max.	0.965	1.000	1.000	0.997
SD	0.086	0.144	0.177	0.108
t-ratio	10.128	6.037	5.220	1.538

For allocative efficiency, results of the t-test are presented in table 6.12. The results show that allocative efficiency of farm households who used hybrid seed were not statistically different from those who did not except in the SFPF model where results show that farm households who adopted hybrid seeds were more allocatively efficient

Table 6.12: Allocative efficiency estimates and test of difference in means for traditional versus improved maize farmers

	HYV			
Improved:	SIDF	VRS DEA	CRS DEA	SFPF
Mean	0.580	0.739	0.657	0.540
Min.	0.230	0.304	0.224	0.229
Max.	0.888	1.000	1.000	0.799
SD	0.121	0.164	0.193	0.118
Traditional:				
Mean	0.569	0.735	0.669	0.473
Min.	0.337	0.288	0.287	0.257
Max.	0.763	0.973	0.940	0.669
SD	0.111	0.180	0.186	0.107
t-ratio	0.591	0.154	-0.388	3.608
	AFERT			
Improved:	SIDF	VRS DEA	CRS DEA	SFPF
Mean	0.580	0.745	0.670	0.530
Min.	0.230	0.288	0.224	0.229
Max.	0.888	1.000	1.000	0.799
SD	0.122	0.170	0.192	0.121
Traditional:				
Mean	0.547	0.637	0.490	0.460
Min.	0.502	0.588	0.445	0.412
Max.	0.596	0.716	0.534	0.565
SD	0.032	0.036	0.029	0.040
t-ratio	1.035	2.447	3.627	2.241
	HERB			
Improved:	SIDF	VRS DEA	CRS DEA	SFPF
Mean	0.569	0.725	0.639	0.543
Min.	0.230	0.288	0.224	0.229
Max.	0.888	1.000	1.000	0.777
SD	0.126	0.167	0.193	0.119
Traditional:				
Mean	0.593	0.762	0.696	0.496
Min.	0.306	0.301	0.299	0.245
Max.	0.830	1.000	0.984	0.799
SD	0.103	0.166	0.184	0.113
t-ratio	-1.497	-1.638	-2.235	2.952
	PRACTICES			
Improved:	SIDF	VRS DEA	CRS DEA	SFPF
Mean	0.590	0.746	0.661	0.551
Min.	0.278	0.364	0.249	0.238
Max.	0.888	1.000	1.000	0.777
SD	0.117	0.152	0.191	0.110
Traditional:				
Mean	0.555	0.725	0.655	0.481
Min.	0.230	0.288	0.224	0.229
Max.	0.803	0.984	0.966	0.799
SD	0.119	0.190	0.194	0.121
t-ratio	2.250	0.950	0.231	4.567

than non-adopters. Farm households who adopted the fertilizer technology were consistently more allocatively efficient than those who did not in all the four models and this difference is significant at 5 percent level except in the SIDF model. Whereas the SFPF model shows that households who used herbicides for weed control were

Table 6.13: Cost efficiency estimates and test of difference in means for traditional versus improved maize farmers

	HYV			
Improved:	SIDF	VRS DEA	CRS DEA	SFPF
Mean	0.515	0.639	0.529	0.454
Min.	0.196	0.304	0.149	0.158
Max.	0.859	1.000	1.000	0.696
SD	0.117	0.142	0.158	0.109
Traditional:				
Mean	0.455	0.560	0.463	0.417
Min.	0.240	0.288	0.287	0.243
Max.	0.731	0.854	0.812	0.601
SD	0.121	0.144	0.136	0.101
t-ratio	3.200	3.494	2.698	2.148
	AFERT			
Improved:	SIDF	VRS DEA	CRS DEA	SFPF
Mean	0.504	0.623	0.520	0.449
Min.	0.196	0.288	0.149	0.158
Max.	0.859	1.000	1.000	0.696
SD	0.124	0.150	0.160	0.111
Traditional:				
Mean	0.486	0.620	0.447	0.406
Min.	0.433	0.541	0.391	0.374
Max.	0.555	0.716	0.534	0.454
SD	0.040	0.047	0.046	0.028
t-ratio	0.556	0.079	1.780	1.515
	HERB			
Improved:	SIDF	VRS DEA	CRS DEA	SFPF
Mean	0.505	0.624	0.520	0.444
Min.	0.196	0.288	0.149	0.158
Max.	0.859	1.000	1.000	0.662
SD	0.127	0.151	0.163	0.113
Traditional:				
Mean	0.498	0.621	0.508	0.451
Min.	0.246	0.301	0.292	0.245
Max.	0.799	1.000	0.984	0.696
SD	0.107	0.136	0.143	0.099
t-ratio	0.440	0.145	0.572	- 0.487
	PRACTICES			
Improved:	SIDF	VRS DEA	CRS DEA	SFPF
Mean	0.531	0.658	0.546	0.465
Min.	0.257	0.364	0.208	0.206
Max.	0.859	1.000	1.000	0.662
SD	0.111	0.132	0.157	0.105
Traditional:				
Mean	0.453	0.560	0.463	0.414
Min.	0.196	0.288	0.149	0.158
Max.	0.714	0.883	0.876	0.696
SD	0.120	0.148	0.140	0.106
t-ratio	5.082	5.265	4.086	3.569

more allocatively efficient than those who did not, the SIDF, VRS and DEA models depict that farm households who used were less efficient than those who did not and these results are statistically significant. It could be that although herbicides were used by some of the farm households, the quantity used was not optimal as to produce a greater allocative efficiency. The allocative efficiency of farm households who adopted conservation practices on their farms was consistently higher than those who did not. However, this observation was only significant in the SIDF and SFPF models.

Results of the t-test results for cost efficiency are reported in table 6.13. Households who adopted hybrid seeds were more cost efficient than those who did not and this is robust to all the approaches. Although, hybrid seed are more costly than local seeds, but yields from hybrid seed is more and therefore the per unit cost is less compared to local seed. Cost efficiency levels are more for households who used fertilizers than those who did not but this is only significant in the CRS DEA model.

Households who used herbicides are more cost efficient than those who did not though this is not significant. Finally households who used conservation practices are more cost efficient than those who did not and results from all the models were statistically significant. Again, one can argue that although, conservation practices are an addition to production cost, but the yield benefit arising from improvement in soil quality reduces per unit cost when compared to non-use. From these tests, one can argue for more public investment in development and diffusion of improved maize technologies especially hybrid maize seed and conservation technologies as these could improve productivity and food security without endangering environmental sustainability.

For direction and magnitude of impact of technological innovation on efficiency, an endogeneity-corrected Tobit model is employed in the second step regression. Summary results for the Smith and Blundell (1986) test of exogeneity of the technological innovation variables is presented in table 6.14. The test was conducted in two steps. In the first step, each potential endogenous variable is estimated with OLS over a set of instruments and the exogenous variables of the Tobit model. In the second step, the predicted residual from the OLS regression is included as an additional explanatory variable and the revised Tobit model is estimated. If the coefficient of the predicted residual is found not to be statistically significant, then the potential endogenous variable is treated as exogenous. However, if the null hypothesis of exogeniety is rejected, then the potential endogenous variable is truly endogenous and its predicted value is included in a second step as additional explanatory variable which yields unbiased estimates of impact of technological innovation on efficiency.

The exogeneity test is repeated for TE, AE and CE cases. TE, AE and CE are different endogenous variables having different values and distributions; therefore it will be wrong to assume that because a particular technology variable is found endogenous in the TE case, it will also be found endogenous in the AE and CE cases. This is proved later in the test results.

Table 6.14: Summary result of Smith-Blundell test of exogeneity

Model	Predicted Residuals			
	RES_HYV	**RES_AFERT**	**RES_HERB**	**RES_PRACTICES**
SIDF:				
TE	0.023** (0.012)	-0.025 (0.016)	-0.016 (0.014)	-0.005** (0.002)
AE	-0.113*** (0.024)	-0.056* (0.033)	-0.041 (0.029)	-0.002 (0.011)
CE	-0.088*** (0.022)	-0.088*** (0.022)	-0.050* (0.027)	-0.004 (0.010)
VRS DEA:				
TE	0.160*** (0.041)	0.003 (0.052)	0.092* (0.049)	0.012 (0.016)
AE	-0.140***(0.041)	-0.027 (0.054)	-0.030 (0.048)	-0.003 (0.017)
CE	-0.043 (0.029)	-0.025 (0.038)	-.009 (0.034)	-0.002 (012)
CRS DEA:				
TE	0.236*** (0.049)	-0.002 (0 .060)	0.045 (0.057)	0.012 (0.019)
AE	-0.198*** (0.041)	-0.043 (0.055)	-0.055 (0.050)	-0.008 (0.018)
CE	-0.063*** (0.024)	-0.058** (0.029)	-0.058** (.027)	-0.008 (0.010)
SFPF:				
TE	-0.083*** (0.025)	0.046 (0.033)	0.051* (0 .028)	-0.005 (0.011)
AE	-0.039 (0.025)	-0.092*** (0 .031)	-0.097*** (0.028)	-0.002 (0 .011)
CE	-0.076*** (0 .020)	-0.057** (0.026)	-0.056** (0.023)	-0.007 (0.009)

***Significant at 1% level; **significant at 5% level; *significant at 10% level. Standard errors are shown in parenthesis.

It is noted that the exogeniety of hybrid seed was rejected in all cases except for allocative and cost efficiency in the SFPF and VRS DEA models, respectively. The exogeniety of conservation practices was rejected in only one case, which is in the SIDF technical efficiency model. In all cases where exogeneity is rejected, the analysis is conducted using predicted values of the endogenous variables.

Tables 6.15 through 6.17 reports the results of the determinants of technical efficiency, allocative efficiency and cost efficiency measures estimated from SIDF, VRS DEA, CRS DEA and SFPF models. The tables include the estimated coefficients and their statistical significance, standard errors and significance level. In addition, the tables report the value of the log-likelihood function, its significance, and finally, the log-likelihood ratio test for each model. In order to assess the causality of technology and household characteristics on efficiency, including a comparison between the models, each estimated coefficient was reported and compared by model. The significance of the likelihood ratio (LR) test in each model implies the joint significance of all variables included in the model. Thus, the hypothesis that the technology and other policy variables included in the model have no significant impact on efficiency is rejected in all the models.

The effect of AGE on efficiency could be ambiguous, depending on whether older farmers are more experienced or more likely to stick to farming traditions and less likely to adopt new technologies. AGE has a positive sign and significant impact on technical efficiency in all the four models but significant on cost efficiency in only the VRS DEA model. Thus, the variable indexes experience and serve as a proxy for human capital showing that farmers with greater farming experience will have better management skills and thus higher efficiency than younger farmers. Increased farming experience may lead to better assessment of the importance and complexity of good farming decision, including efficient use of farming inputs. The positive and significant impact of age is consistent with the findings of Khai et al. (2008).

The second human capital variable, EDU was consistently positive though has significant impact on only the technical efficiency case in all the four models. Similar positive and significant impact of education on technical efficiency of maize farmers in Nigeria was found by Oyewo and Fabiyi (2008). The result is also consistent with that of Wadud and White (2000) and Alene (2003). The lack of significance of education for allocative and cost efficiency may be due to the low average education level of about eight years, depicting a generally non-completion of junior secondary school in the study area. This finding is not strange as similar results were found by Coelli et al. (2002) and Haji (2006).

HHS was found to be positively and significantly related to technical and cost efficiency in all the models with exception of the VRS DEA model. These finding indicates the importance of abundant labour supply especially for labour intensive farming. A possible explanation is that the labour variable in our study dominated by family labour assists in producing maximal output at the least cost since it reduces the need to hire labour. Moreover, a larger household size guarantees availability of family labour for farm operations to be accomplished in time.

The variable LAND is aimed at capturing the effect of scale production on the technical efficiency of the farm. A review by Lundvall and Battese (2000) establish a varied relationship between farm size and technical inefficiency in developing countries using the frontier production function. In this study, we observe that the relationship between LAND and the three efficiency measures in all the models are inconsistent. However, in most cases where it was found statistically significant, it had a positive sign with exception of its relationship with technical efficiency in the SIDF model which was negative and significant. The inverse relationship in the technical efficiency case agrees with the findings of Peterson (1997); Msuya (2008) and Okoye et al., 2006, 2009. The relatively consistent positive and significant relationship in the allocative and cost efficiency measures implies that farmers with larger farm sizes are more efficient in choosing cost-minimizing input combinations and these results are consistent with the findings of Karagiannis et al. (2000). However, there is need for caution in the interpretation of these findings given the contrasting results. A similar contrasting relationship between land and technical, allocative and cost efficiency was found by Coelli et al. (2002) for modern boro rice farmers in Bangladesh, India.

The variable OFFWORK is included to capture the effect of off-farm work on efficiency. The effect of this variable could be ambiguous. While on the one hand, it increases the income base of the farm household thus helping them to overcome credit and insurance constraints and increase their use of industrial inputs. On the other hand, it reduces the labour available for agricultural production especially if hiring agricultural labour incurs transaction costs and if hired labour is not as efficient as family labour (Feng, 2008). In this study, OFFWORK was consistently negative in all the four models but has significant impact on technical efficiency in the SIDF and VRS DEA models only. This implies that farmers who engage in off-farm work are likely to be less efficient in farming as they share their time between farming and other income-generating activities. Productivity suffers when any part of production is neglected. This finding is consistent with that of Mariano et al. (2010).

Table 6.15: Tobit model results of impact of technological innovation on TE

	SIDF	VRS DEA	CRS DEA	SFPF	
Variable	Coeff.	Coeff.	Coeff.	Coeff.	Mean
GENDER	-0.013	-0.037	-0.044	-0.017	0.888
	(0.009)	(0.030)	(0.034)	(0.018)	
AGE	0.002***	0.004***	0.004***	0.002***	47.167
	(0.000)	(0.001)	(0.001)	(0.001)	
EDU	0.002***	0.004**	0.004***	0.002*	8.433
	(0.000)	(0.001)	(0.002)	(0.001)	
HHS	0.001***	0.000	0.003*	0.002***	11.742
	(0.000)	(0.001)	(0.001)	(0.001)	
LAND	-0.034***	0.071**	0.152***	0.098***	1.208
	(0.008)	(0.029)	(0.034)	(0.018)	
OFFWORK	-0.010*	-0.037*	-0.025	-0.000	0.675
	(0.006)	(0.020)	(0.023)	(0.012)	
MFG	0.045***	0.059*	0.111***	0.009	0.454
	(0.010)	(0.033)	(0.037)	(0.021)	
EXT	-0.003**	0.002	-0.005	0.005	2.546
	(0.002)	(0.006)	(0.006)	(0.003)	
CREDIT	0.023***	0.044	0.025	0.059***	0.138
	(0.008)	(0.028)	(0.032)	(0.017)	
MARKET	-0.000	-0.003*	-0.002	-0.002**	6.278
	(0.000)	(0.002)	(0.002)	(0.001)	
HYV	0.011**	0.024	0.038*	0.010	0.895
	(0.006)	(0.020)	(0.022)	(0.012)	
AFERT	0.018**	0.029	0.027	0.025	0.816
	(0.009)	(0.029)	(0.035)	(0.017)	
HERB	0.008	0.000	0.054**	-0.048***	0.591
	(0.006)	(0.014)	(0.025)	(0.009)	
PRACTICES	0.009***	0.024***	0.018**	0.005	1.75
	(0.002)	(0.007)	(0.008)	(0.004)	
INTERCEPT	0.750***	0.592***	0.400***	0.726***	
	(0.019)	(0.065)	(0.074)	(0.040)	
LLF	417.474	38.538	32.413	241.167	
LR TEST	293.72***	104.400***	106.510***	101.970***	

***Significant at 1% level; **significant at 5% level; *significant at 10% level. Standard errors are shown in parenthesis

Table 6.16: Tobit model results of impact of technological innovation on AE

	SIDF	VRS DEA	CRS DEA	SFPF	
Variable	Coeff.	Coeff.	Coeff.	Coeff.	Mean
GENDER	0.012	0.011	0.019	0.016	0.888
	(0.019)	(0.032)	(0.032)	(0.018)	
AGE	-0.000	0.001	-0.002	0.001	47.167
	(0.001)	(0.001)	(0.001)	(0.001)	
EDU	0.000	0.001	0.002	0.001	8.433
	(0.001)	(0.002)	(0.002)	(0.001)	
HHS	0.001	0.001	0.001	0.003	11.742
	(0.001)	(0.001)	(0.001)	(0.001)	
LAND	0.045**	-0.003	0.072**	0.012	1.208
	(0.020)	(0.030)	(0.030)	(0.020)	
OFFWORK	-0.005	-0.003	-0.002	-0.007	0.675
	(0.013)	(0.021)	(0.021)	(0.012)	
MFG	0.002	0.019	0.041	0.031	0.454
	(0.021)	(0.035)	(0.035)	(0.020)	
EXT	0.007*	0.007	0.009	-0.002	2.546
	(0.004)	(0.006)	(0.006)	(0.003)	
CREDIT	0.129***	0.170***	0.176***	0.075***	0.138
	(0.018)	(0.029)	(0.029)	(0.017)	
MARKET	-0.000	-0.001	-0.001	-0.001	6.278
	(0.001)	(0.002)	(0.002)	(0.001)	
HYV	0.034***	0.046**	0.063***	0.027**	0.895
	(0.013)	(0.021)	(0.021)	(0.011)	
AFERT	0.057**	0.078**	0.107***	0.098***	0.816
	(0.027)	(0.032)	(0.032)	(0.025)	
HERB	-0.014	-0.030	-0.031	0.023***	0.591
	(0.013)	(0.023)	(0.022)	(0.008)	
PRACTICES	0.002	0.002	0.002	0.001	1.75
	(0.005)	(0.008)	(0.008)	(0.004)	
INTERCEPT	0.431***	0.689***	0.501***	0.359***	
	(0.041)	(0.068)	(0.069)	(0.039)	
LLF	234.686	112.307	113.035	246.962	
LR TEST	139.09***	66.090***	122.850***	163.400***	

***Significant at 1% level; **significant at 5% level; *significant at 10% level. Standard errors are shown in parenthesis.

Table 6.17: Tobit model results of impact of technological innovation on CE

	SIDF	VRS DEA	CRS DEA	SFPF	
Variable	Coeff.	Coeff.	Coeff.	Coeff.	Mean
GENDER	0.000	-0.010	-0.007	0.003	0.888
	(0.017)	(0.022)	(0.017)	(0.015)	
AGE	0.001	0.001**	0.001	0.000	47.167
	(0.001)	(0.001)	(0.001)	(0.001)	
EDU	0.001	0.001	0.001	0.000	8.433
	(0.001)	(0.001)	(0.001)	(0.001)	
HHS	0.001*	0.001	0.002***	0.001*	11.742
	(0.001)	(0.001)	(0.001)	(0.001)	
LAND	0.025	0.036*	0.123***	0.055	1.208
	(0.018)	(0.021)	(0.018)	(0.016)	
OFFWORK	-0.009	-0.018	-0.012	-0.004	0.675
	(0.012)	(0.015)	(0.012)	(0.010)	
MFG	0.028	0.027	0.039***	0.027*	0.454
	(0.019)	(0.025)	(0.019)	(0.017)	
EXT	0.004	0.007*	0.002	0.001	2.546
	(0.003)	(0.004)	(0.003)	(0.003)	
CREDIT	0.130***	0.177***	0.131***	0.101***	0.138
	(0.016)	(0.021)	(0.016)	(0.014)	
MARKET	-0.000	0.001	-0.001	-0.001	6.278
	(0.001)	(0.001)	(0.001)	(0.001)	
HYV	0.035***	0.018	0.035***	0.032***	0.895
	(0.011)	(0.014)	(0.011)	(0.010)	
AFERT	0.060***	0.053**	0.091***	0.065***	0.816
	(0.024)	(0.023)	(0.024)	(0.021)	
HERB	-0.005	-0.019	0.008	-0.004	0.591
	(0.008)	(0.016)	(0.008)	(0.007)	
PRACTICES	0.006	0.010*	0.007*	0.003	1.75
	(0.004)	(0.005)	(0.004)	(0.004)	
INTERCEPT	0.305***	0.388***	0.163***	0.256	
	(0.038)	(0.047)	(0.038)	(0.033)	
LLF	259.949	194.421	258.991	291.303	
LR TEST	196.07***	168.110***	318.070***	207.520***	

***Significant at 1% level; **significant at 5% level; *significant at 10% level. Standard errors are shown in parenthesis.

Membership in a farmer group (MFG) indexes social capital and affords the farmers opportunity of sharing information on modern maize practices by interacting with others as well as provides farmers with bargaining power in the input, output and credit markets. As expected, MFG was found to be consistently positive. It has significant impact on technical efficiency in almost all the models. It also has significant impact on cost efficiency in the CRS DEA and SFPF models. The positive and significant impact is consistent with the findings of Ogunyinka and Ajibefun (2004).

The extension variable, EXT, is expected to be positive as it enhances farmers' access to information and improved technological packages. However the impact of the extension variable is mixed. It was however found to have negative and significant impact on technical efficiency in the SIDF model, positive and significant impact on allocative efficiency in the same model, positive and significant impact on cost efficiency in the VRS DEA model. Some researchers (Okoye et al., 2006, Ogunyinka and Ajibefun, 2004) in Nigeria have found similar negative sign of the extension variable for technical efficiency. This finding is consistent with the findings of Feeder et al. (2004); Binam et al. (2004); Rahman (2004); Haji (2006) and Demircan et al. (2010). Each of these studies involved farmers in developing countries. The inability to find the correct sign and statistical significance has been attributed to the bureaucratic inefficiency, the deficiency in program design, (Feeder et al., 2004; Binam et al., 2004) and the use of a “top-down” instead of participatory approach (Braun et al., 2002). This negative impact can be explained by the fact that extension services in Nigeria in general has not been effective, especially after the withdrawal of World Bank funding from the Agricultural Development Project (ADP), which is the main agency responsible for extension services. Given this problem of inadequate funding of the extension outfit, dissemination of agricultural innovation to farmers are done in most cases at wrong periods and farmers do not have access to yield improving inputs at the right time. More so, when extension agents do not have new information for farmers, contact with extension agents would only amount to a waste of resources leading to negative impact.

CREDIT is consistently positive and significant in most cases with exception of its impact on technical efficiency in the VRS and CRS DEA models. This is as expected since the availability of credit loses the production constraints thus facilitating timely purchase of inputs and therefore increases productivity via efficiency. The result is consistent with the findings of Muhammad (2009) but contrast with that of Haji (2006) who rather found a negative though not significant impact of credit access to technical, allocative and cost efficiency.

The variable MARKET was included to capture farmers’ access to market. It serves as a proxy for the development of road and market infrastructures. It is generally believed that farms located closer to the market are more technically, allocatively and economically efficient than the farms located farther from the market as this might not only increase production cost but also affect farming operations, especially the timing of input application. This expectation was satisfied in this study as the MARKET variable was correctly signed in most cases but it only had significant impact on technical efficiency in the VRS DEA and SFPF models. GENDER was never significant in any of the models and the signs were mixed.

Finally, an important goal of this study is to evaluate explicitly the impact of technological innovation on efficiency of maize farmers using results from different frontier approaches. Although improve technologies will generally raise production cost in absolute terms, the yield enhancement arising from their usage can reduce per unit cost of production thereby raising not only technical efficiency but cost efficiency as well. Results show that HYV has positive and significant impact on technical, allocative and cost efficiency in almost all the models. Chirwa (2007) employed a production frontier model and found a positive and significant impact of hybrid seed use on technical efficiency of smallholder maize farmers in Malawi. Similar impact of improved maize seed on cost efficiency from a cost frontier model was reported in Zavale et al. (2006). These findings further strengthen the need for hybrid seed improvement and diffusion in Nigeria in line with the current doubling of maize production programme of the federal government.

AFERT have positive and significant impact on technical efficiency in the SIDF model only but positive and significant impact on allocative and cost efficiency in all the four models. The findings are consistent with that of Okoye et al. (2006) and Msuya et al. (2008) who found a positive impact of inorganic fertilizer on allocative and technical efficiency, respectively. The fertilizer technology can be said to corroborate to credit. Thus, failure to use fertilizer may result in irretrievable output loss.

The sign of the variable, HERB, is mixed. Whereas it has positive and significant impact on technical and allocative efficiency in the CRS DEA and SFPF models, respectively, it has negative and significant effect on allocative efficiency in the SFPF model. The dominating negative sign of herbicides could be due to the farmers' perception of the health and environmental effects of herbicides coupled with its high cost and inadequate application knowledge, which constrained its adoption and usage. PRACTICES have positive impact on all the efficiency measures in all the models though this impact is only significant for technical and cost efficiency. This is expected because the use of conservation practices improves land quality and hence yield as well as reduces the unit cost of production. This finding is consistent with that of Solis et al. (2009) who found a positive and significant impact of conservation practices on technical efficiency of peasant farmers in Central America. According to Otsuki et al. (2002) many rural policies in Latin America have been conceived to promote economic development but usually have had costly environmental effects. However, the findings in this study support the hypothesis that the adoption of soil conservation practices is not only a good tool for controlling environmental degradation but is also associated with higher farm efficiency. Thus, economic and environmental sustainability can be viewed as complementary rather than competitive goals.

The marginal effects are also reported in tables 6.18 through 6.20. There are three options for estimating marginal effects namely (1) The marginal effects for the probability of the dependent variable (technical, allocative or cost efficiency) being uncensored, (2) the marginal effects for the expected value of the dependent variable conditional on being uncensored and, (3) the marginal effect effects for the unconditional expected value of the dependent variable. These three options were employed. It is however, noted that the coefficients and marginal effects are numerically similar due to the fact that there are relatively small number of censored observations especially in the SFPF and SIDF models. Thus, only results of option 2 are presented.

As to the interpretation of the marginal effects, using the results of the SIDF model and hybrid seed variable for example, the marginal effect of 0.011 for HYV on technical efficiency shows that, for the sample period, an increase in the area cultivated with hybrid seed by 100 percent would lead, on average to an increase in technical efficiency by 11 percent. The marginal effect of 0.034 for HYV on technical efficiency shows that, for the sample period, an increase in the area cultivated with hybrid seed by 100 percent would lead, on average to an increase in allocative efficiency by 34 percent. Similarly, cost efficiency will increase by 35 percent on average, for a 100 percent increase in the area cultivated with HYV. Similar interpretations hold for all variables in all the three efficiency measures.

Table 6.18: Marginal effects for the expected value of technical efficiency

	SIDF	VRS DEA	CRS DEA	SFPF	
Variable	Marginal Effects	Marginal Effects	Marginal Effects	Marginal Effects	Mean
GENDER	-0.013	-0.021	-0.028	-0.013	0.888
	(0.009)	(0.016)	(0.021)	(0.014)	
AGE	0.002***	0.002***	0.002***	0.001***	47.167
	(0.000)	(0.001)	(0.001)	(0.001)	
EDU	0.002***	0.002**	0.003***	0.001*	8.433
	(0.000)	(0.001)	(0.001)	(0.001)	
HHS	0.001***	0.000	0.002*	0.002***	11.742
	(0.000)	(0.001)	(0.001)	(0.001)	
LAND	-0.033***	0.042***	0.102***	0.080***	1.208
	(0.008)	(0.017)	(0.023)	(0.015)	
OFFWORK	-0.010*	-0.021*	-0.016	-0.000	0.675
	(0.006)	(0.012)	(0.015)	(0.010)	
MFG	0.044***	0.035*	0.073***	0.007	0.454
	(0.010)	(0.019)	(0.025)	(0.017)	
EXT	-0.003**	0.001	-0.003	0.004	2.546
	(0.002)	(0.003)	(0.004)	(0.003)	
CREDIT	0.022	0.024*	0.017	0.045***	0.138
	(0.008)	(0.015)	(0.022)	(0.012)	
MARKET	-0.000	0.002*	-0.001	-0.002**	6.278
	(0.000)	(0.001)	(0.001)	(0.001)	
HYV	0.011**	0.015	0.026*	0.008	0.895
	(0.006)	(0.012)	(0.015)	(0.010)	
AFERT	0.018**	0.017	0.018	0.021	0.816
	(0.009)	(0.017)	(0.023)	(0.014)	
HERB	0.008	0.000	0.036**	-0.039***	0.591
	(0.006)	(0.008)	(0.017)	(0.007)	
PRACTICES	0.009***	0.014***	0.012**	0.004	1.75
	(0.002)	(0.004)	(0.005)	(0.004)	

***Significant at 1% level; **significant at 5% level; *significant at 10% level. Standard errors are shown in parenthesis.

Table 6.19: Marginal effects for the expected value of allocative efficiency

Variable	SIDF Marginal Effects	VRS DEA Marginal Effects	CRS DEA Marginal Effects	SFPF Marginal Effects	Mean
GENDER	0.012	0.009	0.018	0.016	0.888
	(0.019)	(0.027)	(0.030)	(0.018)	
AGE	0.000***	0.001	0.001	0.001	47.167
	(0.001)	(0.001)	(0.001)	(0.001)	
EDU	0.000	0.001	0.002	0.001	8.433
	(0.001)	(0.001)	(0.001)	(0.001)	
HHS	0.001	0.001	0.001	0.003***	11.742
	(0.001)	(0.001)	(0.001)	(0.001)	
LAND	0.045**	-0.003	0.067**	0.012	1.208
	(0.020)	(0.025)	(0.028)	(0.020)	
OFFWORK	-0.005	-0.002	-0.002	-0.007	0.675
	(0.013)	(0.018)	(0.020)	(0.012)	
MFG	0.002	0.016	0.038	0.031	0.454
	(0.021)	(0.030)	(0.033)	(0.020)	
EXT	0.007*	0.006	0.009	-0.002	2.546
	(0.004)	(0.005)	(0.006)	(0.003)	
CREDIT	0.129***	0.123***	0.149***	0.075***	0.138
	(0.018)	(0.018)	(0.022)	(0.017)	
MARKET	-0.000	-0.001	-0.001	-0.001	6.278
	(0.001)	(0.001)	(0.002)	(0.001)	
HYV	0.034***	0.039**	0.058***	0.027**	0.895
	(0.013)	(0.017)	(0.019)	(0.011)	
AFERT	0.057***	0.065***	0.099***	0.098***	0.816
	(0.027)	(0.027)	(0.030)	(0.025)	
HERB	-0.014	-0.025	0.029	0.023***	0.591
	(0.013)	(0.019)	(0.021)	(0.008)	
PRACTICES	0.002	0.002	0.002	0.001	1.75
	(0.005)	(0.006)	(0.007)	(0.004)	

***Significant at 1% level; **significant at 5% level; *significant at 10% level. Standard errors are shown in parenthesis

Table 6.20: Marginal effects for the expected value of cost efficiency

	SIDF	VRS DEA	CRS DEA	SFPF	
Variable	Marginal Effects	Marginal Effects	Marginal Effects	Marginal Effects	Mean
GENDER	0.000	-0.009	-0.007	0.003	0.888
	(0.017)	(0.022)	(0.017)	(0.015)	
AGE	0.001	0.001	0.001	0.000	47.167
	(0.001	(0.001)	(0.001)	(0.001)	
EDU	0.001	0.001	0.001	0.000	8.433
	(0.001)	(0.001)	(0.001)	(0.001)	
HHS	0.001*	0.001	0.002***	0.001*	11.742
	(0.001)	(0.001)	(0.001)	(0.001)	
LAND	0.025	0.025	0.123***	0.055***	1.208
	(0.018)	(0.021)	(0.018)	(0.016)	
OFFWORK	-0.009	-0.016	-0.012	-0.004	0.675
	(0.012)	(0.015)	(0.012)	(0.010)	
MFG	0.028	0.025	0.039***	0.027*	0.454
	(0.019)	(0.025)	(0.019)	(0.017)	
EXT	0.004	0.007*	0.002	0.001	2.546
	(0.003)	(0.004)	(0.003)	(0.003)	
CREDIT	0.130***	0.171***	0.131***	0.101***	0.138
	(0.016)	(0.019)	(0.016)	(0.014)	
MARKET	-0.000	0.000	-0.001	-0.001	6.278
	(0.001)	(0.001)	(0.001)	(0.001)	
HYV	0.035***	0.031**	0.035***	0.032***	0.895
	(0.011)	(0.014)	(0.011)	(0.010)	
AFERT	0.060***	0.054**	0.091***	0.065***	0.816
	(0.024)	(0.022)	(0.024)	(0.021)	
HERB	-0.005	-0.019	0.008	-0.004	0.591
	(0.008)	(0.016)	(0.008)	(0.007)	
PRACTICES	0.006	0.010**	0.007*	0.003	1.75
	(0.004)	(0.005)	(0.004)	(0.004)	

***Significant at 1% level; **significant at 5% level; *significant at 10% level. Standard errors are shown in parenthesis. M.E.

6.9 Conclusions

The objective of this chapter was to estimate and compare efficiency scores and determinants from different approaches namely parametric stochastic input distance function (SIDF), non-parametric input distance functions(VRS DEA and CRS DEA) and parametric stochastic frontier production function (SFPF). In all the models, it was found that maize farmers in Benue State have considerable technical, allocative and cost inefficiency dominated by the later suggesting the immense potential of enhancing production through improvement in overall efficiency. Two approaches were employed in the analysis of technology and farm characteristics impact on efficiency namely t-test of equality in means and second stage Tobit regression. In general, the results from the two approaches suggest that technological innovations and other policy variables had positive and significant impact on technical, allocative and cost efficiency in most cases. The positive and significant impact of the included technological innovation variables shows the role of government technology policy in enhancing farm efficiency in Nigeria and therefore underscores the need for further investment into agricultural research and technology development. Strengthening the hybrid seed sectors was found to be especially very important and the results were robust in both t-test and Tobit analysis and in all the models.

In addition to the comparison of absolute values of efficiency scores from the four models, formal sensitivity tests were conducted. The overall consistency check shows that technical, allocative and cost efficiency measures from the three distance functions (SIDF, VRS DEA and CRS DEA) were consistent whereas similar conclusions could not hold when these were compared to the production frontier (SFPF) especially for technical efficiency estimates. Given the consistency of results from the parametric and non-parametric distance functions, an integrated model is therefore proposed and this is addressed in the next chapter.

CHAPTER 7

AN INTEGRATED INPUT DISTANCE MODEL FOR EFFICIENCY AND POLICY ANALYSIS

7.1 Introduction

Majority of efficiency studies in agriculture have adopted one of several approaches available for efficiency analysis. Reducing error in the calculation of efficiency scores of farm households is very important and necessary for effective agricultural policy making. Most studies have attempted to achieve this goal by comparing various methods of measuring efficiency and subsequently the correlation between these models has been calculated. In spite of this, none of these studies with exception of Alene et al. (2006) provided any method for calculating final efficiency score and rank of the farmers. However, Alene et al. (2006) was limited to obtaining final technical efficiency scores using geometric mean (GM) with neither consideration of overall efficiency and determinants nor the weight of each indicator in the final index. Therefore, the focus of this chapter is to provide final technical, allocative and cost efficiency scores of farm households and analyse impact of some policy variables on these efficiency measures in an integrated approach. The principal component analysis (PCA) is employed in assigning weights to the different indicators in order to compute the final efficiency scores. To the best of our knowledge, this study is the first to explore the possibility of integrating farmer's efficiency scores generated from different approaches into a single index using the PCA methodology. In the next section (two), the PCA method of integration is discussed. In section three, results of efficiency scores from the PCA techniques are presented. The results of determinants of technical, allocative and cost efficiency generated by the integrated model are also reported in section three. The last section concludes on the chapter

7.2 The Integrated Model

The principal component analysis (PCA) is used for integrating efficiency indexes. It is a widely used non-parametric method of extracting relevant information from confusing data sets. It is used to reduce the number of variables under study. The PCA technique has been applied in a number of studies both within and outside agriculture (Zhu, 1998; Azadeh and Jalal, 2001; Azadeh and Ghaderi, 2005; Azadeh et al., 2009; Essa and Nieuwoudt, 2003; Jollans et al., 2004). However, no study in agriculture has extended the PCA for obtaining efficiency index.

The goal of PCA is to decompose a data table with correlated measurements into a new set of uncorrelated variables called principal components. Each principal component is calculated as a linear combination of the standardized values of the original variables used for the definition of the index. The weight given to each of these variables corresponds to its statistical correlation with the latent dimension that the index attempts to measure. The number of principal components to retrieve depends on the correlation of the initial variables. If they are strongly correlated with each other, one factor will be sufficient to explain most of their variance. However, if the correlation is weak, several factors will be required in order to explain a significant percentage of their variance. In this case, one will get a set of intermediate indicators, as many as there were common factors, and the final index will be calculated as their weighted sum. The importance of each factor is given by the proportion of the total variance explained. The first new variable y1 accounts for the maximum variances in the sample data and so on. PCA is performed by identifying the eigen structure of the covariance or singular value decomposition of the original data. This would eventually lead to scoring and rankings of units of interest.

For this study, it is assumed there are three variables (indicators) and 240 farm households. Suppose $X = (x_1,...x_3)_{240x3}$ is a 240 x 3 matrix composed by $x_{ij}'s$ defined as the value of the *j*th index for the *i*th farm household, therefore, $x_m = (x_{1m},...x_{240m})^T\ (m = 1,...,3)$. Again, suppose $\hat{X} = (\hat{x}_1,...\hat{x}_3)_{240x3}$ is the standardized matrix of $X = (x_1,...x_3)_{240x3}$ with $\hat{x}_{ij}'s$ defined as the value of the *j*th standardized index for the *i*th farm household and therefore $\hat{x}_m = (\hat{x}_{1m},...\hat{x}_{240m})^T$. PCA is performed to identify new independent variables or principal components (defined as Y_j for j= 1,…, 3), which are, respectively, different linear combination of $\hat{x}_1,...\hat{x}_3$. This is achieved by identifying the eigen structure of the covariance of the original data. The principal component is defined by 240 x 3 matrix $Y = (y_1,..., y_3)_{240x3}$ composed by $y_{ij}'s$ shown by:

$$y_1 = l_{11}\hat{x}_1 + l_{12}\hat{x}_2 + l_{13}\hat{x}_3$$
$$y_2 = l_{21}\hat{x}_1 + l_{22}\hat{x}_2 + l_{23}\hat{x}_3$$
$$y_3 = l_{31}\hat{x}_1 + l_{32}\hat{x}_2 + l_{33}\hat{x}_3 \qquad (7.1)$$

where l_{mj} is the coefficient of *j*th variable for the *m*th principal component. $l_{mj}'s$ are estimated such that the following conditions are satisfied:

1. y_1 accounts for the maximum variance in the data, y_2 accounts for the maximum variance that has not been accounted for by y_1, and so on.

2. $l_{m1}^{\ 2} + l_{m2}^{\ 2} + l_{m3}^{\ 2} = 1, \qquad m = 1,...,3 \qquad (7.2)$
3. $l_{m1}.l_{n1} + l_{m2}.l_{n2} + l_{m2}.l_{n2} = 0$ for all $m \neq n \quad n = 1,...,3 \qquad (7.3)$

The eigenvectors $(l_{m1},...,l_{m3})$ $(m = 1,...,3)$ are calculated and the components in eigenvectors are respectively the coefficients in each corresponding principal component, Y_i:

$$Y_m = \sum_{j=1}^{3} l_{mj}\hat{x}_{ij} \text{ for } m = 1,...,3 \text{ and } i = 1,...,240 \qquad (7.4)$$

where $\hat{x}_{ij}$ are the values of the standardized indexes for the farm households.

The weights and PCA scores are estimated as follows:

$$w_j = \lambda_j / \sum_{j=1}^{3} \lambda_j = \lambda_j / 3, \qquad j = 1,...,3 \qquad (7.5)$$

$$z_i = \sum_{j=1}^{3} w_j Y_j, \qquad i = 1,...,240 \qquad (7.6)$$

where w_j is the share of eigenvalue *j*th in the population variance , Y_j is the value of the principal component *j*th and z_i is the PCA score. The ranking of the farm households is done on the basis of Z_i and therefore it is important to recognize the elements of Z_i so as to explore and analyze the impact of each indicator in determining the rank of each farm household. Since Z_i is obtained from equation (7.6) and Y_j is computed from equation (7.4), following Azadeh et al. (2009), it can be proved that

$$Z_i = \sum_{j=1}^{3} w_j Y_j = \sum_{j=1}^{3} w_j \left(\sum_{j=1}^{3} l_{mj} \hat{x}_{ij} \right)$$

$$= \sum_{j=1}^{3} \sum_{j=1}^{3} w_j \left(l_{mj} \hat{x}_{ij} \right) = \sum_{j=1}^{3} \hat{x}_{ij} \left(\sum_{j=1}^{3} w_j l_{mj} \right) = \sum_{j=1}^{3} \hat{x}_{ij} \hat{w}_m \qquad (7.7)$$

where $\hat{w}_m = \sum_{j=1}^{3} w_j l_{mj}$, $m = 1,\ldots,3$.

The value of $\hat{w}_j$ for each indicator shows the importance of that indicator in overall ranking of farm households. That means, a high value of an indicator $\hat{w}_j$ has positive impact on the value of Z_i. To calculate efficiency score related to each farm household, the values of $\hat{w}_j{}'s$ are transformed such that they are bounded between zero and one. This is done so that these values demonstrate the difference of indicators importance. To achieve this, each of the values of $\hat{w}_j$ is divided by the sum of the value of indicators importance. The final efficiency score of *i*th farm household is calculated as follows:

$$\varphi_i = \sum_{j=1}^{3} x_{ij} \tilde{w}_j, \; i = 1,\ldots,240; \; j = 1,\ldots,3 \qquad (7.8)$$

where x_{ij} is the efficiency score generated by the *j*th model (j =1,…,3 for SIDF, VRS DEA and CRS DEA models, respectively) for the *i*th farm household and $\tilde{w}_j$ is the transformed $\hat{w}_j$. φ_i is the weighted sum of the efficiency scores generated by the SIDF, VRS DEA and CRS DEA models. The model is implemented in STATA version 10.0.

7.3. Results and Discussion

7.3.1 Final Efficiency Scores and Distribution from the Integrated Model

The results of efficiency distributions and some descriptive statistics from the integrated model are present in table 7.1. Final technical efficiency (TE) ranges from 56.6 to 98.9 with a mean of 84.2 percent. This implies that if farm households will operate on the frontier, they will achieve a cost savings of 15.8 percent without reducing output. On the other hand, if the average farm household in the sample was to achieve the TE level of its most efficient counterpart, then the average farm household could realize a 14.87 percent cost savings (i.e., 1–[84.2/98.9]). A similar calculation for the most technically inefficiency farm household reveals cost saving of 47.8 percent (i.e., 1– [56.6/98.9]).

Table 7.1: Frequency distribution of efficiency scores from the integrated model

Efficiency level (%)	TE		AE		CE	
	Number	Percent	Number	Percent	Number	Percent
≤ 40	0	0.00	20	8.33	44	18.33
41-50	0	0.00	24	10.00	48	20.00
51-60	10	4.17	45	18.75	67	27.92
61-70	18	7.50	47	19.58	61	25.42
71-80	50	20.83	67	27.92	15	6.25
81-90	88	36.67	34	14.17	4	1.67
91-100	74	30.83	3	1.25	1	0.42
Mean	84.2		65.7		54.5	
Min	56.6		25.4		21.4	
Max	98.9		96.1		95.3	
SD	10.8		15.3		13.6	
CV	12.7		23.3		24.9	

CV = coefficient of variation; Min = Minimum; Max = Maximum; SD = Standard deviation

The average allocative efficiency (AE) of the sample is 65.7 percent with a low of 25.4 percent and a high of 96.1 percent. This implies that there is room to improve allocative efficiency of the farm households by 34.3 percent to have them operate on the frontier. It also suggests that if the average farm household was to achieve the AE level of its most efficient farm household, then the average farm household could achieve a cost saving of 31.6 percent while the least efficient farm household would achieve a cost saving of 73.6 percent.

Cost efficiency (CE) ranges from 21.4 to 95.3 with a mean of 54.5 giving room for cost efficiency improvement by 49.5 percent, if farm households were to operate on the frontier and also suggests a gain economic efficiency of 42.8 percent for the average farm household and 75.5 percent for the least efficient farm household. The general conclusion of these results is that maize farmers in Benue State operate with considerable inefficiency which is dominated by cost inefficiency thereby providing an avenue for policy interventions that would help reduce inefficiency.

7.3.2 Impact of Technological Innovation on Efficiency Estimates from the Integrated Model

A major goal of this section is to evaluate the impact of technological innovation on farm efficiency using the integrated model. Two approaches are followed here. First, a t-test of difference in means of technical, allocative and cost efficiency generated from the integrated model for adopters and non-adopters of each technology was conducted. Second, an empirical evidence of the direction and magnitude of the impact of technological innovations and other policy variables on farm efficiency is provided in a second stage Tobit regression.

The test of difference in mean technical efficiency for improved and traditional maize farm households are presented in table 7.2. Results show that for the hybrid seed, the technical, allocative and cost efficiency values are higher for adopters than for non-adopters though only the technical and cost efficiency results are significant. Similar result was obtained for conservation practices variable. The results of the fertilizer technology depict that farmers who applied fertilizer on their maize farms were less technically efficient but more allocatively efficient than those who did not. Further, the t-test result shows that farmers who used herbicides were more technically efficient but less allocatively efficient than those who did not use herbicides on their farm. Since the results for hybrid seed and conservation technology were more

Table 7.2: Efficiency estimates and test of difference in means for traditional versus improved maize farmers

	TE	AE	CE
		HYV	
Improved:			
Mean	0.862	0.657	0.559
Min.	0.588	0.254	0.214
Max.	0.989	0.961	0.953
SD	0.092	0.154	0.134
Traditional:			
Mean	0.767	0.656	0.491
Min.	0.566	0.305	0.272
Max.	0.984	0.871	0.798
SD	0.132	0.153	0.129
t-ratio	5.905	0.063	3.220
		AFERT	
	TE	**AE**	**CE**
Improved:			
Mean	0.837	0.663	0.547
Min.	0.566	0.254	0.214
Max.	0.989	0.961	0.953
SD	0.109	0.156	0.140
Traditional:			
Mean	0.920	0.559	0.514
Min.	0.842	0.514	0.457
Max.	0.981	0.605	0.586
SD	0.045	0.027	0.043
t-ratio	-2.933	2.590	0.912
		HERB	
	TE	**AE**	**CE**
Improved:			
Mean	0.861	0.643	0.547
Min.	0.566	0.254	0.214
Max.	0.989	0.961	0.953
SD	0.100	0.157	0.143
Traditional:			
Mean	0.809	0.681	0.540
Min.	0.576	0.308	0.282
Max.	0.981	0.913	0.900
SD	0.114	0.145	0.122
t-ratio	3.725	-1.883	0.412
		PRACTICES	
	TE	**AE**	**CE**
Improved:			
Mean	0.877	0.665	0.576
Min.	0.610	0.300	0.276
Max.	0.989	0.961	0.953
SD	0.084	0.148	0.129
Traditional:			
Mean	0.781	0.643	0.490
Min.	0.566	0.254	0.214
Max.	0.986	0.886	0.823
SD	0.120	0.162	0.130
t-ratio	7.269	1.041	4.936

consistent than those for fertilizer and herbicides, one can argue for more public investment in development and diffusion of improved maize technologies especially hybrid maize seed and conservation technologies as these could improve productivity and food security without endangering environmental sustainability.

For direction and magnitude of impact of technological innovation on efficiency, an endogeneity-corrected Tobit model is employed in the second step regression. Summary results for the Smith and Blundell (1986) test of exogeneity of the technological innovation variables is presented in table 7.3. It is noted that the exogeniety of hybrid seed was rejected in all the efficiency models. Therefore, the analysis is conducted using the predicted values of the hybrid seed. The exogeniety of other technological innovation variables could not be rejected in any of the efficiency models.

Table 7.3: Summary of Smith-Blundel test for exogeneity

Predicted residuals	TE	AE	CE
RES_HYV	0.080****	-0.150***	-0.066***
	(0.021)	(0.034)	(0.024)
RES_AFERT	-0.019	-0.044	-0.050
	(0.029)	(0.046)	(0.031)
RES_HERB	0.005	-0.042	-0.034
	(0.025)	(0.041)	(0.028)
RES_PRACTICES	0.005	-0.004	-0.005
	(0.009)	(0.015)	(0.010)

***Significant at 1 per cent level; ***significant at 5 per cent level; *significant at 10 per cent level. Standard errors are shown in parenthesis.

The estimated coefficients and marginal effects from the second stage endogeneity-corrected tobit model are presented in table 7.4. The significance of the likelihood ratio (LR) test in each of the integrated efficiency model implies that all the variables included are jointly significant in influencing technical, allocative and cost efficiency. Thus, the hypothesis that the technology and other policy variables included in the model have no significant impact on technical, allocative and cost efficiency is rejected. AGE has positive relationship with technical, allocative and cost efficiency but the influence is significant on technical efficiency only. Thus, the variable indexes experience and serve as a proxy for human capital showing that farmers with greater farming experience will have better management skills and thus higher efficiency than younger farmers. The second human capital variable, education (EDU) has positive and significant impact on technical efficiency implying that the more educated a farmer is the more he is able to produce at or near the frontier. Household size (HHS) was found to be positively and significantly related technical efficiency indicating the importance of abundant labour supply. LAND has positive and significant impact on allocative and cost efficiency only. The implication of this result is that larger farmers are more efficient in choosing cost-minimising input combinations than smallholder farmers.

MFG indexes social capital and affords the farmers opportunity of sharing information on modern maize practices by interacting with others as well as provides farmers with bargaining power in the input, output and credit markets. As expected, MFG was found to be consistently positive but it has significant impact on technical efficiency only. CREDIT has positive and significant impact on allocative and cost efficiency. The availability of credit loses the production constraints thus facilitating timely purchase of inputs and therefore increases productivity via efficiency.

Finally, an important goal of this study is to evaluate explicitly the impact of technological innovation on efficiency of maize farmers. Results from the integrated model show that, hybrid seeds (HYV) has positive and significant impact on technical, allocative and cost efficiency. These findings further strengthen the need for hybrid seed improvement and diffusion in Nigeria in line with the current doubling of maize production programme of the federal government. The use of inorganic fertilizer, AFERT was also found to have positive and significant impact on the allocative and cost efficiency.

PRACTICES have positive impact on all the efficiency measures though this impact is only significant for technical and cost efficiency. This implies that that economic and environmental sustainability can be viewed as complementary rather than competitive goals. The impact of these improved technologies on farm efficiency is not surprising as the yield benefits is expected to cushion the cost implications thereby reducing per unit cost of production, hence farmers who adopted these technologies are more technically, allocativelly and economically efficient than those who did not.

Table 7.4 Tobit model results of impact of technological innovation on efficiency

Variable	Technical efficiency		Allocative efficiency		Cost efficiency		Mean
	Coeff.	M.E	Coeff.	M.E	Coeff.	M.E	
GENDER	-0.024	-0.021	0.013	0.013	-0.008	-0.008	0.888
	(0.016)	(0.014)	(0.026)	(0.026)	(0.018)	(0.018)	
AGE	0.002***	0.002***	-0.001	-0.001	0.001	0.001	47.167
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	
EDU	0.003***	0.002***	0.001	0.001	0.001	0.001	8.433
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	
HHS	0.001*	0.001*	0.001	0.001	0.002**	0.002**	11.742
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	
LAND	0.013	0.012	0.042*	0.041*	0.067***	0.067***	1.208
	(0.015)	(0.014)	(0.025)	(0.025)	(0.017)	(0.017)	
OFFWORK	-0.013	-0.011	-0.004	-0.003	-0.013	-0.013	0.675
	(0.011)	(0.010)	(0.018)	(0.017)	(0.012)	(0.012)	
MFG	0.061***	0.054***	0.018	0.018	0.031	0.031	0.454
	(0.018)	(0.016)	(0.030)	(0.029)	(0.020)	(0.020)	
EXT	-0.003	-0.003	0.008	0.008	0.004	0.004	2.546
	(0.003)	(0.003)	(0.005)	(0.005)	(0.003)	(0.003)	
CREDIT	0.011	0.010	0.157***	0.145***	0.147***	0.147***	0.138
	(0.015)	(0.013)	(0.025)	(0.021)	(0.017)	(0.017)	
MARKET	-0.001	0.001	-0.001	-0.001	0.000	0.000	6.278
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	
HYV	0.021**	0.019**	0.048***	0.047***	0.035***	0.035***	0.895
	(0.011)	(0.009)	(0.017)	(0.017)	(0.012)	(0.012)	
AFERT	-0.017	-0.016	0.069***	0.067***	0.057***	0.057***	0.816
	(0.017)	(0.015)	(0.026)	(0.026)	(0.018)	(0.018)	
HERB	0.014	0.013	-0.023	-0.022	-0.007	-0.007	0.591
	(0.012)	(0.010)	(0.019)	(0.018)	(0.013)	(0.013)	
PRACTICES	0.013***	0.012***	0.001	0.001	0.008**	0.008**	1.75
	(0.004)	(0.004)	(0.006)	(0.006)	(0.004)	(0.004)	
INTERCEPT	0.650***		0.536***		0.281***		
	(0.035)		(0.057)		(0.039)		
LLF	270.354		155.880		249.203		
LR TEST	166.250***		103.130***		232.440***		

***Significant at 1% level; **significant at 5% level; *significant at 10% level. Standard errors are shown in parenthesis; M.E. = marginal effect

7.4 Conclusions

The results show that farmers who used either traditional or improved technologies were technically, allocativelly and cost inefficient. The average technical, allocative and cost efficiency are 84.2, 65.7 and 54.5 percent, respectively implying that farm households' technical, allocative and cost efficiency can be improved by 15.8, 34.3 and 45.5 percent, respectively in order to operate on the frontier. Results also show that use of hybrid seeds, inorganic fertilizer and conservation practices have positive and significant impact on farm efficiency. Control variables which also have significant impact on efficiency include education, age, household size, land size, credit, and membership in a farmer group. The results of the integrated model did not in any way hide any important information that will assist policy making as some opponents of aggregation would argue. Rather, the findings of the integrated model consolidate those of the individual models. Therefore one is confident using the integrated model when the choice between parametric and non-parametric approaches is not clear cut as is often the case in most efficiency studies.

CHAPTER 8

SUMMARY, CONCLUSIONS AND POLICY IMPLICATIONS

In this chapter, the methodology employed in this study is summarized. The summary and conclusions on the results obtained are provided and their policy implications are given. The study recognizes a number of limitations and therefore recommendations for further research are provided based on these.

8.1 Summary and Conclusion

The maize sub-sector has featured in a number of Nigeria's policy initiatives, the most current of which involves doubling of its production and productivity through promotion of improved technologies such as hybrid seed, inorganic fertilizer, pesticides, herbicides, and better management practices. Despite the policy initiatives, maize productivity has remained low raising question about the efficiency of resource use by the farmers and the benefits of the Nigeria's technology policy. For justification of further investment in development and promotion of improved maize technologies, empirical evidence is needed. The broad objective of this study is to evaluate efficiency results from both parametric and non-parametric approaches with application to small-scale maize production in Benue State, Nigeria.

There are a limited number of studies in agriculture that have dealt with technical, allocative and economic efficiency simultaneously. Among these studies only few compared results from different approaches. Majority of the comparative studies involved the parametric stochastic frontier production function and data envelopment analysis which is non-parametric. However, the use of stochastic frontier production function for decomposing cost efficiency into its technical and allocative components involves an imposition of input-oriented framework on the output-oriented stochastic frontier production function results. The resulting efficiency estimates therefore suffer from simultaneity bias. Further, the estimation of the cost frontier is not practical when there is little or no variation in input prices among farmers which is often the case in most developing countries and it is not also appropriate when there is deviation from behavioural assumptions.

This study employed the distance frontier efficiency decomposition techniques that do not suffer from the simultaneous equation bias when analysis extends to allocative and cost efficiency nor does it require variation in input prices across firms to provide valid estimates of allocative and cost efficiency. Both parametric and non-parametric distance frontiers are employed. Four specific objectives are pursued in this study. First is a comparison of the performance of technical, allocative and cost efficiency measures from both parametric stochastic and non-parametric distance functions. Second is an assessment of the impact of measuring technical, allocative and cost efficiencies relative to a distance function versus a production frontier. Third is an analysis of the effect of technology and other policy variables on technical, allocative and cost efficiencies of maize farmers in Benue State Nigeria using the different frontier models. Fourth is a provision of final technical, allocative and cost efficiency estimates and policy impacts in an integrated frontier framework.

The study used data obtained from a field survey for the 2008/2009 agricultural year. A multistage stratified sampling technique was employed in selection of respondents. There are three agricultural zones in Benue State namely, A, B and C. Zones B and C were selected in the first stage through a simple random technique. In the second stage, Buruku and Gwer East were selected from Zone B while Oju and Otukpo were selected from Zone C based on their adequate representation of distinct maize production and on active operation of Benue State Agricultural and Rural Development Agency. In the third stage, a total of 240 farm households were randomly selected and interviewed and data was collected on their production activities, technology adoption and socioeconomic characteristics.

Results from all the approaches indicated considerable technical, allocative and cost inefficiency under both traditional and improved maize technology. For the SIDF model, the average technical, allocative and cost efficiency estimates are 86.7, 57.8 and 50.3 percent, respectively. For the VRS DEA model, the average technical, allocative and cost efficiency estimates are 85.5, 65.9 and 51.6 percent, respectively. For the CRS DEA model, the average technical, allocative and cost efficiency estimates are 80.1, 65.9 and 51.6. For the SFPF model, the average technical, allocative and cost efficiency estimates are 85.3, 52.6 and 44.6, respectively. The result from all the approaches indicated that inefficiency in maize production in Benue State is dominated by cost inefficiency suggesting the immense potential of enhancing production through improvement in overall efficiency.

Two approaches were employed in the analysis of technology impact on efficiency namely t-test of equality in means and second stage Tobit regression after testing and correcting for endogeniety. The impact analysis suggest that use of hybrid seed, fertilizer, herbicides and conservation practices as well as age, education, household size, land, engagement in off farm work, membership in a farmer organization, access to extension, credit and market are significant determinants of technical efficiency in at least one of the models. For allocative efficiency, hybrid seed, inorganic fertilizer and herbicides as well as land, extension and credit are significant determinants in at least one of the models. For cost efficiency, hybrid seed, inorganic fertilizer and conservation practices as well as age, household size, land, membership in a farmer group, extension and credit are significant determinants in at least one of the models.

In addition to the comparison of absolute values of efficiency scores from the four models, formal sensitivity tests were conducted. Both parametric and non-parametric tests were conducted. These include: a t-test of equality in means and Wilcoxon signed-rank test of equality in distribution within the bilateral pairs of the employed approaches, Kruskal-Wallis and ANOVA tests of equality in variances and the Spearman rank correlation test of independence for overall consistency. The overall consistency check shows that technical, allocative and cost efficiency measures from the three distance functions (SIDF, VRS DEA and CRS DEA) were consistent whereas similar conclusions could not hold when these were compared to the production frontier (SFPF) especially for technical efficiency estimates. Given the consistency of results from the parametric and non-parametric distance functions, an integrated input distance model was developed for providing final efficiency estimates and analysis of policy impacts. This final analysis is important given the strengths and weaknesses of the different parametric and non-parametric approaches which make it difficult to justify the preference of one approach to the other.

The results of the integrated model did not in any way hide any important information that will assist policy making as some opponents of aggregation would argue. Although, results show that farmers who used improved technologies were more efficient in general than the traditional farmers. On average both group of farmers were technically, allocativelly and cost inefficient thus giving room for improvement of maize productivity for both groups. When the sample is split according to use of each of the technology innovation packages, results show that the mean technical, allocative and cost efficiency of farmers who used hybrid seeds are 86.2, 65.7 and 55.9 percent, respectively while the corresponding values are 76.7, 65.6 and 49.1, percent for those who did not use hybrid seeds.

For farmers who used inorganic fertilizers, the mean technical, allocative and cost efficiency estimates are 83.7, 66.3 and 54.7 percent, respectively while the corresponding values are 92.0, 55.9 and 51.4 percent for those who did not use inorganic fertilizer. For farmers who used herbicides, the mean technical, allocative and cost efficiency estimates are 86.1, 64.3 and 54.7 percent while the corresponding values for those who did not use herbicides are 80.9, 68.1 and 54 percent.

For farmers who used conservation practices, the mean technical, allocative and cost efficiency estimates are 87.7, 66.5 and 57.6 percent, respectively while the corresponding values for non-users are 78.1, 64.3 and 49 percent. It can be observed that in almost all cases, the technical efficiency of traditional maize producers are lower than those of improved maize producers.

When the full sample is considered, the average technical, allocative and cost efficiency are 84.2, 65.7 and 54.5 percent, respectively implying that there is a possibility of raising maize production by 45.5 percent through overall efficiency improvement. Under the integrated approach, the study revealed that hybrid seeds, inorganic fertilizer and conservation practices have positive and significant impact on farm efficiency. Other determinants of efficiency include education, age, household size, land size, credit, and membership in a farmer group.

8.2 Policy Implications

A number of agricultural policies and or initiatives have been put in place to foster the growth of maize in Nigeria. For instance, the 2006 presidential initiative of doubling maize production and the 2008 President Umaru Yaradua seven-point agenda which also featured maize as an important crop were all targeted at the growth of maize and other major crops. However, productivity still remains low. Based on the findings of this study, resources are not efficiently used by maize farmers owing to a number of factors which include limited use of modern technologies such as improved maize seed, inorganic fertilizers and conservation practices, smallness of farm holdings, inadequate formal education, access to extension services and credit. Similar results were found by other Nigerian researchers. For instance, Ogundele and Okoruwa (2004) found that the use of improved rice varieties and area expansion had positive influence on technical efficiency. Further, Okoye et al. (2006) found that the use of inorganic fertilizer had positive impact on allocative efficiency on cocoyam farmers.

The positive and significant impact of hybrid seed calls for the Nigerian government to invest more in research and development that will produce a viable seed sector in the country. Greater availability and accessibility of inorganic fertilizers is very crucial as these could enhance the efficiency of smallholder farmers. This was also evidenced in the under-utilization of fertilizer as a production input. Given the escalating prices of inorganic fertilizers, alternatives such as soil conservation practices which reduce the effective costs of soil fertility management options are necessary. This should essentially form an important extension package to all farmers since the goal of economic benefits and environmental sustainability must be balanced. In view of the interactions among the agricultural technology packages, it is argued that adoption of the whole package would be more profitable than adopting a component or some components of the technology package. From these findings, a further investment in agricultural research and development is necessary for increasing efficiency and productivity of maize production and subsequently reducing food insecurity and poverty alleviation in Nigeria.

The positive relationship between access to credit and efficiency of the farmers implies that policies that will make micro-credit from government and non-governmental agencies accessible to these farmers will go a long way in addressing their resource use inefficiency problems. These would help farmers to purchase critical inputs like fertilizers and hybrid seeds. Given the significance of education, policies to provide adequate funding for the universal basic education programme in Nigeria should be given urgent priority. The role of education cannot be overstressed as it enhances farmers' skills and understanding of seemingly complex techniques. A review of agricultural policy with regard to renewed public support to revamp the agricultural extension system is needed. The quality and adequacy of extension services in Nigeria needs to be upgraded. Proper training needs to be provided for extension agents in order to enhance effective delivery of the innovation messages to farmers. In other words, additional efforts should be devoted to upgrade the skills and knowledge of the extension agents as well as ensuring timely dissemination of modern technological inputs and practices.

The design and implementation of policies and strategies that would encourage farmers to form farmer organisations or join existing ones will be a step in the right direction to ensuring improvement in technical, allocative and cost efficiency and subsequently maize productivity growth. This is because these organizations serve as social capital which expands a farmer's social network and therefore provides better avenues for farmers to be well integrated into the input and output markets. In order to reap the benefits of strong farmer associations, policy on farmers associations and cooperatives must be based on the context of Nigerian rural institution's socio-economic environment and should be built on it. These associations need to be integrated as important partners within the agricultural research system of Nigeria. Government should create enabling environment for private sector promoters of farmer organizations. Adequate training of executive members of these associations on capacity building, design and implementation of projects, and policy analysis may be necessary. Recognition and reward for farmer organizations that achieve defined objectives and levels of excellence in farm production and marketing and other related areas can serve as a booster in the activities of not only the successful organization but others will attempt to emulate them.

Farmers in the study area cultivate only a small area of land and the results indicate that farmers operate with increasing returns to scale implying that the small scale of operation could be another important source of inefficiency. Hence, policies to ensure large scale of operation are recommended. This does not mean that small scale farmers should be moved out of farming. This is essentially impossible as there are only a handful of large scale farmers in Nigeria. Rather, policies to ensure that more land is allocated for farming purposes are recommended. In essence, commercialization of maize production in Nigeria would be a step in the direction towards increased productivity. In the long run it is expected that these small scale farmers today will eventually become the large scale farmers tomorrow and hence will benefit from any land expansion policy.

In conclusion, appropriate policy formulation and implementation is an effective instrument to improvement in farm efficiency and productivity which promotes overall growth of the economy. Although, the promotion of improved technologies is an important instrument in increasing agricultural productivity, it is not sufficient to make the needed necessary impacts on rural livelihood and the economy at large. Therefore, complementary policies which include investment in education, land expansion, improvement in the extension system, efficient credit delivery system including access to credit from both micro-credit and commercial banks and enabling market oriented policies must also form part of the strategy. Finally, there is a need for all the stake holders (both the public and private sector) to make concerted efforts to remove the bottlenecks that have constrained effective policy implementation and its accrued benefits in the Nigerian agriculture.

8.3 Limitations of the Study and Areas for Future Research

This study was conducted on a single crop, that is, maize production. Farms may neither keep good records nor recall accurately input allocations among different crops and hence this poses a limitation in this study. However, the methodology employed in this study accommodates multiple outputs and therefore, an extension of this study to analysis of either the multiple crops is recommended. The study is limited by dearth of household panel data in Nigerian agriculture. A better understanding of impact of technology on production efficiency and productivity could be provided in a dynamic framework. An extension to a panel study that incorporates both the fixed and random effects parameters is recommended.

The study estimated a single frontier for both adopters and non-adopters given the wide range of technology innovation variables studied. Aggregate index of technological innovation may be computed to verify the impact of this single index on production efficiency and productivity. In this case, separate frontiers can be estimated for each group of farmers. Further, the study did not consider scale effects on the estimated efficiencies. This can be another area of study.

The study considered non-statistical DEA models. An understanding of the statistical properties of efficiency estimates from DEA models cannot be overstressed. Given recent developments in statistical DEA models, an extension of this work using the bootstrapped DEA model will be interesting. This might eliminate or reduce some of the bias often witnessed in non-statistical DEA results.

Finally, frontier analysis is, by definition, a best practice benchmark methodology, therefore the efficiency scores and results obtained in this study are relative to the observed population, in this case maize farms in Benue State Nigeria, characterized by low level of productivity by hectare. Therefore, absolute efficiency scores may drop dramatically if same farms were pooled in the same sample with maize farms in other countries and regions of the world. Therefore, an extension of the study to other countries and regions where it is possible to study efficiency of large scale farmers using similar methodology as in this study may be a good idea.

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APPENDIX 1: QUESTIONNAIRE

RESEARCH QUESTIONNAIRE FOR SMALLHOLDER MAIZE PRODUCTION IN BENUE STATE NIGERIA

Please carefully read and complete the questionnaire. All revealed information will be treated confidentially. Where exact figures are not available, please provide careful estimates. This questionnaire should be completed for the 2008/2009 farming season

PART A. GENERAL INFORMATION

1. Household Identification number…………………………………………………..

2. Local Government Area……………………………………………………………….

3. District…………………………………………………………………………………

4. Village/community…………………………………………………………………

5. Name of Interviewer………………………………..Date of Interview……………

PART B. RESPONDENT (HOUSEHOLD HEAD)

6. Name……………………………………………………………………………….

7. Age……………………………………………………………………………years

8. Sex: Male ( ) Female ( )

9. Ethnic/Language Group…………………………………………………………

10. Educational Level:

(a) No formal Education ( )

(b) Primary school ( )

(c) Secondary school ( )

(d) University ( )

(e) Other (specify)……………………………………………………………...

11. Total number of years of formal education if any…………………………Years

12. Main occupation:

(a) Farmer ( )

(b) Civil Servant ( )

(c) Self-employed ( )

(d) Employee in a private company ( )

13. What is your household size including yourself? Please specify below:

Household member	Number
Adult male (age 15 years and above)	
Adult female (age 15 years and above)	
Children (below 15 years of age)	
Total household size	

14. How long have you been farming? ……………………..……………………years

PART C: COMPOSITION AND TOTAL LAND AREA IN HECTARES

(Note: 1 hectare (ha) is about 2.5 acres or equivalent of a standard football field; 1 acre =0.4 hectares. Please always indicate the area unit if not in hectares)

15. Total land owned by you and farmed on by yourself…………………...(hectares)

16. Total land not owned by you but on which you farm

Share farming…………………………………………………..…………..(hectares)

Rented/leased from others ………………………………..…………….….(hectares)

17. Total land owned by you and rented or leased out to others**…………...**.(hectares)

PART D: INPUT UTILIZATION AND COST OF PRODUCTION OF MAIZE

(Note: 1 kg is approximately a muudu; 50kg =a bag of fertilizer; 1000kg = 20 bags of fertilizer. Illustrate this clearly to the farmer for all quantities to be specified in kg).

19. What area of land did you cultivate **maize** during the last farming season?..........ha

20. Did you rent any part of the cultivated maize farm in No. 19? Yes ☐ No ☐

21. If yes, how many hectares did you rent for maize production?...............................

22. How much did a hectare of farm land cost last farming season?…………………₦

23. What quantity of maize seed did you plant last farming season?.........................Kg

24. How much did you spend on purchase of maize seed for planting?.....................₦

25. Are you aware of any improved maize seed variety? Yes ☐ No ☐

26. If yes give names of the improved maize seeds you know:

(a)...

(b)...

(c)...

(d)...

(e)...

27. Please indicate if you use/apply any of the following technology on your **maize** farm last farming season?

Type of technology	Yes	No
Improved/hybrid maize seed		
Inorganic fertilizer		
Herbicide		
Pesticide/insecticide		
Organic fertilizer		

28. If yes to any in No. 27 complete the table below for the technology (ies) used

Type of chemical	Quantity used	Unit e.g. kg, litre etc	Cost per unit ₦	Total amount spent ₦	Area of total maize farm (ha) cultivated with	Source e.g open market, govt, friend, etc
Improved seed						
Inorganic Fertilizer						
Pesticide/insecticide						
Herbicide						
Organic fertilizer						

29. How much was a kg (muudu) of local maize seed last farming season?...............₦

30. How much was a kg of improved maize seed last farming season?.....................₦

31. Please give an estimate of the number of days and hours per day each of this category of your family members (including yourself) was involved in the following operations done on maize farm last farming season?

Type of activity	Adult male No. of members	No. of Days	Adult female No. of members	No. of Days	Children No. of members	No. of Days
Land preparation						
Planting						
Weeding						
Fertilizer application						
Spraying						
Harvesting						
Total						

32. What was labour cost **per day** in your area last farming season for an adult male…………₦; an adult female…………………₦; Children…………….

33. Did you hire labour to work on your maize farm last farming season? Yes ☐ No ☐

34. If yes please fill the table below with respect to hired labour on your maize farm?

Type of activity	Adult male No. of hired labour	No. of Days worked	Cost (₦) for	Adult female No. of hired labour	No. of Days	Cost (₦) for	Children No. of hired labour	No. of Days	Cost (₦) for
Land preparation									
Planting									
Weeding									
Fertilizer application									
Spraying									
Harvesting									
Total									

35. Please give an estimate of the amount it costs to hire labour to carry out all the farm operations listed above for **a hectare** of maize farm?........................... (₦)

36. Did you do any form of soil conservation on your maize farm last season? Yes ☐ No ☐

37. If yes please tick the type of soil conservation practice (s) you did:

(a) Composting ( )

(b) Terracing ( )

(c) Fallowing ( )

(d) Crop rotation ( )

(e) Mulching ( )

(f) Contour ploughing ( )

(h) Minimum tillage ( )

(i) No tillage ( )

(j) Manuring ( )

(k) Planting of trees ( )

(l) Other (specify)…………………………………………………………………………

38. If you paid money for any of the conservation practices done, how much?.................₦

39. If you sold all or part of your last season maize output in the market, how much did you pay for transport to and fro the market…………………………. …………₦

PART E: PRODUCTION AND GROSS FARM INCOME

(Note: 1 kg is approximately a muudu; 50kg =a bag of fertilizer; 1000kg = 20 bags of fertilizer. Illustrate this clearly to the farmer for all quantities to be specified in kg).

40. Please complete the table below for your maize production last farming season.

Area planted (ha)	Area harvested (ha)	Quantity harvested (kg)	Quantity sold (kg)	Price per kg (₦)	Income from maize farm (₦)

41. How much did a standard 100kg bag of maize cost last farming season in your area?...................................₦

42. Apart from income earned from your own farming operations and lease or renting out of land, did you have any other income last agricultural seaso Yes ☐ No ☐

43. If yes to no. 42, specify how much you received from any of the following sources?

(a) Farm work done for other farmers..₦

(b) Money as remittance from friends/relatives etc……………………………₦

(c) Wages from non-agricultural work…………………………………………...₦

(d) Pension…………………………………………………………………………₦

(e) Other sources (specify)......……………………………………...………₦

PART F – ACCESS TO SERVICES

44. Are you a member of any farmer group or cooperative? Yes ☐ No ☐

Yes ☐ No ☐

45. Were you visited by extension agent(s) last farming season?

46. If yes, how many times were you visited by the extension agent(s)?......

47. Did you receive credit for maize farming from any source last season? Yes ☐ No ☐

48. If yes, please indicate the source (s) of your farm credit last farming season:

(a) Commercial Banks ( )

(b) Friends and relatives ( )

(c) Farmer organizations ( )

(d) Private money lenders ( )

(e) Other (Specify)…………………………………………………………………..

49. How far is the nearest market from your house?..Km

PART G: TECHNOLOGY CHARACTERISTICS AND FARMER PERCEPTION

50. Do you think hybrid maize produces more than the local maize? Yes No

51. Do you think hybrid seed is sweeter than the local maize variety? Yes No

52. Do you always get fertilizer at the right time and quantity? Yes No

53. What are your expectations about rainfall this year? Low High

54. Do you perceive a need for weed control in your maize farm? Yes No

55. How would you assess the dangers of herbicide use to the environment? Low High

56. Please can you assess the topographic nature of your maize farm (s)? Flat Steep

57. Do you think that soil erosion is a problem in your maize farm? Yes No

PART H: PROBLEMS ENCOUNTERED IN MAIZE FARMING

58. In general what are the five (5) most important problems in your maize farming?

(a)………………………………………………………………………………………

(b)………………………………………………………………………………………

(c)………………………………………………………………………………………

(d)………………………………………………………………………………………

(e)………………………………………………………………………………………