TECHNICAL EFFICIENCY, TECHNOLOGICAL CHANGE, AND RETURNS TO SCALE IN THE PRODUCTION OF SELECTED FOOD CROPS IN UGANDA

BY

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A DISSERTATION SUBMITTED TO THE DIRECTORATE OF RESEARCH AND GRADUATE TRAINING FOR THE AWARD OF THE DEGREE OF DOCTOR OF PHILOSOPHY IN ECONOMICS OF MAKERERE UNIVERSITY

DECEMBER 2018

DECLARATION

I, **REBECCA MUTEBI KALIBWANI**, do hereby declare that this dissertation is my own work and has not been submitted to any institution of higher learning for any award.

Signature

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Date ……7th December, 2018

This dissertation has been submitted with our approval as University Supervisors.

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DEDICATION

To Andrew, Philip, and Simon

ACKNOWLEDGEMENT

I wish to acknowledge a number of people who have supported me in this study. First, my supervisors; Dr. John Mutenyo and Dr. James Muwanga, for making it possible for me to complete the study. My sincere gratitude to my colleagues in project work; Edward Kato, of the International Food Policy Research Institute (IFPRI), Washington, U.S.A, and Laban B. Wasswa of the Medical Research Council in Entebbe, for their valuable contribution in giving direction to the study.

I am grateful to the Uganda Bureau of Statistics (UBoS) for providing me with the Uganda National Panel Survey data for 2005/06 and 2010/11 which was used for the study and Dr. Isaac Shinyekwa of the Economic Policy Research Centre (EPRC), Makerere, for making time to review and provide comments to the first draft of this dissertation. I am equally grateful to Bishop Stuart University, Mbarara, Uganda for funding the research, and all my friends and colleagues at this University for their support and encouragement.

Finally, I wish to appreciate my parents, brothers and sisters; the entire family of the Rt. Rev Wilson and Mrs. Faith Mutebi, for being there for me and always providing me with moral, emotional and spiritual support in the journey of life. I will for ever be grateful.

Rebecca Mutebi Kalibwani

Mbarara, December, 2018

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ACRONYMS AND ABBREVIATIONS

CAADP	Comprehensive Africa Agriculture Development Programme
DSIP	Development Strategy and Investment Plan
EPRC	Economic Policy Research Centre
EU	European Union
FAO	Food and Agriculture Organization
GDP	Gross Domestic Product
MAAIF	Ministry of Agriculture, Animal Industry and Fisheries
MFPED	Ministry of Finance Planning and Economic Development
ML	Maximum Likelihood
NAADS	National Agricultural Advisory Services
NAP	National Agriculture Policy
NARO	National Agricultural Research Organization
NARS	National Agricultural Research System
NEMA	National Environment Management Authority
NRM	National Resistance Movement
NUSAF	Northern Uganda Social Action Fund
OLS	Ordinary Least Squares
PEAP	Poverty Eradication Action Plan
PFA	Prosperity for All
PMA	Plan for Modernization of Agriculture
PRDP	Peace, Recovery and Development Program for Northern Uganda

RoU	Republic of Uganda
TDS	Technology Development Site
UBoS	Uganda Bureau of Statistics
UNHS	Uganda National Household Survey
UNPS	Uganda National Panel Survey
ZARDI	Zonal Agricultural Research and Development Institute

ABSTRACT

Although the agriculture sector is an important sector for food security, poverty reduction and overall economic growth in Uganda, the productivity of the food crop sub-sector remains unsatisfactory. While existing studies have mainly been cross-sectional due to lack of panel data, it is imperative that evidence is provided on the temporal performance of the sector across specific major subsectors, highlighting the aspects that have consistently resulted into favourable positive impacts and those that have resulted into poor performance, in order to enhance existing strategies aimed at improving productivity in the sector. The study estimated and investigated three components of productivity; technical efficiency, technological change, and returns to scale in four of the country's major food crops; maize, beans, banana, and cassava for the period between 2005-2010. The study also established the determinants of the observed technical efficiency during the same period. Using national panel data for 2005/06 and 2009/10 collected by the Uganda Bureau of Statistics, the study utilized two econometric approaches; a *translog* stochastic frontier production function model to estimate technical efficiency, technological change and returns to scale, and a robust ordinary least squares regression to establish the determinants of technical efficiency.

The results revealed that mean technical efficiency across the four food crop farming households was low during the study period, estimated at 22%, 15%, 15% and 14% for maize, beans, banana and cassava farming households respectively. These results imply that there would still be a possibility to produce 78%, 85%, 85%, 86% more output of maize, beans, banana, and cassava respectively, using the same resources and at the existing technology. Mean technical efficiency declined between the two time periods, and significantly so (at 1% level) for both beans and banana farming households. The key factors that determined technical efficiency across the four farming households were education, extension visits, crop area, location where a household was located, whether in the rural or urban area, and housing index which was composed of a number of features that would indicate the well-being of a household. Although purchased inputs would ordinarily be expected to increase food crop productivity, improvement in productivity among the farming households was propelled more by technical change, resulting from intensified use of both family and hired labour, than technical efficiency. Maize and cassava farming households exhibited increasing returns to scale, implying that expanded use of purchased inputs and crop area would be beneficial to raise their productivity. On the contrary, bean and banana production exhibited decreasing returns to scale, implying that it would neither be worthwhile expanding the use of purchased inputs, nor crop area at the existing technology.

In terms of policy, the results underscore the need for government to promote the use of purchased farm inputs through market interventions that will enable input and output prices to motivate investment by maize and cassava farming households, and effort to improve the level of technology to raise returns to scale for beans and banana. Across the four crops, government should pursue a land reform policy that will support farming households to secure and expand food crop area in rural areas, provide market supportive road and physical infrastructure, education and extension support for household heads and spouses, specifically on market dynamics of purchased inputs and food crop output, in order to enhance food crop productivity.

CHAPTER ONE

INTRODUCTION

1.1 Background

Agriculture is an important sector for sustaining economic growth in developing countries. It employs 62% of the population of SSA (excluding South Africa) and generates 27% of GDP of these countries, with the majority of the poor living in rural areas (World Bank, 2006). An agriculture-led strategy of economic growth is therefore expected to offer most countries of sub-Saharan Africa (SSA) rapid economic growth and poverty alleviation (Staatz and Dembele, 2007) However, SSA is the only region of the world where poverty and undernourishment have been on the increase and where those living on less than $1/day have become poorer (World Bank, 2005 in Staatz and Dembele,2007). This weak economic performance is closely linked to slow productivity growth in the agricultural sector, the sector that is the key determinant of their overall economic growth and poverty reduction (Christiansen and Demery, 2007; Fuglie, 2010). Boosting agricultural productivity therefore remains key for poverty reduction in most of these countries (Christiensen, 2017).

Agricultural productivity is conceptually a measure of output to input, whose appropriate indicator and measure is either partial factor or total factor productivity (Benin *et al.*, 2011). Partial Factor Productivity (PFP) is a ratio of output to a specific subset of the total input factors, and it is usually limited to one input factor. It is hence described as single factor productivity. Two commonly used measures of PFP are labor productivity which is output per worker or the ratio of output to total number of hours worked, and land productivity which is crop output per hectare (Benin *et al.*, 2011; Fuglie and Rada, 2013). These measures make it possible to focus on a given variable such as labor or land, to assess how that variable is influencing or contributing to the level of output (Benin *et al.*, 2011). However, sustainable agricultural growth can only be achieved through increased total factor productivity (TFP) (Nin-Pratt and Yu, 2009). TFP measures the total conventional resource cost of producing economic outputs, and takes into account contributions of all conventional inputs to production; land, labor, capital and materials (Fuglie and Rada, 2013). Because TPF is a ratio of output to all factors and inputs used in producing the output, the variables measured in PFP are by definition components of TFP (Benin *et al.*, 2011).

In the analysis of productivity, TFP is usually favored because long-run agricultural growth depends on it, and its two constituents; efficiency and technical change or technological advancement (Benin *et al*., 2011). Efficiency arises from a reallocation of inputs of productive factors, while technical change is used to describe a change in the amount of output produced with unchanged levels of input (Benin *et al*., 2011; Torero 2013). Such a change is typically technological and may arise from investment in research and development (R&D) infrastructure, and institutional development among others.

In Uganda, agriculture is a strategic sector in the country's economy, targeted for the transformation of the economy from a peasant to a modern prosperous society in 30 years (Ministry of Agriculture, Animal Industry and Fisheries [MAAIF], 2010). It plays a dominant role in export earnings, contributing 85% of the country's total exports (Ministry of Finance Planning and Economic Development [MFPED], 2010a), and employing the largest proportion of Uganda's labour force. The sector provided employment to about 72% of the working population in 2012/13, and a livelihood to about 86% of the population (MFPED, 2014). Although the contribution of agriculture to Gross Domestic Product (GDP) at current market prices stands at only 20.9%, the sector has contributed to the growth of the industrial sector whose contribution to overall GDP is estimated at 25.4%, through agro processing activities (Republic of Uganda [RoU], 2015a). Nonetheless, this means that the biggest proportion of the working population, 72%, who are employed by the sector, contribute the least to GDP than the remaining 28% who contribute 79%. The performance of the sector is therefore an issue of great policy concern where the major concern relates to overall agricultural productivity. Improvement of agricultural productivity is believed to contribute to national economic development and transformation through various channels. These include supplying an economic surplus that can be consumed or used for further production in agriculture, enabling the release of labour and other resources for use in the non-agricultural sectors, and increasing the purchasing power of the rural people.

Although agriculture in Uganda performed well in the years between 1987-2009, growing at an average of 3.8 percent, the sector has been declining in the years that followed, growing at a rate below 2% per annum, and slower than population growth (MAAIF, 2010; RoU, 2013). For instance, real growth in agricultural output declined to 0.1 percent in 2006/07 (Uganda Bureau of Statistics [UBoS], 2009), before recovering to 1.3 percent and 2.6 percent in 2007/08 and 2008/09, respectively. This rate of growth was below the population growth rate of 3.2 percent, implying that per capita agricultural GDP was declining at the time. In the recent past, growth has continued not to be impressive, at 1.4% far below the economy's average growth rate which has been above 5 percent for the past 10 years (RoU, 2014). It is also far short of the 6 percent growth target for the agricultural sector set by African Governments under the Comprehensive Africa Agriculture Development Program (CAADP). Given that 66 percent of all households in Uganda are engaged in agriculture, a declining performance matters greatly for their livelihoods and represents a setback in the drive to eradicate poverty and create wealth (MAAIF, 2010; RoU, 2014).

In Uganda, as in most African countries, because of its importance in overall GDP, export earnings and employment as well as its forward and backward linkages to the non-farm sector, growth in the agricultural sector will continue to be the cornerstone of poverty reduction. Growth in the productivity of the agriculture sector is recognized to be one major way that will contribute to the process of economic growth. The relevant question then, for agricultural policymakers is whether the agricultural sector can be made more efficient, by achieving more output with the current input level, or by achieving the current output with less input usage than is currently observed. In answering these questions, it is important to understand the pathway of productivity and its components. Among the key factors in improving productivity are technical change and/or efficiency change, and improving agricultural returns to scale (Nkamleu, 2004; Takeshima, 2015). Agricultural productivity can be improved either through the development and adoption of new technologies or technical change, or through the efficient use of the existing technologies, hence technical efficiency (Abdulai, Nkegbe, & Donkoh, 2013).

Further, returns to scale also have profound implications on how effective governments' various efforts in developing countries lead to agricultural transformation. While historically, agricultural transformation has often accompanied increasing returns to scale, understanding the drivers of growth in agricultural returns to scale is important because it offers insights into the key areas in which government should intervene to transform the agricultural sector (Takeshima, 2015). Although there is a substantial body of literature measuring agricultural productivity change in the developed countries (Kalirajan *et al.,* 1996; Fare *et al.*, 1994), in sub-Saharan Africa, empirical studies to systematically characterize the agricultural productivity in the region are scarce (Nkamleu, 2004).

1.2 Statement of the Problem

Although several policy reforms have been undertaken in the agricultural sector in Uganda, with investment of donor development funds, the performance of the sector has continued to remain unsatisfactory. For instance in 2001, the National Agriculture Advisory Services (NAADS) was set up to focus the country's extension services towards technology dissemination (Kasirye 2013), with about 45% of the country's agricultural budget devoted to technology development and stocking of agricultural inputs (MAAIF, 2010). Available literature shows that even despite availability of productivity enhancing technologies on the market, crop yields remain low (Nabbumba and Bahiigwa, 2003). While to some extent this is due to reluctance and hence poor adoption of the technologies by the farmers (Okoboi, Muwanga, &Tumwebaze, 2012; Kasirye, 2013), it is also true that other farm/farmer characteristics factors persist over time and across specific sub-sectors, to constrain productivity growth.

The growth of the sector has remained below 2%, well below the 6% target that would half poverty in the country by 2015 (MAAIF, 2010; RoU, 2015a). The food crop sub sector that comprises 52% of the sector (RoU, 2015a) and contributes up to 54% of agricultural GDP is most vulnerable. This poses a challenge on how to continue addressing this cardinal problem through agricultural intensification, specifically through the constituent components of productivity, namely, technical efficiency, technological change and returns to scale, and trucking those factors that over time work to constrain productivity. It is therefore important that evidence is provided on the temporal performance of the sector across specific major subsectors, highlighting which aspects have consistently resulted into favourable positive impacts and those that have resulted into poor performance, in order to enhance the existing strategies aimed at improving productivity in the sector. This study aims to provide this evidence using a national panel dataset.

1.3 Objectives of the Study

1.3.1 Overall Objective

The overall objective of the study was to examine the factors that drive the components of agricultural productivity; technical efficiency, technological change and returns to scale, in Uganda's food crop subsector. The study considers four of Uganda's major staple food crops; Maize, beans, Banana, and Cassava, between 2005 and 2010.

1.3.2 Specific Objectives

i) To estimate and investigate technical efficiency and investigate its determinants among the selected food crop farming households,

ii) To estimate and investigate technical change among the selected food crop farming households,.

iii) To examine the status of returns to scale among the major food crop sub-sectors.

1.4 Research Hypotheses

i) Food crop farming households in Uganda are not technically efficient,

ii) There was no technological change in Uganda's food crop sub sector between 2005 and 2010.

iii) There are positive returns to scale in Uganda's food crop sub sector.

1.5 Significance of the study

Attempts have been made to study productivity in Uganda's agriculture (Bagamba, Ruben & Rufino, 2007;Okoboi 2010; Okoboi *et al.*, 2012; Bategeka, Kiiza & Kasirye, 2013; Sebuwufu *et al.*, 2015) however the lack panel data has restricted analysis to cross sectional units. The studies have also been limited in scope by focusing on a sub-sector, or one location, so their findings cannot be generalized to other places in Uganda. This study provides micro-econometric based evidence using two waves of panel data collected by UBoS and representative of the heterogeneity in the country. The use of panel data allows the study of the components of productivity (technical efficiency, technological change and returns to scale) and the determinants of technical efficiency over time. The study captures the heterogeneity among the selected food crops, and enables the understanding that the factors influencing productivity vary not only with time but across sectors.

Furthermore, while a number of studies attempt to examine production efficiency between farmer groups, no attempt was directed at examining the rate of technological change overtime if any and the possible factors that would be crucial in influencing it. Most studies have not looked at technological change. It would be important to know whether the sector experiences technical progress, whether it is stagnant over time and whether a given technology is being used in such a way as to realize its full potential. In growing economies, technical progress has been credited for much of the improvement in sector and firm level productivity.

It is hoped that the study will provide useful insights to policy makers, farmers and extension workers to enable the development of interventions that will sustainably enhance productivity in the food crop sub-sector.

1.6 Scope of the study

The study focuses on the production of four of the major food crops grown in the country; Maize a cereal, Cassava a root crop, beans a grain legume, and bananas a staple crop in most of the central and western regions. The four food crops are priority crops in the country's National Development Plan (2015/16-19/20) that were selected for their high potential for food security, great potential to increase productivity through better management, and high returns on investment among other things. The study was concerned with three issues; the mean technical efficiency scores of the producer households per crop as well the determinants of the efficiency, technological change in the food crop sub-sector and its sources during the period of study, as well as the partial productivities of the inputs of production to determine returns to scale.

1.7 Definition of Key Terms

Productivity

This refers to the amount of output obtained from given levels of inputs. The concept of productivity examines the relationship between input and output in a given production process.

Technical Efficiency

This is the ability of a firm to produce a given level of output with a minimum quantity of inputs given the technology. It reflects the ability of the firm to obtain maximal output from a given set of inputs (Farrell, 1957).

Technological Change

This is the change or a shift in the best practice production frontier with all input quantities held constant (Nishimizu and Page, 1982; Karagiannis, Midmore & Tzouvelekas, 1999).

Returns to Scale

This is the sum of the elasticities of production or the sum of the partial productivities of the selected inputs of production.

1.8 The Conceptual Framework

Efficiency reflects the ability of a firm to obtain maximum output from a given set of inputs (Farrell, 1957; Benin *et al.*, 2011). Technical efficiency will tell us whether the resources and technology available are being properly used. However the efficiency of a production unit or farm is determined by a set of farm/farmer characteristics such as the age of the farmer, education level and access to extension services among others. Efficient farms are also more productive and the productivity of the different factors used in production can be increased by improving technical efficiency (Benin *et al.*, 2011; Torero, 2013). However efficiency is enhanced by innovation and adoption of technologies by the production units in the sector. These subsequently influence technological change in the sector. Technological progress is the consequence of innovation or adoption of new technology by best practice firms. Both technological change and efficiency influence the partial productivities of the factors of production; land, labour and other inputs, and the sum of these partial productivities gives an indication of the returns to scale in the agriculture sector. The three components; technical efficiency, technological change, and returns to scale, are components of agricultural productivity as illustrated in Figure 1.

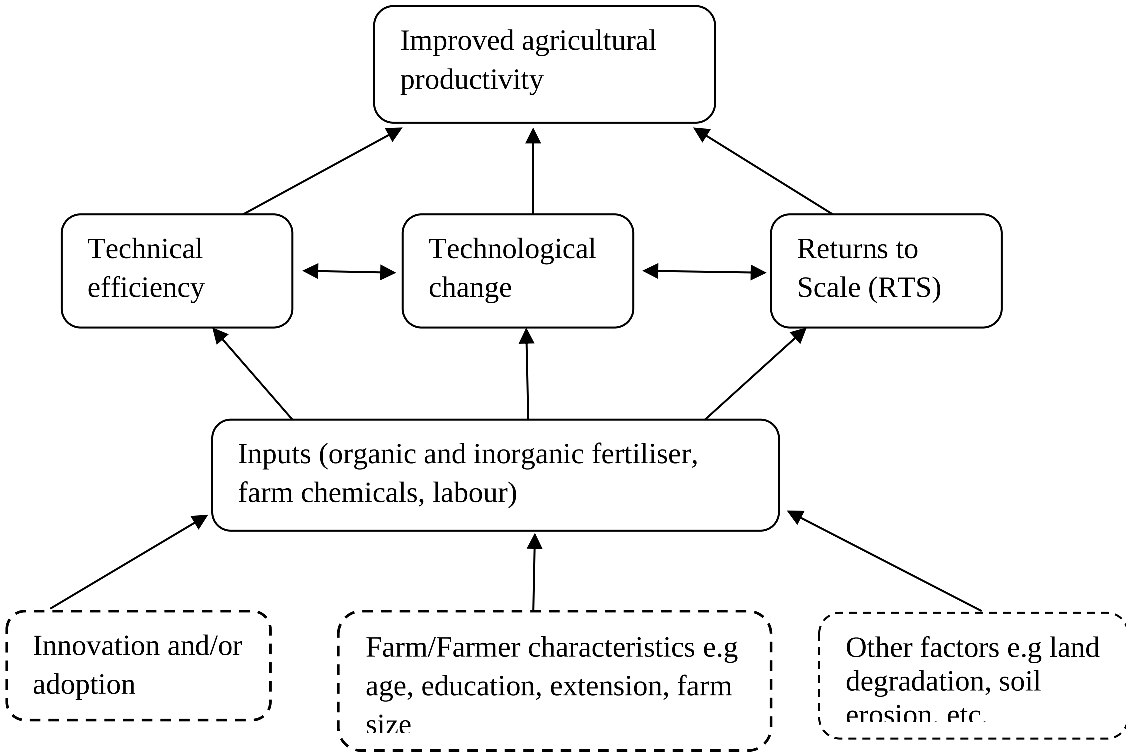

Figure 1 : **Conceptual framework illustrating technical efficiency, technological change and returns to scale as components of agricultural productivity**

1.9 Organisation of the Dissertation

Chapter 1 presents the introduction to the study, while a background to Uganda's agriculture sector is presented in chapter 2. Chapter 3 discusses the concept of technical efficiency; the definition, theoretical and empirical literature reviews on the concept, and the findings on the investigation of technical efficiency among the sampled farming households. Chapter 4 similarly discusses the concept of technological change and presents the findings on the investigation of technological change. The concept of returns to scale and findings are discussed and presented in chapter 5. Finally chapter 6 presents a summary, conclusion and recommendations drawn from the study.

CHAPTER TWO

BACKGROUND TO THE AGRICULTURE SECTOR IN UGANDA

2.1 Introduction

Chronic poverty and food security have continued to be outstanding problems in Sub-Saharan Africa mainly emanating from low agricultural productivity in the region (Conway, 2001;FAO 2001; World Bank 2003b; IFDC 2005, 2006). Uganda's agriculture is characterized by low yields partly due to low application of modern technology, resulting in low returns to investments. Yet if long run productivity can be improved, through existing or new enterprises, it is believed that rural incomes, livelihoods, and general prosperity will rise. The vision of the agricultural sector in Uganda is "A competitive, profitable and sustainable agricultural sector with the mission to transform subsistence farming to commercial agriculture (RoU, 2010). One of the immediate objectives of the plan is to sustainably enhance factor productivity (land, labour, capital) in crops, livestock and fisheries. Programmes in the agricultural sector are expected to lead to an increase in the technical capability of the farmers in producing farm output from a given set of inputs. The measurement of the efficiency of farmers then becomes important, given the fact that this efficiency is directly related to the overall productivity of the agricultural sector (Ajibefun, Daramola & Falusi, 2006). The performance of the agricultural sector can therefore be quantified by the concepts of productivity and technical efficiency.

Agriculture has historically been and remains the main source of livelihoods for the majority of Ugandans. Most of the country is blessed with a bimodal rainfall pattern with two growing seasons a year. However as one moves north the mid-year dry season gets shorter and the year-end dry season becomes longer and more intense. Average rainfall in most areas ranges from 1,000 to 1,750mm/annum although the northeast and parts of the southwest receive as little as 750mm/annum making these areas (the county's cattle corridor) more suited to grazing than crop production (Laker-Ojok, 2012). On average Uganda's climate favors agricultural production. This chapter presents the general background of the sector (2.2), the recent policy reforms (2.3), technology development and input use (2.4), and performance in the sector over the last decade (2.5).

Uganda has a total land area of 241,551 sq.km, about 60% of which is already cultivated. Although this indicates good scope for expansion of acreage under cultivation, land is increasingly becoming a constraint in some parts of the country particularly in the southern, south-western and eastern regions where population density is very high (Laker-Ojok, 2012;UBoS, 2014). About 70% of the cultivated land is planted to food crops. The agriculture sector is dominated by food crops, forestry and livestock production. These accounted for 51.6, 18.2 and 17.8 percent respectively of the sector's gross value added in 2013/14 (RoU, 2015a). In the same period, cash crops accounted for 7.2 %, fishing 5.1% and agriculture support services for 0.1%.

Uganda has about 3.95 million agricultural households of which 20% are female headed, according to the Uganda Census of Agriculture in 2008 (UBoS, 2011a). 28.5%, 28.1%, 22.4% and 21% of these households are found in the western, eastern, northern and central regions respectively. The vast majority of Ugandans have access to some land. The agricultural households are majorly involved in small scale farming with a national average holding size of 1.1ha. The average land holding size per region is 0.8ha, 1.1 ha, 1.6ha, 1.0ha in the western, eastern, northern and central regions respectively (UBoS, 2011a). Among the major food crops in the country are bananas (*matooke*), maize, beans, and cassava; the food crops selected for this study.

2.2 Background of the selected food crops

2.2.1 Maize

Maize (*Zea mais*) is an important staple food crop in Uganda. It is an important staple for the urban poor, used by institutions, hospitals and the military (Okoboi, 2010). It is also a major source of income for most farmers in the eastern, northern, and north-western Uganda (Ferris *et al.,* 2006). Other than food, maize has a wide range of other uses including processing of livestock and poultry feeds, making of local brew, and a number of industrial formulations, making it the most traded food crop. Besides, in 2006, Maize topped the list of food exports, earning the country over $24 million (Okoboi, 2010). Statistics from the Uganda Census of Agriculture indicate that in 2008/09, maize was cultivated on an estimated area of 806, 627 Ha (UBoS, 2011a). The eastern region produced the highest contribution of 46.9%, followed by western (21.1%), central (19%) and the northern region producing the least (12.9%) (UBoS, 2010). Maize yield was equally highest in the eastern region at 2.9mt/Ha, followed the western (2.6 mt/Ha), central (2.3 mt/Ha) and least in the northern region (1.2 mt/Ha). Due to its importance both for household food and income, the government of Uganda has selected maize as a strategic food security crop and one of the 10 priority crops to be supported in the second National Development Plan (RoU, 2015a).

2.2. 2 Beans

Beans (*Phaseolus vulgaris* L.) are the most widely grown pulses, and the fifth most important food crop in Uganda (Sibiko *et al*., 2013). Bean production is mostly concentrated in the central, eastern and western regions of the country, dominated by small scale farmers who have limited resources and produce the crop under unfavourable conditions (such as little use of inputs, marginal lands and intercropping with competitive crops). The average plot size for these farmers ranges from 0.1 to 0.5 hectares per household.

Beans are readily available and a popular food to both the urban and rural population in Uganda. It also provides about 25% of the total calories and 45% of the protein intake of the diets of many Ugandans (National Agricultural Research Organisation [NARO] 2000). However, the productivity of beans in Uganda is less than 30% of the yield of improved varieties grown on research stations. The average bean yield in the country has been recorded as 0.6-0.8 Mt Ha-1, which depicts a major shortfall from the potential yield of 1.5-2.0 Mt Ha-1 realized with improved varieties and good crop husbandry under farm level conditions (Kalyebara, 2008). This yield gap has been attributed mainly to low soil fertility and susceptibility of local varieties saved by farmers to pest and disease infestations (Sebuwufu *et al*., 2015).

The low productivity of the bean crop is also attributed partly to widespread reliance on local varieties, which farmers save and sow year after year. According to the Uganda Census for Agriculture 2008/9, approximately 92% of rural households use saved seed; only 31% used improved or hybrid seed (UBOS, 2011a). The widespread dependence on saved seed is attributed to limited access to improved seed due to poor distribution of formal seed outlets across the country, reliance on a few commercial varieties, poor marketing and marketing information systems, very narrow product range or low value addition, storage constraints, and high cost of certified seed (Sebuwufu *et al*., 2015).

2.2.3 Bananas

Banana (*Musa* spp.) is one of the major staple food crops over much of Uganda (Bagamba *et al*., 2004; UBoS, 2014). By 2006, Uganda was the largest producer and consumer of banana, according to FAOStat, 2006, producing up to 10 million tonnes per annum, and accounting for approximately 15% of total global production (Bagamba *et al*., 2004). Production is mainly by smallholder farmers with total number of plots up to 2.7 million and averaging 0.24 ha, making it the most widely cultivated crop in the country (Bagamba *et al*., 2004). In the Uganda Census of Agriculture (UCA), the western region produced 67.9% of the country's total banana (food type) with a total output of 2.7 million Mt (UBoS, 2011a). However, there was a decline in actual banana production in the country for over a decade; from 7,909 Mt in 1995/96 to 4,018 Mt in 2008/09 (UBoS, 2011a), raising serious sustainability and food security concerns especially as food demand increases. At the same time, actual yields on many smallholder banana farms (5−20 Mg ha per year) in Uganda are far below the estimated potential yield (100 Mg ha per year). Farmers cite soil fertility decline, pests (banana weevils and nematodes) and moisture stress as the major factors responsible for yield decline (Nyombi, 2013). Due to its importance in the diet of Ugandans, and its role both as a cash and food crop, the government of Uganda has selected bananas as one of the target crops for poverty alleviation and national food security in the National Development Plan (RoU, 2015a).

2.2.4 Cassava

Cassava (*Manihot esculenta*) is one of the most important staple foods in Uganda. In fact, Uganda was Africa's sixth largest cassava producer at the 2004/05 production records estimated at 5.5 million MT (United States Agency for International Development [USAID], 2010). In Uganda, cassava production is second to banana, although it is increasingly facing competition from other crops, such as wheat and maize. In terms of regions, the Eastern Region reported the highest production of Cassava with the total output 1.1 Mt (36.7%) followed by the Northern Region with 983,000 Mt (34.0%) and the least was the Central Region with 410,000 Mt (14.2%).(UBoS 2011a; UBoS 2014) Cassava production in Uganda is dominated by smallholders who cultivate between 0.4-0.8 hectares of land (Kilimo Trust, 2012). Cassava production is largely subsistence with 60% going to consumption and 40% to markets (USAID 2010). Although for a long time cassava has been known as a 'poor man's crop', this perception is changing so that it is currently considered as one of the 16 strategic commodities expected to contribute to the transformation of the agricultural sector in Uganda (MAAIF, 2014).

2.3 Recent policy reforms in the agriculture sector

Since assuming power in early 1986, the National Resistance Movement (NRM) government has taken important steps toward economic rehabilitation and adopted policies that have promoted rapid economic development. These policies resulted in relative economic stability and low inflation for many years, until the global economic crises in the years after 2000. Since 2000, agricultural investments were guided by the Plan for the Modernization of Agriculture (PMA) whose main objective was poverty reduction through agricultural commercialization. The PMA was designed as a multi-sectoral approach to agricultural development, under the over-arching national policy framework of the Poverty Eradication Action Plan (PEAP).

Implemented between 2001 and 2009, the PMA had the aim of transforming subsistence farming to commercial agriculture. Implementation was based on the recognition that some of the necessary investments lay outside the mandate of the Ministry of Agriculture Animal Industries and Fisheries (MAAIF). Examples included roads, financial services, energy, natural resource management and agricultural education. While the PMA was both comprehensive and appealing, implementation proved more difficult than was envisaged because of problems in coordinating the activities of some thirteen ministries and agencies. As a result, the seven pillars of the PMA, namely; agricultural research, advisory services, rural finance, agro-processing and marketing, rural infrastructure, agricultural education, and sustainable natural resource management were not all implemented to the extent envisaged during formulation.

Significant progress was principally made in only two of the seven investments pillars of the PMA; agricultural research whose overall mandate lies with the National Agricultural Research Organisation (NARO) and agricultural advisory services under the National Agricultural Advisory Services (NAADS). As such, government identified areas of weakness in the PMA and earlier policy frameworks and addressed them in a five-year Agricultural Sector Development Strategy and Investment Plan (DSIP) 2010/11 – 2014/15. The DSIP was designed to be in line with the agricultural priorities in the National Development Plan (NDP), the new national policy framework after the PEAP expired in 2010. The strategic objective of the NDP and its agriculture sector component, the DSIP, is the achievement of Prosperity for All (PFA), the national development objective. The DSIP was designed to address four main challenges that face the agricultural sector in Uganda: low production and productivity; low value addition to agricultural produce and limited market access; weak implementation of agricultural laws and policies; and weak public agricultural institutions. In addition, MAAIF began developing a new agricultural sector policy for Uganda in 2010. The National Agricultural Policy (NAP) is guided by the principles learned from implementing the PEAP, the PMA, and other government Acts. The NAP was finally approved by cabinet on 25th September 2013.

2.4 Performance of the Agriculture Sector between 2005-2014

Over the last decade, agriculture in Uganda has registered very slow growth. On average the sector has experienced growth of less than 2% per annum as shown in Table 2.2 putting to question the role of NAADS in advisory service delivery, and the NARS in technology development.

Table 2.1 GDP growth of the agriculture sector at constant 2002 prices

	2005/06	06/07	07/08	08/09	09/10	10/11	11/12	12/13
Total GDP growth at market prices	10.8	8.4	8.7	7.2	5.8	6.6	3.4	5.1
Agriculture, Forestry, Fisheries	0.5	0.1	1.3	2.5	2.1	0.7	0.8	1.4
Cash crops	-10.6	5.4	9	5.6	-2.9	-6.5	8.2	3.9
Food crops	-0.1	-0.9	2.4	2.6	2.7	0.7	-1.7	0.2
Livestock	1.6	3	3	3	3	3	2.8	2.8
Forestry	4.1	2	2.8	6.3	2.4	2.8	3.5	2.8
Fishing	5.6	-3.0	-11.8	-7	2.6	1.8	4.9	1.9

(Source: MFPED, 2010b; 2012; 2013)

Food crops, which include most of the items produced for home consumption and for regional exports (e.g. maize, beans, simsim or cassava), contributed 52.5 percent to the total value added in the sector but recorded almost no growth (0.2%) during financial year 2012/13. However, this was better than the negative growth of 1.7 percent in the previous year. Overall, this highlights the largely subsistent nature of Uganda's agriculture, and hence the urgent need to invest in increased commercial production and productivity enhancement (MFPED, 2013).

Technology dissemination through the NAADS program has however had some success in improving crop production although a lot remains to be done. By the end of 2006, over 4,000 improved technology demonstrations had been set up by the NAADS programme of the PMA, benefiting approximately 30,000 farmer groups in the country (MAAIF, 2006). Studies internally commissioned by the NAADS secretariat indicate that by 2006, 73% of the farmer groups had benefited from the Technology Development Sites (TDSs) at the model farmers' farms, and 64% had adopted the improved technologies and practices that they had been exposed to, with positive economic impact on their farm incomes according to a survey by MAAIF (2006).

An assessment of the impact of the NAADS programme on farm households similarly revealed an increase in the average value of crop production per acre and income per capita of 27% and 41% respectively higher in NAADS sub counties than in non-NAADS sub counties. The survey also indicates that 64% had adopted improved technologies supported by NAADS while 80% of the NAADS farmer groups stated that they had increased their access to agricultural technologies. Although there is clear indication that increased access and adoption of improved technologies contributed to increased productivity, production per acre still falls below potential. Table 2.2 indicates the average farm yields of selected crops in 2005/06 compared to yields obtained at a research station.

Table 2.2 Yield Gap of Selected Crops in Uganda (2005/06)

Crop	**Average Farm Yield (kg/ha): 2005/06**	**Research Station yields (kg/ha)**	**Yield Gap (%)**
Maize	551	5,000-8,000	92
Beans	358	2,000-4,000	88
Groundnuts	636	2,700-3,500	79
Matooke	1,872	4,500	58
Coffee	369	3,500	89

(Source: PMA, 2007)

When farm yields are compared with research stations figures, the yield gap (proportion of the difference between the two yield figures to research station yields) is glaringly big, which leaves a lot of room for improvement (Plan for Modernisation of Agriculture [PMA], 2007). The budget allocation to the agriculture sector stands at Ug.shs. 479.96 billion representing about 2.05% of the national budget (RoU, 2015b). Although this lies far below the stipulated 10% of the CAADP, government continues to be committed to the rehabilitation and reconstruction as well as maintenance of national, district, urban and community access roads. Improvement of transport infrastructure is expected to improve the efficiency of agricultural marketing and agribusiness with indirect benefits on the growth of the agriculture sector.

CHAPTER THREE

TECHNICAL EFFICIENCY IN THE FOOD CROP SUBSECTOR IN UGANDA

3.1 Introduction

The ability of farming households to increase productivity and achieve sustainable food crop production depends on efficient farm practices, and hence technical efficiency. In Uganda, although food crop productivity has always been a major focus of intervention in the agriculture sector, it is not clear what factors have persistently contributed to efficiency or its lack of it at national level. The objective of this chapter is two-fold. First to determine the technical efficiency of farming households growing four of the country's major food crops; Bananas, Maize, Beans, and Cassava, and secondly to establish the determinants of efficiency among the farming households using a national panel data set. The following section presents the theoretical and empirical literature on the concept of technical efficiency. The theoretical literature deals with the definition and measurement of the concept, while the empirical literature provides evidence from past studies including studies carried out in Uganda and related to the subject. The review of the literature helps to identify the gaps in past studies which the present study attempts to close. Further, the chapter through the theoretical framework helps to support the identification of the model that is used for analysis. Thereafter, we present and provide a discussion of the empirical findings on the drivers of technical efficiency among the four crops across the four regions of the country.

3.2 Literature Review

3.2.1 Theoretical Review

Much of the literature on efficiency is based directly or indirectly on the work of Farrell (1957) who argued that efficiency of a firm could only be gauged in a relative sense, as a deviation from the best practice of a representative peer group of producers (Farrell, 1957 in Colman and Young, 1989). Farrell (1957) proposed that the efficiency of a firm consists of two components: technical efficiency, which reflects the ability of a firm to obtain maximal output from a given set of inputs, and allocative efficiency, which reflects the ability of a firm to use the inputs in optimal proportions, given their respective prices. Farrell (1957) defined technical efficiency as the ability to produce a given level of output with a minimum quantity of inputs under certain technology. Farrell (1957) distinguished between technical and allocative efficiency (or price efficiency) in production through the use of a 'frontier' production function and defined a simple measure of firm efficiency which could account for multiple inputs.

The concept of technical efficiency relates to whether a firm uses the best available technology in its production process (Chavas and Cox, 1988 in Llewelyn and Williams, 1996). While technical inefficiency refers to failure to operate on the production frontier and generally is assumed to reflect inefficiencies caused by the timing and method of application of production inputs (Byerlee, 1987).

3.2.2 Measurement of technical efficiency

A variety of methods have been used to measure efficiency, but the development of frontier production functions has become commonplace (Piesse and Thistle, 2000). The concept of the efficient frontier assumes that deviations from the frontier represent inefficiencies. Various types of frontier production functions exist. These functions differ with respect to the assumptions on the outer bound of the frontier, which may be deterministic, where all deviations from the frontier are attributed to inefficiency, or stochastic, which is a considerable improvement, since it is possible to discriminate between random errors and differences in inefficiency (Piesse and Thistle, 2000). The deterministic approach utilizes the whole sample of observations but constrains all observed points in output space to lie on or below the frontier. Although this technique corresponds most closely to the theoretical concept of the frontier as an outer boundary on the production set, empirically it is sensitive to errors in observations (Nishimizu and Page, 1982).

The functions also differ with respect to the method of measurement, parametric or non-parametric. The non- parametric methods include approaches such as the Data Envelopment Approach (DEA). For the parametric approach, estimation of production functions (or profit or cost functions) consists of specifying a parametric form for the function and then fitting it to observed data by minimizing some measure of their distance from the estimated function. This method attributes variation from the most efficient farms to technical inefficiency. As Chavas and Aliber (1993) note, the parametric approach provides a consistent framework for analyzing efficiency, however, this approach has an important weakness, in that the maintained hypothesis of parametric form can never be detected directly (Varian, 1984; Banker and Maindiratta, 1988). This method thus imposes restrictions on the technology that may not hold and that affect the distribution and measurement of the efficiency terms (Chavas and Aliber, 1993).

An advantage of the parametric approach is that it can segregate deviations from the frontier technology into the systematic or actual inefficiencies of the firm and the random components, such as weather, that are stochastic and not due to operator inefficiency. Some stochastic formulations of frontier production functions have been developed since, that sort out the effects due to random errors from those caused by technical inefficiencies. The two most common functional forms which have been used in empirical studies on production, and frontier analyses are the trans-logarithmic and the Cobb-Douglas production functions (Battese and Broca, 1997).

3.2.3 Empirical Review on technical efficiency

It is widely accepted that technical inefficiencies exist in agricultural production *albeit* at varying degrees and efforts to identify their sources are vital. Battese and Coelli (1995) confirm this when they specify a stochastic frontier production function for panel data which they apply to data from a sample of 14 Indian paddy farmers observed over a 10 year period. Their results indicate that the model for the technical inefficiency effects, involving a constant term, the age of the primary decision maker in the farming operation, the years of formal schooling of farmers and year of observation, is a significant component in the stochastic frontier production function. A number of studies have since analysed the determinants of technical efficiency using both the deterministic and stochastic approaches. The most common determinants alluded to include the age of the decision maker, his/her education level, as observed by Battese and Coelli (1995) and the availability of extension services. In addition to these some studies find other inefficiency effects that are specific to particular locations.

Brock *et al*. (2006), attempt to explain why many sectors of the Russian economy could not achieve higher productivity and higher technical efficiency when market forces prevailed. Their findings indicate different regions having significantly different technical efficiency scores. Farms that had been profitable before the Soviet Union collapse were found to be more profitable as well as those that had specialized in a specific output or actively acquired land. The authors propose that this could be a proxy for better management of farms or simply their activeness. Technical efficiencies were estimated using input- oriented DEA models using variable returns to scale. However the impact of external factors on technical efficiency is estimated by second-step regression analysis as the use of Z- variable in a one-step procedure is not available in the DEA. The external factor that is found to have a significant effect on technical efficiency is the land holding which is believed to be an indicator of management ability and quality.

Coelli *et al*. (2002) observe that past studies which seek to measure efficiency differentials among farms are dominated by the use of simple measures, such as yield per hectare and cost per unit of output. While these are easy to calculate and understand, they tell very little about the reasons for any observed differences among farms. Yield-per-hectare figures are of little use when the amounts of non-land inputs used (such as labour and fertiliser) differ among farms. Cost per unit of output figures go some way towards addressing the problems with yield comparisons, but they can also be quite misleading measures of performance when input prices differ across geographical regions. Furthermore, Coelli *et al.* (2002) argue that simple cost comparisons do not tell us what portion of the cost difference is due to inefficient use of the given input bundle (technical inefficiency) and what part is due to the incorrect choice of input ratios, given the input prices faced by the farmer (allocative inefficiency). In addition, neither yield nor unit cost measures tell us anything about the existence, or otherwise, of scale economies.

Ajibefun *et al.(*2006) estimate and analyse the technical efficiency of rural and urban small-scale food crop farmers in Ondo state of Nigeria, using the stochastic frontier production function. The hypothesis that inefficiency effects are absent from the frontier model, is rejected for the farms. In addition, the hypothesis that the explanatory variables in the inefficiency model have no effect on technical efficiency is strongly rejected for the two groups of farms. Specifically, the level of education, farming experience and farm size are found to have negative effects on technical inefficiency of both rural and urban farms. The marginal effect is found to be highest for education for both rural and urban farms, while farm size has the least marginal effect on technical efficiency for rural farms and experience has the least marginal effect on technical efficiency of urban farms. Although the variables are found to be important in improving the technical efficiency of both rural and urban farms, the marginal effects are different supporting the segregation of farms according to location.

Balcombe *et al. (*2007) estimate and explain technical efficiency for a sample of rice farmers growing local varieties (LV) and others growing modern varieties (MV) in Bangladesh employing Bayesian methods. For LV, contact with extension services was positively related to output and the leading variable in explaining higher technical efficiency. Others considered priority areas for attention were farmer education and credit access. Based on the conventional assumption for frontier studies that at least some of the farmers in the sample are progressive farmers who differ from others in adapting available knowledge and technologies to local conditions to attain high yields, the technical efficiency estimates suggest that the scope to narrow the 'yield gap' in the area of study was less than was anticipated from earlier studies. Nonetheless the area was characterized as relatively 'backward' in terms of farming practice so that efforts to develop improved technologies, including new varieties and hybrids with higher yield potential would be vital to improve efficiency.

Kalirajan and Shand, (2001) study paths of productive efficiencies over time using data from India. They find that, left to learn from their own experience, farmers will be slow to realise the full potential of a new technology. This is reinforced by the finding that, once high levels of allocative efficiency have been achieved, further improvements in economic efficiency depend almost exclusively on the achievement of higher technical efficiency. The slow rate of increase in technical efficiency in the two samples over time was found to be due to lack of information about the best practice techniques of the technology. In the absence of this information, the shift in farmers' perceived frontiers toward the true potential frontier is slow, consistent with a learning-by-doing process. In this situation, farmers can gain close to full knowledge of their perceived production functions and of market conditions, and so are able to achieve higher levels of allocative efficiency at a relatively rapid rate to be sustained by technical efficiency.

3.3 Studies of Technical Efficiency (TE) in Uganda

Bagamba *et al*., 2007 analyse technical efficiency of banana production among Ugandan small holders by estimating a stochastic production frontier model with inefficiency effects. Using a sample of 508 farmers in 3 subcounties of Ntungamo, Bamunanika and Kisekka, the production function is estimated for households with cooking bananas. In their study, output was found to respond positively to area and labor, in two of the areas, consistent with expectation, and that labor contributed more to production as compared to crop area. Manure was found to have a positive and significant effect on productivity. Okoboi (2010) uses a stochastic frontier model to estimate yield and gross profit function in order to examine the productivity of improved input use by small holder maize farmers in Uganda. Improved input use by Ugandan farmers in maize cultivation was found to yield sub-optimal profits due to higher marginal costs compared to the marginal revenue arising from increased output associated with improved input use.

Sibiko *et al*., (2012) evaluated the factors influencing bean productivity and technical efficiency among small holder farmers in eastern Uganda, using a stochastic frontier model and Tobit model. The authors found bean productivity to be positively and significantly influenced by plot size and fertilizer. Mean technical efficiency that was estimated at 48% was positively influenced by value of assets, extension services, and group membership, and negatively by age of the farmer and distance to factor market. Sebuwufu *et al.* (2015) evaluated the impact of improved varieties of bean and soil fertility improvement on small holder farms in 3 agro-ecological zones in Uganda. Their results confirmed the yield advantage of growing improved varieties on small holder farms across the 3 zones, although genetic improvement and fertility intensification alone did not seem to eliminate the yield gap between on-farm and potential bean yields. This is left as a research gap for further investigation.

Hyuha *et al.* (2007) analyse sources of technical and allocative inefficiency of rice production using cross-sectional data from a sample of 253 households in 3 districts of eastern and northern Uganda. The study uses stochastic profit and inefficiency functions and also estimates the magnitude of profit losses. Rice farmers were found not to operate on the profit frontier due to firm-specific causes of inefficiency which include low levels of education and limited access to extension services.

Asiimwe (2008) analyses the technical efficiency of upland rice producers in the districts of Bushenyi and Rukungiri in South Western Uganda. The study examined whether farmers were technically efficient in input use to generate the required output levels and the farm specific factors that were affecting the technical efficiency. The findings reveal that TE of upland producers were below the frontier level averaging 61% and the existing output was being achieved through land expansion. Education was found to improve efficiency as well as specialized extension services targeting upland rice production. Yield improving technologies notably soil enriching aspects like the use of fertilizers, as well as labour saving technologies such as pre or post emergency herbicides and mechanization are equally found to improve efficiency.

Asekenye (2012) analyses the potential for increasing productivity in groundnut farming in order to improve livelihoods of the farm households engaged on this crop in Uganda and Kenya. Overall, groundnut farmers in the study area were found to be inefficient. At the same time the mean TE of female managers was not significantly different from that of male managers suggesting that the vast experience that women had in cultivating groundnuts did not translate in better output and thus higher TE.

3.4 Empirical Conceptual Framework

The cornerstone of the economic theory of production is the production function which postulates a well-defined relationship between a vector of maximum producible outputs and a vector of factors of production (Nishimizu and Page, 1982). A production function has been theoretically defined and accepted as expressing the maximum amount of output obtainable from given input bundles with fixed technology (Aigner, Lovell & Schmidt,1977) . The stochastic frontier production function postulates the existence of technical inefficiencies of production of firms involved in producing a particular output. A number of empirical papers raise the issue of the explanation of the inefficiency effects. Pitt and Lee (1981) and Kalirajan (1981) adopt a two-stage approach, in which the first stage involves the specification and estimation of the stochastic frontier production function and the prediction of the technical inefficiency. The second stage involves the specification of a regression model for the *predicted* technical inefficiency effects, which contradicts the assumption of identically distributed inefficiency effects in the stochastic frontier. Others propose models for the technical inefficiency effects involved in stochastic frontier functions whose parameters are estimated simultaneously with those of the stochastic frontier function, and given appropriate distributional assumptions associated with cross-sectional data on the sample firms. However when measuring efficiencies and productivity at the household level, researchers face the choice of alternative approaches, such as the conventional production functions, data envelopment analysis (DEA), and stochastic frontier production function. Each of these approaches has its merits and demerits. The debate over which approach is appropriate continues (Coelli *et al*, 2005). For this study, I have adopted the stochastic production frontier approach because it has been widely used in a number of contexts world-wide and has strong asymptotic properties.

3.4.1 Stochastic Frontier Production Functions

Since the stochastic frontier production function was independently proposed in Aigner *et al*., 1977) and Meeusen and van den Broeck (1977), there has been considerable research to extend and apply the model. For instance, Battese and Coelli (1995) propose a model for technical inefficiency effects in a stochastic frontier production function for panel data which permits the estimation of both technical change in the stochastic frontier and time-varying technical inefficiencies, such that;

$$Y_{it} = \exp(x_{it}\beta + v_{it} - u_{it}) \quad \text{...(3.1)}$$

Where Y_{it} denotes production at the *t-th* observation (*t = 1, 2, 3…..T*) of the *i-th* firm (*i = 1, 2, 3….N)* x_{it} is a *(1 x k)* vector of values of known functions of inputs of production and other explanatory variables associated with the *i-th* firm at the *t-th* observation,

β Is a *(k x 1)* vector of unknown parameters to be estimated,

v_{it} These are assumed to be *iid* $N(0,\sigma_v^2)$ random errors, independently distributed of the $u_{it}s$. The u_{it}s are non-negative random variables, associated with technical inefficiency of production, which are assumed to be independently distributed, such that u_{it} is obtained by truncation (at zero) of the normal distribution with mean, $z_{it}\delta$ and variance, σ^2,

z_{it} is a (1 x m) vector of explanatory variables associated with technical inefficiency of production of firms over time, and

δ is an (m x 1) vector of unknown coefficients.

The technical inefficiency effects, the u_{it}s are assumed to be a function of a set of explanatory variables, the z_{it}s and an unknown vector of coefficients, δ. The technical inefficiency effect, u_{it}, in the stochastic frontier model (3.3) above is therefore specified as follows;

$$u_{it} = z_{it}\delta + W_{it} \qquad \text{……………………………………………………………......(3.2)}$$

Where the random variable, W_{it} is defined by the truncation of the normal distribution with zero mean and variance, σ^2, such that the point of truncation is $-z_{it}\delta$.

The technical efficiency of production for the i-th firm at the t-th observation is defined by Battese and Coelli (1995) as;

$$TE_{it} = \exp(-u_{it}) = \exp(-z_{it}\delta - W_{it}) \quad \text{..(3.3)}$$

3.4.2 Model specification

In order to select an appropriate model for the investigation, tests of hypothesis were performed to select between the Cobb-Douglas and the more flexible translog specification. The following null hypothesis was tested;

1. $H_0; \beta_{jk} = 0 \quad j \leq k = 1,2,..........27$ This hypothesis specifies that the Cobb-Douglas frontier model is an adequate representation of the data. The Cobb-Douglas functional form is a restricted form of the translog model in which the second-order terms in the model are restricted to be zero. If the hypothesis is true, the model becomes an ordinary linear model, otherwise the translog specification is used. The results are shown in Table 3.1

In order to test whether technical inefficiencies among the farming households were an important component of the selected model, the following hypothesis was tested.

2. $H_0; \gamma = \delta_0 = \delta_1 = ...\delta_7 = 0$ This specifies that the inefficiency effects are not important in describing the variations in output of the farming households. If the hypothesis is true, then inefficiency effects are not included in the specified model above. The results are shown in Table 3.2

The tests of hypothesis were performed using the *log likelihood ratio test* command in STATA version 13.

Table 3.1 Model Specification

Null Hypothesis	Critical Value χ^2	p-value	Decision
$H_0; \beta_{jk} = 0$ $j \leq k = 1,2,..........27$			
Maize	560.18	0.000	Reject
Beans	269.07	0.000	Reject
Cassava	167.57	0.000	Reject
Bananas	289.74	0.000	Reject

(Source: Author computations from the national panel dataset, 2005/06-2009/10)

Given the results in Table 3.1 above, the null hypothesis is rejected for all the four crops. Therefore the *translog* specification of the stochastic frontier model is the preferred specification that best fits the data.

Table 3.2 Tests of hypothesis for the coefficients of the inefficient effects in the stochastic frontier model

Null Hypothesis	Critical Value χ^2	p-value	Decision
$H_0; \delta_1 = \delta_2 = ...\delta_n = 0$			
Maize	-6.30	1.000	Accept
Beans	-33.41	1.000	Accept
Cassava	-81.34	1.000	Accept
Bananas	-65.74	1.000	Accept

(Source: Author computations from the national panel dataset, 2005/06-2009/10)

According to the results of the tests in Table 3.2, we fail to reject the null hypothesis, implying that inefficiency effects are not an important component of the specified model. As a result of this, the translog stochastic frontier model is run without inclusion of inefficiency effects. Rather, a two-step approach is undertaken; first to estimate technical efficiency from the translog stochastic frontier model, and secondly, regress the resultant technical efficiency scores on selected farm/farmer characteristics hypothesised to determine technical efficiency.

3.5 The Model

In step one, the translog stochastic frontier production function model that is specified for the Ugandan food crop farming households is defined below;

$$\ln(Y_{it}) = \beta_0 + \beta_1 \ln X_{1it} + \beta_2 \ln X_{2it} + \beta_3 \ln X_{3it} + \beta_4 \ln X_{4it} + \beta_5 \ln X_{5it} + \beta_6 X_{6it} + 0.5\beta_7 X^2_{1it} + 0.5\beta_8 X_{2it}^{\ 2} + 0.5\beta_9 X_{3it}^{\ 2} + 0.5\beta_{10} X_{4it}^{\ 2} + 0.5\beta_{11} X_{5it}^{\ 2} + 0.5\beta_{12} X_{6it}^{\ 2} + \beta_{13} X_1.X_2 + \beta_{14} X_1.X_3 + \beta_{15} X_1.X_4 + \beta_{16} X_1.X_5 + \beta_{17} X_1.X_6 + \beta_{18} X_2.X_3 + \beta_{19} X_2.X_4 + \beta_{20} X_2.X_5 + \beta_{21} X_2.X_6 + \beta_{22} X_3.X_4 + \beta_{23} X_3.X_5 + \beta_{24} X_3.X_6 + \beta_{25} X_4.X_5 + \beta_{26} X_4.X_6 + \beta_{27} X_5.X_6 + v_{it} - u_{it}$$

……………………………………………………………………………………..(3.4)

Where ln represents the natural logarithm (i.e to the base *e*),

Y_{it} represents the quantity (kg per acre) of food crop harvested by the *i-th* household at the *t-th* observation,

X_1 is the sum of money (Ug.shs) spent on purchasing organic fertiliser per acre,

X_2 is the sum of money (Ug.shs) per acre, spent on purchasing inorganic fertiliser,

X_3 is the amount (Ug.shs) per acre, spent on purchasing chemicals such as pesticides, and herbicides.

X_4 is the amount (Ug.shs) per acre, spent on hired labour in a given year,

X_5 represents the total number of person days of family labour per acre, in a given year,

X_6 represents the time period of the observation (expressed in terms of 1, 2)

$\beta_0 ......\beta_{27}$ are unknown parameters to be estimated,

$(v_{it}$ - $u_{it})$ is the error term;

After running the translog stochastic frontier model 3.4, TE scores of the farming households are estimated by using the *predict* command in STATA version 13.

In step two, the obtained TE scores are regressed in a robust ordinary least squares regression, on the selected farm/farmer characteristics that are hypothesised to determine the technical efficiency of a household, as specified in equation 3.5 below.

$$TE_{it} = \delta_0 + \delta_1 age_{it} + \delta_2 sex_{it} + \delta_3 Hhsize_{it} + \delta_4 educ_{it} + \delta_5 value\_assets_{it} + \delta_6 value\_lvstk_{it} + \delta_7 No.ext\_visits_{it} + \delta_8 off\_farm_{it} + \delta_9 HI_{it} + \delta_{10} location_{it} + \delta_{11} crop\_area_{it} + e$$

…………………………………………………………………………………………(3.5)

Where age represents the age of the household head measured in years,

Sex represents the sex of the household head, (dummy so that male=1, otherwise=0)

Hhsize represents the number of members in a household,

Educ represents the number of years of schooling of the household head,

Value_assets represents the value of assets (shs) owned by the household,

Value_lvstk represents the value of livestock (shs) owned by the household, *No.ext_visits* represents the number of extension visits received by the household in one year,

Off_farm represents off farm income received by the household in one year,

HI represents Housing Index assigned to a given household,

Location Location of the household (Urban=1; rural=0)

crop_area represents the total area in acres under the food crops harvested,

Time represents the time period of observation (i.e 1, 2,)

$\delta_0.......\delta_{11}$ Are unknown parameters to be estimated.

The method of maximum likelihood is used for the estimation of the parameters of the stochastic frontier using STATA version 13.

3.6 Definition and Measurement of Variables

The yield of a given crop in kilograms per acre was used as the dependant variable (Y_{it}). The amount of harvest from each crop that the farmer planted on the recorded crop area was estimated in various local measurements, and later converted to kilograms. The quantity of produce was divided by the crop area to obtain the yield of a given food crop per acre. The agricultural inputs used in crop production include fertilizers which are divided into the organic (X_1) and inorganic (X_2) fertilisers. Inorganic or chemical fertilizers are divided into four types; the nitrogenous, potash, phosphate and mixed complex fertilizers, while the organic fertilizers include farm yard manure, compost, green manure and seaweed. Farm chemicals (X_3) include insecticides, fungicides, herbicides and pesticides. The value of the purchased inputs by each household was obtained as given by the respondents for the respective inputs, in Ug.shs, and divided by the crop area to obtain the value per acre. Each of them is expected to have a positive effect on the yield of food crop.

The value of hired labour *(X_4)* is used as given by the respondents in shillings, while that used by the household members for the different tasks in crop production was collected in person days. A person day, according to UBoS, 2009 is a measurement that is used to reflect the total amount of time that a team spends full time in any activity. The value of hired labour is expected to have a positive effect on yield since the few households that are able to hire labour are also in better position to employ other yield enhancing technologies such as fertilizers. On the other hand, family labour *(X_5)* is expected to have a negative effect as more family members are not necessarily likely to be more productive. X_6 represents the time period of a given observation as explained above. In the main model (3.4) it is expected that technical change occurred over the period of study and so the coefficient may be positive or negative.

The farm/farmer characteristics that were included in the model to explain the determinants of technical efficiency in food crop farming included: age, sex, the education level, and household size. The sign on the *Age* coefficient may be either positive or negative. At a certain age, individuals are expected to be relatively more productive, while at older age, they may become less productive. Similarly the sign on the level of education (*educ*) may either be positive or negative. More educated household members may be less productive, as they leave farming activities to look for other employment. This makes the sign negative with higher levels of education. However, under normal circumstances higher levels of education would be expected to increase the level of output through better knowledge on production, hence a positive sign.

The *Sex* of the household head has sometimes been indicated to influence the efficiency with which a household would use resources in agricultural production. Women farmers have been found to be more efficient than their male counterparts although women headed households have been found to be less efficient than male headed households. The sign on the coefficient of *sex* is therefore indeterminate. Other household characteristics that were included in the model were household size *(Hhsize),* number of extension visits *(No. ext_visits),* off-farm income *(off_farm inc),* location, crop area *(crop_area)*, value of livestock *(value_lvstk)* and assets *(value_assets)* owned by the household, and a housing index *(HI),* computed from the house features where the household resides, such as the type of roof, walls, floor, and selected community infrastructure where the house is located. Table 3.3 summarises the variables used in the model, and their expected signs.

Table 3.3 Summary of variables used in the model

Variable	Definition	Unit of measurement	Expected Sign
X_1	Value of purchased Organic fertilizer	Ug.shs.	+ use is expected to improve output
X_2	Value of Inorganic fertilizer	Ug.shs.	+ use is expected to improve output
X_3	Value of pesticides, herbicides and other Chemicals	Ug.shs.	+ use is expected to improve output
X_4	Value of Hired labour	Ug.shs.	+/- use is expected to improve output given sufficient supervision, otherwise not.
X_5	Family labour	person days	+/- may be efficient, other times not.
X_6	year of observation	1, 2,	+/- technical efficiency may improve or not, technical change may be positive or not.
Sex	Sex of household head	1=male, 0=female	+/- male household heads are less poor, although sometimes they may
Age	Age of household head	Years	+/- older farmers are more experienced, but other times they are rigid and do not easily change their practices.
Educ	education level	0=None; 1=primary, 2=secondary, 3=tertiary	+/- more educated farmers are likely to be more productive, although sometimes they engage themselves elsewhere and not in farming activities
Hhsize	Household size	No. of members	- more hhold members may not improve Hh technical efficiency

Value_ lvstk	Value of livestock	Ug.shs.	- higher value may reduce technical inefficiency
Value_ Assets	Value of assets	Ug shs.	+/- may increase or reduce technical inefficiency
No.ext_visits	Number of extension visits	Number	+ extension visits are expected to improve technical efficiency
Off_farm inc	Off farm income	Ug.shs	+/- may increase or decrease technical efficiency
Crop_area	total area under crops in the study.	Acres	+ when crop area increases, output is expected to increase.
Location	Location of household, whether rural or urban	Urban=1, Rural=0	+/- location may improve or reduce technical efficiency
HI	Housing Index	5 quantiles	- better housing index represents better living standards and might reduce inefficiency effects

3.7 Data Description

The study uses panel data that combines two national household surveys conducted by the Uganda Bureau of Statistics (UBoS); in 2005/06 and 2009/10 periods. Data were collected for the period July-December, 2004 also called the second season in the 2005/06 data set, and January-June 2005 called the first season. Data for the 2009/10 data set was collected for the second season, July-Dec, 2008, and the first season January-June 2009. The study was national in context, since households were drawn from all the districts of Uganda.

The production inputs that were considered were; the land acreage under the crop or crop area, family labour used in person days, the value of hired labor, the value of purchased inputs of organic, inorganic fertilizers, and chemicals (pesticides and herbicides). The yield of the food crops was obtained in kilograms per acre of land planted. The factors expected to influence technical efficiency include household characteristics such as age, sex, education level of the household head, value of livestock owned, household assets, off farm income among others.

UBoS has conducted a number of well executed nationally representative cross-sectional household surveys since 1989 (UBoS, 2009). The Uganda National Panel Survey (UNPS) which entails a multi-topic panel household survey was implemented in 2009 with an initial sample as a sub-set of 3,220 households, selected from 7,426 households visited in the 2005/06 survey. This initial sample was intended to be revisited in 2009/10, but the actual number of households that were visited were 2,556. It is from this sample that the study households that participated in growing the four food crops; Maize, beans, bananas and cassava, were selected.

3.8 Attrition

While a number of households in the UNPS data set were found to have grown the four food crops, it was not possible to capture the same numbers in the two time periods of the study, resulting into attrition. The reasons for this were that some of the households that grew the crops in 2005/06 and were followed in 2009/10, did not grow the same crop, or had missing values in recording the data. In some cases, new households participated in growing a crop that they did not grow in 2005/06, and hence more households considered in 2009/10. The following table 3.4 shows the number of households considered per crop between the two years of the study.

Table 3.4 Number of households considered in the study

	Number of Households	
Food Crop	**2005/06**	**2009/10**
Maize	2,295	2,343
Beans	2,294	2,132
Bananas	2294	2259
Cassava	1,462	1,064

(Source: UNPS data collected by UBOS)

3. 9.0 Descriptive statistics of selected farming household characteristics

3.9.1 Maize farming household characteristics

The average age of the household heads significantly increased from 44 years to 47, understandably due to the difference between the two time periods of the panel survey which was 4 years. During the same period, household sizes significantly increased, at the 1% level, from 6 to nearly 7 members. The number of female headed households significantly increased at the 10% level from 26% to 29%. The majority of maize farming households (up to 63%) were located in the rural areas, with household heads that had spent on average 6 years at school, which represents minimal formal education, at primary level. Selected household characteristics, value of purchased and other inputs, and the yield of maize in the two panel survey waves are described in Table 3.5 below.

While the use of purchased inputs in the production of maize is minimal as represented by the low values recorded, the results also show a significant reduction in the amount of money spent on them, hence further reduction in their use; in particular inorganic fertilizer, herbicide/pesticide, and hired labour. The mean area under maize significantly increased at 10% level, from 0.49 – 0.62 acres per household. The mean plot size of maize was estimated to be 0.45 acres in 2005 and 0.86 acres in 2010 by UBOS (2010). Although there was a reduction in the value of purchased inputs, as crop area significantly increased, the yield too significantly increased from 908.93 – 1,511.14kg/acre. The results show that the input that was increasingly engaged to contribute to increased yield was family labour effort, as indicated by the significant increase in person days between the two waves.

3.9.2 Descriptive statistics of selected bean farming household characteristics

The households that indicated to have grown beans in 2005/06 were up to 2,294 representing 89.7% of the households in the UBOS sample of 2,556 households. In 2009/10, up to 2,132 households participated in growing beans. The descriptive statistics of selected household characteristics and changes between the two waves are shown in the Table 3.6 below.

Table 3.5 Descriptive statistics of selected maize farming household characteristics between 2005-2010

	2005/06			2009/10			
Variable	**Obs.**	**Mean**	**Std.Dev**	**Obs.**	**Mean**	**Std.Dev**	**Mean Difference**
Household characteristics							
Age (years)	2, 291	43.67	15.48	2,192	47.49	15.04	3.83***
Sex of household head (male=1; female=0)	2,291	0.74	0.44	2,194	0.71	0.45	-0.027*
Household size	2,293	6.26	3.2	2,194	6.76	3.3	0.5082***
Education (years of schooling)	2,280	5.82	5.11	2,194	5.76	5.34	-0.053
Location (urban=1; rural=0)	2,295	0.37	0.48	2,343	0.38	0.48	0.0038
Value of purchased inputs (shs)							
Organic fertiliser	2,295	58.91	1,581.19	2,343	117.07	2,961.52	58.158
Inorganic fertiliser	2,295	316.97	7,122.79	2,343	54.58	1,749.64	-262.382*
Herbicide/Pesticide	2,295	423.37	5,198.49	2,343	203.83	2,613.24	-219.534*
Hired labour	2,295	7,508.49	40,071.29	2,343	4,068.66	32,738.49	-3439.83***
Other inputs							
Family labour (person days)	2,295	22.98	46.65	2,343	248.36	3,645.65	225.37***
Maize area (acres)	2,295	0.49	0.89	2,343	0.62	2.66	0.118*
Yield (kg/acre)	2,295	908.93	2,023.14	2,343	1,511.14	2,128	602.2***

(Source: Author's computations from the UNPS data sets 2005/06 and 2009/10 collected by UBOS)

The mean household age significantly increased as did household size at the 1% level, from 6 to nearly 7 members. The household head sex ratio also significantly increased in favour of female heads, at the 10% level. Although mean plot size did not significantly increase, results show that there was significant intensified engagement of family labour, increased expenditure on hired labour (both at the 1% level), and increased expenditure on inorganic fertiliser (10% level). Bean yield subsequently significantly increased (1%) between the two years from 333- 613.1 kg/acre. UBOS (2010) similarly finds the mean yield of beans to be 600 kg/acre, from the Uganda Census of Agriculture in 2008/09.

3.9.3 Descriptive statistics of selected banana farming household characteristics

A total of 2,294 households were found to participate in banana farming in 2005/06, while 2,259 out of the 2,550 households of the UNPS responded to have banana plots in 2009/10. The household characteristics, value of purchased and other inputs, and banana yield between the two study periods are described in Table 3.7

The mean age of the household heads significantly increased by 4 years as expected. While the number of female headed households is found to have significantly increased at the 10% level, household size significantly increased at the 1% level. Both mean area under banana and yield did not significantly change. However the value of herbicides and the use of family labour increased significantly indicating the importance of the two inputs in banana production between the two time periods.

Table 3.6 Descriptive statistics of selected bean farming household characteristics between 2005/06 and 2009/10

	2005/06			2009/10			
Variable	**Obs.**	**Mean**	**Std.Dev**	**Obs.**	**Mean**	**Std.Dev**	**Mean Difference**
Household characteristics							
Age (years)	2,290	43.7	15.47	2,130	47.44	14.94	3.74***
Sex of household head (male=1; female=0)	2,290	0.73	0.44	2,132	0.71	0.453	-0.0251*
Household size	2,292	6.26	3.2	2,132	6.81	3.28	0.55***
Education (years of schooling)	2,294	5.78	5.12	2,132	5.74	5.3	-0.07
Location (urban=1; rural=0)	2,294	0.46	0.49	2,132	0.47	0.49	0.01
Value of purchased inputs (shs)							
Organic fertiliser	2,294	134.94	4,876.48	2,132	322.04	4,857.25	187.09
Inorganic fertiliser	2,294	76.59	1,738.81	2,132	200.98	2,869.19	124.38*
Herbicide/Pesticide	2,294	148.05	2,922.12	2,132	256.18	2,600.34	108.13
Hired labour	2,294	3,631.07	16,697.10	2,132	7,831.05	42,605.43	4,199.98***
Other inputs							
Family labour (person days)	2,294	15.34	26.03	2,132	416.72	3,516.08	401.38***
Bean area (acres)	2,294	0.66	0.85	2,132	2.28	38.9	1.62
Yield (kg/acre)	2,294	333.26	799.50	2,132	613.11	1,576	279.85***

(Source: UNPS data collected by UBOS, 2005/06 and 2009/10)***,**,* significant at the 1%,5% and 10% levels.

Table 3.7 Descriptive statistics of selected banana farming household characteristics between 2005/06 and 2009/2010

Variable	2005/06 Obs.	2005/06 Mean	2005/06 Std.Dev	2009/10 Obs.	2009/10 Mean	2009/10 Std.Dev	Mean Difference
Household characteristics							
Age (years)	2,290	43.7	15.48	2,173	47.45	15.09	3.75***
Sex of household head (male=1; female=0)	2,290	0.74	0.44	2,173	0.71	0.453	-0.025*
Household size	2,292	6.26	3.201	2,173	6.77	3.3	0.51***
Education (years of schooling)	2,279	5.82	5.115	2,173	5.76	5.332	-0.056
Location (urban=1; rural=0)	2,294	0.46	0.498	2,259	0.466	0.498	0.0054
Value of purchased inputs (shs)							
Organic fertilizer	2,294	158.67	2,116.00	2,259	269.19	4,802.33	110.52
Inorganic fertilizer	2,294	190.36	5,040.34	2,259	157.76	4,494.45	-32.603
Herbicide/Pesticide	2,294	147.36	1,836.73	2,259	315.39	2,930.41	168.029**
Hired labour	2,294	2,591.63	33,009.37	2,259	2,594.50	23,658.33	2.865
Other inputs							
Family labour (person days)	2,294	19.71	55.71	2,259	282.503	4,044.97	262.79***
Banana area (acres)	2,294	0.902	4.97	2,259	0.577	13.6	-0.325
Yield (kg/acre)	2,294	17,599.49	234,690.10	2,259	24,370.33	475,375	6,770.85

(Source: Author computations from UNPS data collected by UBOS, 2005/06 and 2009/10)***,**,* significant at the 1%,5% and 10% levels respectively

3.9.4 Descriptive statistics of selected cassava farming household characteristics

A total of 1,462 households were identified to have grown cassava in 2005/06 while 1,064 grew it in 2009/10. Between the two time periods, household size increased significantly from 6 to 7 members, while the value of purchased inputs used by the households increased significantly for organic fertiliser (5%), chemicals(10%), and hired labour (at 5%). The use of family labour was also significantly intensified at the 1% level. While crop area did not significantly change between the two years, cassava yield is found to have significantly increased although with large standard deviations. These results are shown in Table 3.8 below.

3. 10 Technical efficiency among the food crop farming households

The translog stochastic frontier production function (3.4) was used to estimate the technical efficiency of the farming households. The inputs that contribute to crop yield and the estimated technical efficiency scores are discussed below.

3.10.1 Technical efficiency among the maize farming households

Although there was a significant reduction in the use of hired labour, farm chemicals, and inorganic fertilisers by the households (table 3.5) , both hired and family labour positively and significantly contributed to increasing maize yield, as shown by the results of the stochastic production function in Table 3.9. However, the significant coefficients on these two; hired and family labour, must be interpreted in consideration of their interactions with other purchased inputs. When their interactions are considered, a 1% increase in the value of hired labour would raise maize yield by 0.15%, while a similar increase (1%) in the use of family labour would increase maize yield by 1.2%. The computations that give these percentages are shown in Annex 2.1, and the method is as discussed by Wooldridge (2006), on pages 207-209. Although both hired and family labour contributed to increasing maize yield, increasing family labour days would contribute relatively more than increasing hired labour, during the study period.

The range of technical efficiency scores of the maize farming households that were obtained from this model are shown in Table 3.9. The results show that during the study period, over 90% of the maize farming households attained efficiency scores below 0.4. This means on average they only achieved 40% of the maximum possible maize production, at the current level of technology, during the study period, an indication that there is still plenty of room (60%) for improvement in productivity and hence technical efficiency. Poor performance in the maize sub-sector has been attributed to low adoption of inorganic fertilizer, as cited by Mugisha *et al*. (2011). The authors argue that low adoption of inorganic fertiliser was due to the perceived price riskiness of maize output. Farmers did not have the incentive to plant improved maize varieties that required complementary inorganic fertilizer, in an environment where maize output was perceived as most price risky. Besides, improved varieties were costly and farmers preferred to plant recycled seed with subsequent significant reduction in yield (Mugisha *et al*., 2011). This study estimated the mean TE score over the study period at 0.218 (Table 3.10), and a reduction in efficiency over the two time periods, although not significant (Table 3.11).

Table 3.8 Descriptive statistics of selected cassava farming household characteristics

	2005/06			2009/10			
Variable	**Obs.**	**Mean**	**Std.Dev**	**Obs.**	**Mean**	**Std.Dev**	**Mean Difference**
Household characteristics							
Age (years)	1,377	43.936	15.45	922	47.05	14.553	3.068***
Sex of household head (male=1; female=0)	1,377	0.76	0.425	922	0.742	0.437	0.02
Household size	1,379	6.47	3.27	922	7.212	3.255	0.746***
Education (years of schooling)	1,372	6.107	5.067	922	6.303	5.341	0.196
Location (urban=1; rural=0)	1,379	0.433	0.495	922	0.419	0.493	0.0132
Value of purchased inputs (shs)							
Organic fertilizer	1,462	101.823	1,384.76	1,064	400.48	4,985.76	298.657**
Inorganic fertilizer	1,462	96.54	1,795.03	1,064	448.77	8,218.22	352.23
Herbicide/Pesticide	1,462	253.764	253.76	1,064	483.789	3,072.14	230.02*
Hired labour	1,462	6,949.00	28,858.89	1,064	10,439.24	46,359.66	3490.13**
Other inputs							
Family labour (person days)	1,462	56.676	78.091	1,064	548.99	5,391.24	492.31***
Cassava area (acres)	1,462	0.956	0.956	1,064	1.64	27.172	0.685
Yield (kg/acre)	1,462	1,462.23	10,423.71	1,064	47,236.08	536,822	45,770***

(Source: UNPS data collected by UBOS, 2005/06 and 2009/10) ***,**,* significant at the 1%,5% and 10% levels.

Table 3.9 Results of the stochastic production function of the maize farming households

Variables	Parameter	coeff.	std.err
Stochastic production frontier			
Constant	β_0	1.306***	0.3295
ln (value of organic fertiliser)	β_1	0.3323	0.3748
ln (value of inorganic fertiliser)	β_2	-0.0121	0.2972
ln (value of pesticide/herbicide)	β_3	-0.0841	0.1616
ln (value of hired labour)	β_4	0.3181***	0.0574
ln (family labor days)	β_5	1.733***	0.0545
Time	β_6	2.4744***	0.1953
0.5 ln (value of org. fertiliser)sq	β_7	-0.0692	0.0819
0.5 ln (value of inorg.fert)sq	β_8	-0.0007	0.0497
0.5 ln (value of chem.)sq	β_9	0.0185	0.0344
0.5 ln (value of hired labour)sq.	β_{10}	0.0028	0.0106
0.5 ln (family labor days)sq.	β_{11}	-0.2308***	0.0169
ln(val_org).ln(val_inog)	β_{13}	0.0269	0.0274
ln(val_org).ln(val_chem)	β_{14}	0.001	0.0211
ln(val_org).ln(val_hrdlb)	β_{15}	-0.0204	0.0143
ln(val_org).ln(fmlb)	β_{16}	0.0657	0.0476
ln(val_org).time	β_{17}	-0.0431	0.1805
ln(val_inorg).ln(val_chem)	β_{18}	-0.0068	0.0092
ln(val_inorg).ln(val_hrdlb)	β_{19}	-0.0082	0.0078
ln(val_inorg).ln(fmlb)	β_{20}	0.01609	0.0296
ln(val_inorg).time	β_{21}	0.1101	0.1211
ln(val_chem).ln(val_hrdlb)	β_{22}	0.0045	0.0062
ln(val_chem).ln(fmlb)	β_{23}	-0.0231	0.0157
ln(val_chem).time	β_{24}	0.0681	0.059
ln(val_hrdlb).ln(fmlb)	β_{25}	-0.0751***	0.0054
ln(val_hrdlb).time	β_{26}	0.0005	0.0238
ln(fmlb).time	β_{27}	-0.1917***	0.0414
Variance parameters			
Sigma sq.	σ^2	6.1361	0.181
Gamma	γ	0.4825	0.022
Sigma-u. sq.	σ_u^2	2.9604	0.2048
Sigma-v. sq.	σ_v^2	3.175	0.0991
Log likelihood		-10,192	
No. of observations		4,638	

(Source: UNPS data collected by UBOS, 2005/06 and 2009/10)***,**,* significant at the 1%,5% and 10% levels respectively

Table 13.10 The range of technical efficiency scores across the four crops

Range	Food Crop (Cumulative %)			
	Maize	Beans	Banana	Cassava
$0 \leq TE \leq 0.1$	0	5.08	22.79	0.39
$0.11 \leq TE \leq 0.2$	69.86	97.56	99.76	97.84
$0.21 \leq TE \leq 0.3$	87.49	100	100	99.93
$0.31 \leq TE \leq 0.4$	94.35	0	0	99.96
$0.41 \leq TE \leq 0.5$	98.02	0	0	0
$0.51 \leq TE \leq 0.6$	99.61	0	0	0
$0.61 \leq TE \leq 0.7$	99.96	0	0	100
$0.71 \leq TE \leq 0.8$	100	0	0	0
$0.81 \leq TE \leq 0.9$	0	0	0	0
$0.91 \leq TE \leq 1.0$	0	0	0	0
Mean	0.218	0.147	0.151	0.137
Standard Deviation	0.086	0.024	0.039	0.024
Minimum	0.118	0.065	0.054	0.089
Maximum	0.747	0.243	0.277	0.689
No.of observations (for two time periods)	4,638	4,426	4,553	5,699

Source: Author computations from UNPS datasets 2005/06 and 2009/10 collected by UBOS

Table 3.11 Change in mean technical efficiency scores across the four crops

Food Crop	2005/06			2009/10			
	Obs.	Mean	St.dev.	Obs.	Mean	St.dev.	Mean difference
Maize	2,295	0.2198	0.0861	2,343	0.2168	0.0859	-0.0030
Beans	2,294	0.152	0.0081	2,132	0.144	0.0327	-0.0081***
Bananas	2,294	0.175	0.0082	2,259	0.088	0.0121	-0.0864***
Cassava	3,035	0.137	0.0231	2,664	0.1374	0.024	-0.0003

Source: Author computations from UNPS datasets 2005/06 and 2009/10 collected by UBOS

3.10.2 Technical efficiency among the bean farming households

The results show that while there was a significant increase in the number of households using inorganic fertiliser, hired and family labour for bean production (table 3.6), increases in the value of all the selected purchased inputs resulted in a reduction in bean yield each over the two time periods. The coefficient on the value of hired and family labour were negative and significant, although these have to be interpreted along with their interactions with other inputs. After computations to consider the interactions (Annex 2.2), a 1% increase in each of the variables; the value of hired labour, farm chemicals, and family labour, is found to result into a reduction of 0.1%, 0.1%, and 0.4% of bean yield respectively during the study period.

Sebuwufu *et al* (2015) attribute the persisting poor productivity in bean production on one hand to widespread reliance on local varieties which farmers save and sow from year to year. According to the Uganda Census of Agriculture, 92% of rural households used saved seed (UBoS 2010; Sebuwufu *et al.,* 2015). Furthermore, the local varieties saved by the farmers are susceptible to pest and disease infestation (Sebuwufu *et al.*, 2015). On the other hand the authors (Sebuwufu *et al*.) attribute the poor performance to other factors such as poor soils and low soil fertility enhancement by the farmers, high cost of certified seed and their limited supply among small holder farmers in the rural areas (Sebuwufu *et al.*, 2015).

In this study, the mean TE of the bean farming households was estimated at only 14.7%, and all the selected households had TE below 30% (Table 3.10). This implies technical inefficiency in bean production, as households could only achieve 30% of the maximum possible yield at the existing level of technology. Moreover, efficiency significantly reduced over the two time periods (Table 3.11).

3.10.3 Technical efficiency among the banana farming households

This study finds that there was intensified use of family labour and farm chemicals in banana production during the study period, although these were not associated with increased productivity as shown in Table 3.13. The purchased inputs that were significant and/or had significant interactions contributing to banana yield were inorganic fertiliser, hired and family labour. A 1% increase in each of the value of inorganic fertiliser, hired and family labour was associated with an increase of 0.2%, a reduction of 0.1% , and an increase of 1.4% in banana yield respectively during the study period. The computations are shown in Annex 2.3.

The mean TE during the study period was estimated to be 15% with a significant reduction between the two time periods. All the households in the sample had an estimated TE less than 30%. Nyombi (2013) attributes the poor performance in banana productivity in Uganda to soil fertility decline, pests especially banana weevils and nematodes, and moisture stress. Bagamba *et al*, (2007) acknowledge that animal manure and mulches had a significant impact on banana productivity, this study finds that the value of organic fertiliser had a positive effect on productivity although not significant. Nyombi (2013) recommends a systems approach in addressing constraints to banana productivity.

Table 3.12 Results of the stochastic production function of the bean farming households

Variables	Parameter	coeff.	std.err
Stochastic production frontier			
Constant	β_0	6.9906***	0.3697
ln (value of organic fertiliser)	β_1	-0.2537	0.1942
ln (value of inorganic fertiliser)	β_2	-0.0781	0.214
ln (value of chem)	β_3	-0.0943	0.1375
ln (value of hired labour)	β_4	-0.2228***	0.0467
ln (family labor days)	β_5	-0.546***	0.0891
Time	β_6	-0.8929***	0.1939
0.5 ln (value of org. fertiliser)sq	β_7	0.0467	0.0379
0.5 ln (value of inorg. fert)sq	β_8	0.0568	0.0406
0.5 ln (value of chem)sq	β_9	0.0701**	0.0347
0.5 ln (value of hired labour)sq.	β_{10}	0.0407***	0.0091
0.5 ln (family labor days)sq.	β_{11}	0.0892***	0.0103
ln(val_org).ln(val_inog)	β_{13}	0.0237	0.0136
ln(val_org).ln(val_chem)	β_{14}	-0.0062	0.0075
ln(val_org).ln(val_hrdlb)	β_{15}	0.0058	0.0072
ln(val_org).ln(fmlb)	β_{16}	0.0341**	0.0158
ln(val_org).time	β_{17}	-0.0621	0.0584
ln(val_inorg).ln(val_chem)	β_{18}	-0.0084	0.0083
ln(val_inorg).ln(val_hrdlb)	β_{19}	0.0047	0.0063
ln(val_inorg).ln(fmlb)	β_{20}	-0.0261	0.0214
ln(val_inorg).time	β_{21}	-0.0872	0.0615
ln(val_chem).ln(val_hrdlb)	β_{22}	-0.0032	0.0046
ln(val_chem).ln(fmlb)	β_{23}	-0.0145	0.0176
ln(val_chem).time	β_{24}	0.1164***	0.0438
ln(val_hrdlb).ln(fmlb)	β_{25}	-0.0013	0.0039
ln(val_hrdlb).time	β_{26}	0.0291*	0.0154
ln(fmlb).time	β_{27}	0.4729	0.0462
Variance parameters			
Sigma sq.	σ^2	12.724	30.569
Gamma	γ	0.9025	0.2308
Sigma-u. sq.	σ_u^2	11.4831	30.525
Sigma-v. sq.	σ_v^2	1.2408	0.0794
Log likelihood		-2,545.83	
No. of observations		4,426	

(Source: UNPS data collected by UBOS, 2005/06 and 2009/10)***,**,* significant at the 1%,5% and 10% levels respectively

Table 3.13 Results of the stochastic production function of the banana farming households

Variables	Parameter	coeff.	std.err
Stochastic production frontier			
Constant	β_0	2.2416***	0.716
ln (value of organic fertiliser)	β_1	0.0269	0.1097
ln (value of inorganic fertiliser)	β_2	0.2571*	0.1529
ln (value of pesticide/herbicide)	β_3	-0.0453	0.1087
ln (value of hired labour)	β_4	-0.1067**	0.0558
ln (family labor days)	β_5	-0.2846**	0.1429
Time	β_6	3.662***	0.1874
0.5 ln (value of org.fert)sq	β_7	0.0064	0.0357
0.5 ln (value of inorg. fert)sq	β_8	0.0603**	0.0306
0.5 ln (value of chem)sq	β_9	-0.001	0.0232
0.5 ln (value of hired labour)sq.	β_{10}	0.0448***	0.0098
0.5 ln (family labor days)sq.	β_{11}	0.0422***	0.0134
ln(val_org).ln(val_inog)	β_{13}	-0.0239	0.0149
ln(val_org).ln(val_chem)	β_{14}	-0.0081	0.0074
ln(val_org).ln(val_hrdlb)	β_{15}	0.0064	0.0088
ln(val_org).ln(fmlb)	β_{16}	0.0143	0.0138
ln(val_org).time	β_{17}	-0.0447	0.0923
ln(val_inorg).ln(val_chem)	β_{18}	-0.0061	0.0073
ln(val_inorg).ln(val_hrdlb)	β_{19}	0.0066	0.0079
ln(val_inorg).ln(fmlb)	β_{20}	0.0286*	0.0174
ln(val_inorg).time	β_{21}	-0.2945***	0.0981
ln(val_chem).ln(val_hrdlb)	β_{22}	-0.0045	0.0044
ln(val_chem).ln(fmlb)	β_{23}	-0.0135	0.0125
ln(val_chem).time	β_{24}	0.0206	0.0782
ln(val_hrdlb).ln(fmlb)	β_{25}	0.0027	0.0068
ln(val_hrdlb).time	β_{26}	-0.0435	0.0367
ln(fmlb).time	β_{27}	0.4236***	0.0987
Variance parameters			
Sigma sq.	σ^2	1.8081	0.0839
Gamma	γ	0.5647	0.037
Sigma-u. sq.	σ_u^2	1.0211*	0.0975
Sigma-v. sq.	σ_v^2	0.7869	0.0606
Log likelihood		-2,032.92	
No. of observations		4,058	

(Source: UNPS data collected by UBOS, 2005/06 and 2009/10)***,**,* significant at the 1%,5% and 10% levels respectively

3.10.4 Technical efficiency among the cassava farming households

The value of inputs that significantly contributed most to cassava yield comprised of organic fertiliser, hired and family labour. When interactions among these inputs are considered, a 1% increase in the value of organic fertiliser, hired labour and family labour, is associated with an increase of 0.8%, 0.06%, 1.07% in cassava yield respectively. Family labour contributed most to cassava yield over time. These computations are shown in Annex 2.4. The results indicate that over 90% of the cassava farming households achieved a technical efficiency below 40% in the study period. The mean technical efficiency was estimated at only 14% with no significant difference between the two time periods.

Table 3.14 Results of the stochastic production function of the cassava farming households

Variables	Parameter	coeff.	std.err
Stochastic production frontier			
Constant	β_0	7.2926***	1.7997
ln (value of organic fertiliser)	β_1	0.8252*	0.4539
ln (value of inorganic fertiliser)	β_2	0.3475	0.4539
ln (value of chemicals)	β_3	-0.2585	0.2227
ln (value of hired labour)	β_4	0.1847***	0.0696
ln (family labor days)	β_5	1.2399***	0.0506
Time	β_6	0.2175*	0.1222
0.5 ln (value of org.fert)sq	β_7	-0.0405	0.0848
0.5 ln (value of inorg.fert)sq	β_8	0.0415	0.1006
0.5 ln (value of chem)sq	β_9	0.0264	0.0462
0.5 ln (value of hired lab)sq.	β_{10}	0.0176	0.0136
0.5 ln (family labor days)sq.	β_{11}	-0.0277**	0.0122
ln(val_org).ln(val_inog)	β_{13}	-0.0249	0.0268
ln(val_org).ln(val_chem)	β_{14}	0.0164	0.0149
ln(val_org).ln(val_hrdlb)	β_{15}	-0.0014	0.0111
ln(val_org).ln(fmlb)	β_{16}	-0.0101	0.0402
ln(val_org).time	β_{17}	-0.3947***	0.1394
ln(val_inorg).ln(val_chem)	β_{18}	-0.024	0.0151
ln(val_inorg).ln(val_hrdlb)	β_{19}	-0.0044	0.0112
ln(val_inorg).ln(fmlb)	β_{20}	-0.0693	0.0501
ln(val_inorg).time	β_{21}	-0.1522	0.1417
ln(val_chem).ln(val_hrdlb)	β_{22}	0.0089	0.0062
ln(val_chem).ln(fmlb)	β_{23}	-0.0202	0.0164
ln(val_chem).time	β_{24}	0.1914	0.0617
ln(val_hrdlb).ln(fmlb)	β_{25}	-0.0499***	0.0049
ln(val_hrdlb).time	β_{26}	-0.0474**	0.0199
ln(fmlb).time	β_{27}	-0.1121***	0.0302
Variance parameters			
Sigma sq.	σ^2	5.0728	0.1091
Gamma	γ	0.3646	0.0181
Sigma-u. sq.	σ_u^2	1.8499	0.1149
Sigma-v. sq.	σ_v^2	3.2228	0.0884
Log likelihood		-12,471	
No. of observations		5,699	

(Source: UNPS data collected by UBOS, 2005/06 and 2009/10)***,**,* significant at the 1%,5% and 10% levels respectively

3.11 Determinants of technical efficiency among food crop farming households

The determinants of technical efficiency were obtained by regressing the technical efficiency scores from step one, on selected household socio-economic characteristics. The findings are presented in Table 3.15 and discussed below per food crop.

3.11. 1 Maize

This study finds the determinants of technical efficiency among maize farming households to include education, household size, off-farm income, location, acreage under maize and housing index. Of these, the factors that have a significant positive influence are education, household size, acreage under maize and housing index at 5%, 1%, 1% and 1% levels respectively. Education of a household head has been found vital in improving efficiency of maize production in this and other studies such as Okoboi *et al.*, (2012), while Kibirige (2014) further finds the education of a spouse equally important. Education is believed to enhance adoption of improved technologies which consequently enhance efficiency in production (Kibirige, 2014; Mutyebere, 2016), and profit (Okoboi *et al.*, 2012). Larger household sizes have been found to contribute to efficiency due to an increased labour force especially in peak seasons, from adult members (Kibirige 2014), as well as children (Bagamba *et al.*, 2007). Expansion of area is found to contribute to increased profit (Okoboi *et al.*, 2012). Off-farm income and location were found to significantly reduce efficiency, at 5% and 1% respectively. Off-farm income represents income obtained from employment away from farming activities (Bagamba, 2007), which implies that where opportunities exist for such employment and farmers take them up, this is likely to reduce their efficiency in farm activities including maize production. Similarly location in the urban areas is likely to increase off-farm opportunities for a farmer, resulting in reduced efficiency.

3.11.2 Beans

The determinants of technical efficiency among the bean farming households were found to be number of extension visits, location in the urban area, and acreage under beans. These were found to significantly contribute positively to technical efficiency at the 5%, 5% and 1% levels respectively. Sibiko *et al*., (2012) argued that the more farm land a farmer allocated to bean farming, the higher the yields obtained. The authors further argued that most smallholder farmers usually fail to maximize bean yields due to underutilization of farm land. This might be due to limited availability of other production factors or due to farmers' risk averseness coupled with rainfall fluctuations due to climate change (Koc, 2011; Sibiko *et al.*, 2012). This study finds household size and housing index to be negatively associated with technical efficiency of bean production, both at the 5% level.

3.11.3 Bananas

The determinants of technical efficiency among the banana farming households were found to be education level and number of extension visits, which positively and significantly contributed to technical efficiency at 5% and 1% levels respectively. Although the impact of education on technical efficiency, in literature may be mixed as pointed out by Bagamba *et al*.(2007), Battesse and Coelli (1995) observe that education increases the household's ability to utilise the existing technology to attain higher levels of efficiency. For this reason, Bagamba *et al.,* (2007) use education in their study as a proxy for management skills. The findings in this study concur with the propositions; that education does improve a household's ability to utilise technology, and is associated with better management skills that can result in efficiency.

Access to off-farm income by the household was found to significantly reduce technical efficiency, at the 5% level. This is not surprising since the availability of off-farm income means employment outside the farm, with less time and effort invested in banana production, resulting in reduced efficiency.

3.11.4 Cassava

The determinants of efficiency in cassava production were found to include age and sex of household head. These positively and significantly contributed to efficiency at the 10% and 1% levels respectively. The age of the farmer is associated with experience in farming and hence improved efficiency as age advances, while male household heads are likely to have the resources and undertake the necessary decisions to improve production (Bagamba *et al.,* 2007). The other factors that contributed positively to technical efficiency included the number of extension visits, acreage under cassava and housing index, at the 10%, 1% and 1% levels respectively. Abass *et al* (2017) find similar results regarding farm size and access to markets in a study of the impact of mechanised processing of cassava on production efficiency of cassava in Uganda. Farm size is found to significantly contribute to efficiency among the mechanised cassava processing farmers, who at the same time had better access to markets. In this study, housing index is composed of a number of factors including distance to markets and road infrastructure. The results therefore are in agreement with Abass *et al.,* (2017) that access to markets and area under cassava do contribute positively to efficiency in cassava production. On the contrary while education is expected to improve a household's efficiency of production, as observed by Abass *et al.,* (2017), this study finds the opposite for cassava production. Higher levels of education are instead found to be significantly associated with reduced technical efficiency at the 10% level. The difference might be due to mechanisation that would be easier to adopt by farmers with relatively higher levels of education than the average small holder farmers in Uganda. Otherwise in the absence of such mechanisation and subsequent production for the market, it is likely that farmers with higher levels of education invest their effort elsewhere away from cassava production. This study also finds that households that are located in the urban areas are relatively less efficient than those in the rural areas, a finding that is significant at the 5% level. Location in the urban areas provides household members with more opportunities off-farm and therefore less time spent on farming activities (Bagamba *et al.,* 2007).

3.13 Summary and Conclusion

In this section of the study, technical efficiency among the selected food crop; maize, beans, banana and cassava farming households in Uganda is estimated and investigated for the period between 2005/06 and 2009/10. Mean technical efficiency for maize, beans, banana and cassava over the two time periods, is estimated to be 22%, 15%, 15%, and 14% respectively. These levels of efficiency in the food crop are considered to be low. These results imply that there would still be a possibility to produce 78%, 85%, 85%, 86% more output of maize, beans, banana, and cassava respectively, using the same resources and at the existing technology. Moreover technical efficiency declined in all the four crops during the study period, and significantly so in beans and banana, at the 1% level. Based on these findings, the performance of the food crop sector is therefore still worth the concern in Uganda.

The selected inputs that were believed to be crucial for improving food crop productivity in this study were organic and inorganic fertilizer, farm chemicals, family and hired labour. During the study period, the use of both family and hired labour, was significantly intensified with a positive and significant impact on productivity of maize and cassava, although not in bean and banana production where there was instead a decline in productivity. It is widely recognized that labour is the most important of all the resources used in agricultural sector in Africa, and that household members are the most important source of labour for major field operations (Enete *et al.*, 2005; Mugisha *et al*., 2011). Therefore the significant use of human labour in food crop production is not surprising. This only points to the need, at the existing level of technology, to build the capacity of human labour through imparting technical skills that can contribute to improvements in food crop yield.

Organic and inorganic fertilizer were found to significantly contribute to cassava and banana respectively, although there was no significant increase in the number of households using them between the two time periods. In fact, for maize there was a significant reduction in the number of households using inorganic fertilizer during the study period, and the contribution of inorganic fertilizer to maize productivity was not even significant. Similar findings have been reported in other studies carried out in Uganda; for example Nkonya, *et al*. (2003) reported that adoption of inorganic fertilizers was very low, and that the use of organic methods of soil fertility management was also limited. However, it is also a recognized fact that purchased inputs including organic and inorganic fertilizer are associated with improved agricultural productivity (Pender *et al*., 2004; Okoboi, 2012; Kasirye, 2013), improved nutrition (Kumar and Quisumbig, 2010) and higher incomes (Kassie *et al*. 2011). The factors that have been cited to constrain adoption of such inputs include unaffordability of improved planting material that would warrant the use of inorganic fertliser, when compared to output price, and lack of market information specifically regarding their purchase and use (Mugisha *et al*., 2011; Okoboi, 2012). The findings of this study seem to suggest that interventions to enhance wide use of purchased inputs in food crop production should be of major focus if productivity is to be improved. Such interventions should take into consideration the market dynamics of both inputs and resultant output, and accessibility of information regarding input use, among others.

The determinants of technical efficiency were education, number of extension visits, crop area, the location of a household, whether in the urban or rural area, and the housing index. Education was found to have a positive and significant effect in bananas and maize. Bagamba *et al*.,2007 attributed a positive and significant effect of education on crop productivity to better management skills imparted to the farmer through education. While a number of studies would be referring to the education of a household head, Kibirige (2014) recommends the education of a spouse to be equally important in food crop production since women commonly manage food crops. The importance of extension service delivery has been widely acknowledged and can similarly not be over emphasized.

Crop area had a positive sign for all the four crops, implying that increases in crop area, even at the existing level of technology, would contribute to increased efficiency. This result was significant for maize, cassava, and beans. Expansion of crop area is likely to be more feasible in rural compared to urban areas, and the results for maize and cassava seem to indicate that households located in the rural area were associated with efficiency. Apparently, over 50% of the households in the sample resided in rural areas. Households that were located in rural areas for maize, beans, banana and cassava, were 62%, 53%, 58% and 59% respectively. However a likely challenge for crop area expansion in the rural area might be inappropriate land tenure system as observed by Bategeka *et al.,* (2013). The authors observed that those who owned the land did not use it, while those that used it did not own it and were condemned to the status of tenants or peasants who typically owned small holdings of land (Bategeka *et al.,* 2013). They recommend that a land reform that gives entitlement to the 'tiller' would underpin successful agricultural productivity. The findings of this study support securing land entitlement to households involved in food crop production especially in the rural areas.

Housing index (HI) was computed from house features where the household resides, such as the type of roof, walls, floor, and selected community infrastructure where the house is located. Community infrastructure included distance to nearest tarmac road, and distance to market. Households with a high HI were expected to have a combination of better living standards, accessibility to markets and by traders searching for produce in the rural areas. HI was positive and significant for maize and cassava implying that households participating in the production of these food crops also participated more in marketing, so that distance to markets and accessibility by traders would increase efficiency in their production. The negative and significant sign on HI for beans might imply relatively less participation in the market, and that attention be paid to issues that constrain market participation by bean farming households.

Table 3.15 Determinants of technical efficiency among food crop farming households

Dependent variable (TE scores)	Parameter	Food Crop							
		Maize		Beans		Bananas		Cassava	
		Coeff.	Robust std.err	Coeff.	Robust std.err	Coeff.	Robust std.err	Coeff.	Robust std.err
Independent variables									
Constant	δ_0	0.18674***	0.0606	0.1564***	0.0055	0.10627***	0.01069	0.12802***	0.00262
Age (yrs)	δ_1	0.00004	0.00008	-0.00005	0.00007	-0.00007	0.00014	0.00006*	0.00003
Sex of household head (1=male; 0=female)	δ_2	0.0026	0.00307	-0.00395	0.00263	-0.00159	0.00474	0.00354***	0.00131
Education level (yrs)	δ_3	0.000607**	0.000268	-0.00007	0.00023	0.00086**	0.00043	-0.00019*	0.00011
Household size	δ_4	0.00202***	0.000423	-0.00086**	0.00036	0.00079	0.00061	0.00019	0.00017
Value of livestock (shs)	δ_5	0.00399	0.00307	0.00163	0.00171	0.00037	0.00037	0.00098	0.00001
Value of household assets (shs)	δ_6	-0.000213	0.000166	0.00002	0.00003	-0.00021	0.00007	-0.00075	0.00067
Number of extension visits (shs)	δ_7	-0.000173	0.00065	0.00095**	0.00041	0.00314***	0.0006	0.00033*	0.00018
Off-farm income (shs)	δ_8	-0.00058**	0.00029	0.00114	0.00146	-0.00163**	0.00077	-0.00108	0.00077
Location (1=urban; 0=rural)	δ_9	-0.00787***	0.00267	0.00478**	0.00225	-0.00311	0.00397	-0.00249**	0.0011
Crop Area (acres)	δ_{10}	0.00385***	0.00085	0.0096***	0.00114	0.00003	0.00005	0.00082***	0.0003
Housing Index (5 Quantiles)	δ_{11}	0.0045***	0.00093	-0.00215**	0.00084	-0.00074	0.00163	0.00178***	0.00041
R-squared		0.0255		0.1288		0.1423		0.0302	
Adjusted R-squared		0.0231		0.1145		0.1143		0.0245	
No.of observations (n)		4,443		4,426		4,553		5,699	

(Source: UNPS data collected by UBOS, 2005/06 and 2009/10)***,**,* significant at the 1%,5% and 10% levels respectively

CHAPTER FOUR

TECHNOLOGICAL CHANGE IN UGANDA'S AGRICULTURE SECTOR

4.1 Introduction

Productivity growth in the agriculture sector is considered an important issue to the development process; allowing countries to produce more food at lower cost, improve nutrition and welfare, and release resources to other sectors (Singh and Singh, 2012). Technological change is an important driver of productivity growth. Yet, many African farmers are still using low yielding agricultural technologies, which lead to low productivity and production. In Uganda, technological change is one of the avenues that are believed can contribute to increases in productivity and a sustained increase of production in the agriculture sector. In this chapter, the rate of technological change in Uganda's agriculture between 2005 and 2010 is estimated and the factors thought to be associated with it are discussed. Section 4.2 reviews literature; both theoretical and empirical on the concept of technological change, section 4.3 discusses the model used to estimate technological change. The resultant partial effects from the model are presented and discussed in section 4.4 as estimates of technological change, while section 4.5 concludes.

4.2 Literature Review

4.2.1 Theoretical Review

In the Harrod-Domar model of economic growth, the natural rate of growth is assumed to depend on the increase of the labour force, while warranted growth depends on the saving and investing habits of households and firms (Solow, 1956). These two opposing notions flow from the crucial assumption that production takes place under conditions of fixed proportions, and that there is no possibility of substituting labour for capital. Technological change is considered exogenous to the process of economic growth. However, Solow (1956) argues that when production takes place under the usual neo-classical conditions of variable proportions and constant returns to scale, opposition between the natural and warranted rates of growth need not be. A system can adjust to any given rate of growth, for instance of the labour force, and achieve a state of steady proportional expansion. When this happens, perfectly arbitrary changes over time in the production function can be expected to occur, and when they do, they blow up the function.

A production function is the basic neo-classical tool for the study of technology and technological change, which specifies a quantitative relationship between inputs and outputs. It is also regarded as the specification of all conceivable combinations of inputs to realize a certain output (Rip and Kemp, 1997), and it conceptualizes technology as the determinant of the location of the production function in the input (labor and capital) factor space (Maio, 2003). Technological change is hence defined by Nishimizu and Page (1982) as the change in the best practice production frontier. It can also be defined as a shift in the production function with all input quantities held constant (Karagiannis *et al.*, 1999). The shift may be outward (technical progress) or inward toward the origin (technical regress). Given a level of technology, explicit resource allocation may be required to reach the 'best-practice' level of technical efficiency over time. There is accumulating evidence that the productivity gain due to such 'technological mastery' is substantial in developing economies, and may out-weigh gains from technological progress. It is therefore important to know how far one is off the technological frontier at any point in time, and how quickly one can reach the frontier (Nishimizu and Page, 1982).

Agricultural performance can be evaluated by identifying the sources of output growth. In general, output growth is attributed to shifts of the production frontier or technological change

(Giannakas *et al*., 2001; Si and Wang, 2011) among other things. Nishimizu and Page (1982) observe that technological progress and technical efficiency change are not neatly separable either in theory or in practice. In a methodological approach, they define technological progress as the movement of the best practice or frontier production function over time. All other productivity change, for example learning by doing, diffusion of new technological knowledge, improved managerial practice as well as short run adjustment to shocks external to the enterprise should be referred to as technical efficiency change.

4.2.2 Methods used in the measurement of technological change

In the neo-classical theory of growth, aggregate output, *Y* depends on two in puts, labour, *L* and capital, *K* according to a constant returns to scale production function. Technological change can then be introduced in terms of an aggregate parameter (*A*) reflecting the current state of labour-augmenting technical knowledge (Mulder *et al*.,2001). While the estimation of the parameters of aggregate production functions is central to much of today's work on growth, productivity and technological change, the Cobb-Douglas production function is the most widely used form in theoretical and empirical analyses. Hence in Cobb-Douglas functional form, the production function can be expressed as follows;

$$Y = (AL)^{(1-\alpha)} K^{\alpha}; 0 < \alpha < 1 \qquad \text{...}(4.1)$$

Where α is the output elasticity of capital, and a constant determined by the available technology.

The change in output with respect to time is considered to be a result of the change in technical efficiencies, change in output elasticities, as well as technological change (Nishimizu and Page, 1982; Si and Wang, 2011). When the change in output over time is decomposed into these constituent components, technological change can be obtained. In a translog functional form, which is a generalisation of the Cobb-Douglas production function, Nishimizu and Page (1982) express technological change of the $i\ th$ unit in time t as;

$$TC_{it} = \frac{\delta \ln f(X_{it} t; \beta)}{\delta t} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(4.2)$$

Where TC_{it} is the technological change of the *i-th* household in time period *t*,

X_{it} is a vector of input variables, and

β is a vector of unknown parameters to be estimated as in equation 3.3

In other applications as Rossi (2000) observes both a time trend and its square are included, in order to provide consistency with the second order application notion of the translog form. The impact of technological change on output growth is then through its influence on the coefficients of production. This impact can further be decomposed into neutral and biased technological change. A number of studies such as Yao and Shively (2007); Rossi,(2000), include a time (or year) variable in the stochastic frontier, to account for Hicksian neutral technological change, following the proposition by Battese and Coelli (1995). Otherwise non-neutral technological change can also be accounted for based on the interaction of time with the inputs as in Piesse and Thirtle (2000);Caldas and Rebelo (2003); Rossi (2000). Where both the time variable and the interaction of time with the inputs are included, it is possible to determine the nature of technological change based on the resulting coefficients. Piesse and Thirtle (2000) include both as follows;

$$y_{it} = \beta_o + \sum_{j=1}^{5} \beta_j x_{jit} + \sum_{j=1}^{5} \sum_{h=1}^{5} \beta_{jh} x_{jit} x_{hit} + v_{it} - u_{it} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(4.3)$$

Where y is the log of output and the 5 independent variables x_j are the logs of the 5 inputs which include the year of observation. Neutral technological change is present if the coefficients of the interactions between the observed year and the input variables are zero (Caldas and Rebelo, 2003). If the coefficients of the interactions are significant, then the null of neutrality can be rejected.

Alternatively hypotheses of zero and hicks neutral technological change can be statistically tested to validate the nature of technological change (Giannakas *et al*, 2001). In Rossi, 2000 the null that there was no technical change is tested using the LR test. This is done by running two models; one with a time trend and another without. Since the LR test rejects the null $H_o; t = 0$, Rossi, 2000 concludes that there is no technological change. If the null cannot be rejected then technical change can simply be calculated using the first derivative of the production function with respect to time, at a particular data point.

Giannakas *et al*, 2001 determine the rate of technological change for farms in their study as follows;

$$\frac{\partial y_{it}}{\partial t} = \beta_1 + \beta_2 t + \sum_{j}^{J} \delta_j X_{jit} \qquad (4.4)$$

Where by the component $\beta_1 + \beta_2 t$ represents the effect of technological accumulation *per se* or neutral technological change, while the component $\sum_{j}^{J} \delta_j X_{jit}$ represents the effects of technology on the productivity and therefore the use of various inputs or biased technical change. Piesse and Thistle (2000) calculate an index of technological change *TCi(t+1)* between two adjacent periods, t+1 and t, for firm *i*, directly from the estimated parameters of the stochastic production frontier.

This is done by evaluating the partial derivatives of the production frontier with respect to time for the two periods. If technological change (TC) drives the production frontier to shift upward, downward or remain constant, TC indexes can be greater than, equal to or less than zero respectively (Si and Wang, 2011). If the value of TC is greater than 1, it implies the existence of technological progress.

Technological change can also be analysed from a stochastic parametric Malmquist Index approach (Rossi, 2000). The malmquist index construction allows the decomposition of secular productivity into frontier shift effects and catching up effects. Although this method is different, in that Coelli *et al.*, (1998) rely on econometric estimation of the technological change term, they argue that this method is an easier alternative than estimating the distance functions directly, and can be expected to give similar results.

4.2.3 Empirical review of technological change

Nishimizu and Page (1982) point out that it is important to distinguish between technological progress and changes in technical efficiency for appropriate policy intervention, although this is not often done by conventional measures of total factor productivity change. Technological progress, as defined by Nishimizu and Page (1982), is the consequence of innovation or adoption of new technology by best practice firms. Total factor productivity change, however, is the sum of the rate of technological progress and changes in technical efficiency. Nishimizu and Page (1982) further observe that high rates of technological progress can co-exist with deteriorating technical efficiency - perhaps due to failures in achieving technological mastery or due to short-run cost-minimizing behavior in the face of quasi-fixed vintage capital - and thus with low or the often observed negative overall rates of total factor productivity change. On the other hand, relatively low rates of technological progress can co-exist with rapidly improving technical efficiency. Policy actions intended to improve the rate of total factor productivity growth might be badly misdirected if focused on accelerating the rate of innovation for example in circumstances where the cause of lagging total factor productivity change is a low rate of mastery or diffusion of best practice technology. They therefore outline a methodological framework for decomposing total factor productivity growth into technological progress and changes in technical efficiency. Nishimizu and Page (1982) establish the rate of technological change by direct estimation of a deterministic frontier production function and find that many of these activities are mature industries, both in Yugoslavia and internationally, in which rapid movement of the frontier is not expected. In several sectors, however, the lack of technical progress is indicative of failures in investment planning and implementation to allow for acquisition of new technology. In others, the movement of the frontier reflects the success of explicit policies to facilitate the acquisition of foreign technology.

Giannakas *et al.*,(2001) examine the level and the driving forces of technical efficiency and technological change for an unbalanced panel data set of 100 wheat farms in Saskatchewan during the period 1987–95 using the stochastic decomposition methodology. Saskatchewan wheat farms were found to enjoy considerable technological progress during the period of study although with modest efficiency improvements. They conclude that technological change was a result of the introduction of technological innovations in wheat farms although this was not accompanied by significant improvement in producers' ability to fully utilize them.

Si and Wang (2011) specify a stochastic frontier production function to examine productivity growth, technical efficiency, and technical change in China's soybean sector. Using a panel data set of 12 major soybean producing provinces across the nation during the period of 1983 to 2007 they find that total factor productivity growth for China's soybean production increased by 1.5%

annually, mainly from technological progress. However, both technical efficiency and technical progress showed a decreasing trend through time. The explanation they give for the decreasing trend is that these provinces benefited from numerous soybean-related technical research and extension institutions which do facilitate technical progress. However, summer sowing soybean provinces which are major rural labor migrating regions, recorded a lower technical progress rate. They find that with increasing opportunity cost and freedom of rural labourers to choose their place of work, these provinces are expected to confront greater challenges in attaining technological progress in soybean production.

Yao *et al*. (2007) used panel data from 300 farms in the Philippines to examine productive efficiency in rice production. They examined data from the period 1995–2002, a period in which farms in the sample underwent a transition from rain-fed production to irrigation production. Using a time-variant stochastic production frontier, estimated jointly with a model of technical inefficiency, they studied productive efficiency within the overall context of irrigation development, measuring the influence of irrigation whilst controlling for specific features of the farms under study. In the model, the binary year variables account for Hicks-neutral technological change and irrigation development was found to be associated with gains in productive efficiency vis-à-vis rain-fed production.

4.2.4 Studies of technological change in Uganda

Although it was widely believed that successful implementation of the PMA would come from technological progress through the introduction of new technologies that would increase factor productivity and profitability, studies of technological change have been scanty. Dorosh *et al*, (2003) use a Computable General Equilibrium (CGE) model of the Ugandan economy to capture regional variations in agricultural production and household incomes. They also examine the implications of policy changes and shocks including changes in agricultural productivity. Their simulation results suggest that small productivity increases in food crops may have greater potential to raise rural incomes, provided that markets perform well and producer incentives are maintained. Mosley (2002) in Dorosh *et al.*(2003) reports that one-tenth of the total 6 percentage point reduction in the poverty headcount index was due to technical change in maize and cassava. Ainembabazi *et al.*, (2005) examine the nature of technological change in sorghum production between improved technology and traditional technology using cost-function analysis in eastern Uganda. They also estimate returns to scale in sorghum production. The results indicate that farmers using improved sorghum use higher quantities of factors of production and therefore incur higher costs of production compared to farmers using traditional sorghum technology. However the production function was found not to have undergone structural change between traditional and improved technologies. Under the existing traditional and improved technologies there was potential for improving sorghum productivity with proper re-allocation of the existing resources to exploit the economies of scale.

Mbowa *et al.*, (2012) use calculations based on UNPS data 2005/06 and 2009/10 and find the diary sector in Uganda to have been transformed into a more competitive and dynamic sector. Milk production between 2005 and 2009 was partly an outcome of a 20% increase in number of households engaged in dairy farming, and an increase of 21% in the proportion cross-bred dairy cows in the national herd. At farm level concerted efforts were found to have been directed towards technological change i.e transforming the farming system from predominantly extensive grazing of local breeds to more intensive rearing of fewer but improved breeds. They report an incredibly good response in the adoption of high grade cattle and replacement of indigenous breeds to increase milk production countrywide.

4.3 The use of purchased inputs and labour for food crop production

Across the four food crops, the use of the purchased inputs remained low during the study period. For example only 1.48% of the sample maize farming households used inorganic fertilizer in 2005/06 and 1.32% in 2009/10. The proportion of households using chemicals, hired and family labour, although low in 2005/06, significantly reduced in 2009/10 as shown in Table 4.1. The significant reduction in the proportion of households using these inputs coincides with the significant reduction in the value of these inputs, and hence the amount of money spent on the inputs per acre for the households that remained using them (Table 3.3). It is only the number of person days of family labour per acre that significantly increased, for the households that continued to engage their family labour in maize production, otherwise the number of households also significantly reduced by 47%.

Banana farming households had the same scenario. The number of households using purchased inputs was low in the first place, for example 1.26% of the sample in 2005/06 used purchased organic fertilizer, and this percentage significantly reduced by 0.51 in 2009/2010. While it is possible that the majority of the users did not purchase the organic fertilizer, the proportion of households using inorganic and chemicals did not significantly change. There were significant reductions in the proportion of households using both hired and family labour, but with a significant increase in the number of person days of family labour.

The number of households engaging family labor in cassava production significantly increased during the study period, as did the proportion using chemicals, but the proportion using hired labor reduced. Bean farming households using purchased inputs and engaging family labour did not significantly change during the study period.

Table 4.1 Proportion of sample households using the selected inputs between 2005/06 and 2009/10

Food Crop	% of Households using inputs				
	2005/06		2009/10		
	Obs.	% Hhs using	Obs.	%Hhs using	%Change
Maize					
Organic fertiliser	2,295	0.57	2,343	1.32	10.76***
Inorganic fertiliser	2,295	1.48	2,343	1.32	-0.16
Pesticide/Herbicide	2,295	3.05	2,343	1.54	-1.51***
Hired Labour	2,295	24.88	2,343	7.55	-17.33***
Family Labour	2,295	65.62	2,343	19.04	-46.59***
Beans					
Organic fertiliser	2,294	0.96	2,132	0.7	-0.26
Inorganic fertiliser	2,294	0.83	2,132	1.08	0.25
Pesticide/Herbicide	2,294	2.75	2,132	2.58	-0.17
Hired Labour	2,294	20.49	2,132	18.67	-1.82
Family Labour	2,294	56.93	2,132	56	0.93
Bananas					
Organic fertiliser	2,294	1.26	2,259	0.75	-0.51*
Inorganic fertiliser	2,294	0.74	2,259	0.44	-0.3
Pesticide/Herbicide	2,294	1.66	2,259	2.08	0.42
Hired Labour	2,294	10.2	2,259	6.06	-0.041***
Family Labour	2,294	39.01	2,259	22.08	-0.162***
Cassava					
Organic fertiliser	1,462	0.75	1,064	1.41	0.66
Inorganic fertiliser	1,462	0.75	1,064	1.41	0.66
Pesticide/Herbicide	1,462	2.6	1,064	4.89	2.29***
Hired Labour	1,462	31.87	1,064	26.03	-5.84***
Family Labour	1,462	90.08	1,064	97.46	7.38***

(Source: Author computations from UNPS data collected by UBOS, 2005/06 and 2009/10) ***, **, * significance at the 1%, 5% and 10% levels respectively

4.4 Technological Change among the food crop farming households

Technological change in this study is estimated using the *Year* variable, a measure of technological change in the Battesse and Coelli, 1995 specification of the production function. Therefore in model 3.4 specified earlier, the parameter (β_6), represents technological change.

The rest of the variables remain as explained in section 3.4. The results of the *Year* variable estimates for the four crops between the two study years, 2005/06 and 2009/10 are as shown in Tables 3.9; 3.12; 3.13; 3.14 and summarized below in Table 4.2.

Table 4.2 Results of the *Year* variable representing technological change between 2005/06-2009/2010

Food Crop	Coefficient	Std.dev
Maize	2.4744***	0.1953
Beans	-0.8929***	0.1939
Bananas	3.662***	0.1874
Cassava	0.2175*	0.1222

(Extracted from Tables 3.9, 3.12, 3.13, 3.14 in chapter 3)

The results in Table 4.2 show that there was positive and significant technological progress among the maize, banana, and cassava farming households, and significant technological regress among the bean farming households. This was mainly as a result of increased labour effort in the production of the food crops and not necessarily the use of purchased inputs; inorganic and organic fertiliser, and farm chemicals. Intensified labor effort if coupled with improved management practices over the years, would create this technical progress, an effect similar in results to technological progress.

CHAPTER FIVE

RETURNS TO SCALE AMONG THE SELECTED FOOD CROPS

5.1 Introduction

The concept of returns to scale is one of those concepts that are commonly used to investigate relationships among levels of outputs and inputs with a view to establish the performance of agriculture. In this chapter the returns to scale in Uganda's agriculture between 2005-2010 are discussed. Section 5.2 presents a review of literature; theoretical and empirical, while the model used to estimate the returns to scale is presented in section 5.3. In the results section 5.4 the partial output elasticities arising from the use of the selected input values that represent the household's resources are presented. The subsequent returns to scale for the respective regions and the country data are finally computed and discussed.

5.2 Literature review

5.2.1 Theoretical review

The theoretical importance of differing rates of factor substitution among productive inputs was realized as early the 1930s. However the serious challenge to the simplifying assumption of constant rates embodied in the Cobb-Douglas production function came much later, in the 1960s (Boisvert, 1982). Before then much of the empirical work in production economics was at an aggregate level (aggregate labour and capital inputs), and data pointed to constant returns to scale (Douglas, 1976 in Boisvert, 1982). These simplistic assumptions were not only made out of mathematical convenience, but there had also been little empirical evidence to the contrary. The seriousness of this limitation became more apparent when it was observed that the value added per unit of labour used within a given industry varied across countries. This had implications for varying degrees of factor substitutability and the need for more flexible analytical models for such instances (Boisvert, 1982). Efforts have since intensified to estimate substitutability among productive inputs.

In economic literature, aggregate productivity refers to the amount of output obtained from given levels of inputs in an economy or a sector (Fulginitis and Perrin, 1998). At a basic level, productivity examines the relationship between input and output in a given production process (Coelli, *et al*. 1998). Thus, productivity is expressed in an output versus input formula for measuring production activities. It does not merely define the volume of output, but output obtained in relation to the resources employed. In this context, the productivity of the firm can be defined as a ratio (Coelli *et al.* 1998) as shown in equation 5.1.

Productivity=Output(s)/Input(s) ……………………………………….(5.1)

However there are changes of scale when there is a simultaneous increase of all productive inputs. If this simultaneous increase is identical in all resources, and results in the same percentage increase in output, it is referred to as constant returns to scale, sometimes referred to simply as returns to scale. If it results in a smaller percentage increase in output it is diminishing returns to scale, and if it results in a larger percentage increase in output it is increasing returns to scale. Returns to scale refers therefore to a technical property of production that examines changes in output subsequent to a proportional change in all inputs (where all inputs increase by a constant factor). The received wisdom on returns to scale in agriculture is that they tend to be constant, although as Ellis (1993) observes, in practice this is rarely so.

5.2.2 Estimation of returns to scale in agriculture

Estimation of returns to scale begins with the measurement of productivity of the inputs used in production. Productivity measure can be sub-divided into partial or total measures. Partial measures are the amount of output per unit of a particular input e.g land productivity is output per unit of land, while labour productivity is output per agricultural person-hour. Literature on productivity growth has been dominated by two methodologies; the parametric stochastic frontier approach and the non-parametric malmquist index approach (Fare *et al*, 1994 in Feng and Serlettis, 2008). The stochastic frontier approach involves the estimation of parametric production, cost, or profit frontiers with a composite error term consisting of nonnegative inefficiency and noise components. With this approach, the contribution of scale economies and even more components can be easily identified.

However, as Feng and Serletis (2008) observe, the decomposition of productivity growth using a production frontier suffers from the problem of not allowing for multiple output analysis. Thus, it is not suitable for the study of many industries including agriculture, where multiple outputs are a common feature of the production process. Moreover, the decomposition of productivity growth using cost and profit frontiers involves the use of prices, thus losing its appeal in many situations where information on prices is missing, distorted, or inaccurate.

The non-parametric Malmquist index approach involves fitting distance functions to data on input and output quantities using the nonparametric, linear programming techniques. This approach has two major advantages: it does not require behavioural assumptions and it does not require information on prices. Feng and Serlettis (2008) observe that the latter advantage is especially desirable for the study of productivity growth for sectors where price information is missing or distorted, such as public sectors. It is also very useful in the case where price information cannot be obtained as accurately as quantity information. However, the nonparametric Malmquist index approach suffers from several drawbacks. It assumes away any measurement error and so could potentially suffer from outliers. It cannot provide deep insights into important production structures (i.e. substitution elasticities), since it is nonparametric. More importantly, it has problems in measuring the contribution of scale economies, which has been proved to have important implications for market structure.

Returns to scale in the agriculture sector can be estimated using the concept of the productivity. The partial productivities of the respective inputs of production are used, and their sum is used to indicate the returns to scale so that when;

$\beta_1 + \beta_2 + \beta_3 \angle 1$ then there is decreasing returns to scale,……………………………….(5.1)

$\beta_1 + \beta_2 + \beta_3 = 1$ there is constant returns to scale, and ………………………………..(5.2)

$\beta_1 + \beta_2 + \beta_3 \rangle 1$ there is increasing returns to scale. …………………………………….(5.3)

Where $\beta_{1,}\beta_2, \beta_3$ are partial productivities of inputs 1, 2 and 3.

5.2.3 Empirical reviews

Si and Wang, 2011 specify a stochastic frontier production function to examine productivity growth in China's soybean production, among others. They utilize a panel data set of 12 major soya bean producing provinces across the nation during the period of 1983-2007. They find productivity growth during the study period to arise mainly from technological progress. Partial input elasticities indicate that when any of the 3 input factors; labour, seed and fertilizer, increased by 10%, soybean yield increased by 11%, 0.2% and 13% respectively. Elasticities of labour and fertilizer rose over time, while that of seed decreased over time. The rising labour input elasticities in China's agricultural economy were attributed to enhanced ability to make choices in agricultural operations for rural labour. Negative elasticities are obtained for machine input.

Changes in agricultural productivity in 18 developing countries over the period 1961-1985 were examined by Fulginiti and Perrin (1998) using a non-parametric, output based malmquist index and a parametric variable coefficients Cobb-Douglas production function. Their findings confirm previous findings that at least half of these countries experienced productivity declines in agriculture during that period. Most output growth was associated with commercial inputs like machinery and fertilizers, but the phenomenon of negative productivity trends was attributed to diverse factors. Major among these were price policies, such that countries that heavily taxed agriculture had the most negative rates of productivity change.

The productivity of maize producers in eastern Ethiopia is considered by Seyoum *et al*, 1998 in a study of farmers within and outside the Sasakawa-Global 2000 project. The study uses stochastic frontier production functions on cross-sectional data obtained for the 1995/96 agricultural year. The elasticities of labour for both groups of farmers were estimated to be greater than one indicating increasing returns to labour. This was believed to be because both groups of farmers were growing maize on a one-half hectare plot of land. If there was opportunity for them to expand to a larger scale with adequate trained extension advisors who are committed to assisting farmer implement simple new technologies of production, there was hope that agricultural productivity might be significantly increased in the future on a national scale.

The changes on the productive performance of the Douro farming system during 1988-98 were analysed using a stochastic production frontier effects model to compute returns to scale, total factor productivity growth and technical efficiency indices (Caldas and Rebelo, 2003). The farms were found to experience increasing returns to scale after 1995 and a total factor productivity growth of 4.7% per year on average as a consequence of a positive technical efficiency change. In all situations, the production partial elasticities of the inputs are between 0 and 1, and with the expected sign, implying that the producers were in the well-known second stage of production (the rational zone of production). Labour exhibits the highest partial elasticity averaging 0.445, followed by other inputs (0.248) which include seeds, fertilizers, fuel, lubricants and other variable costs. These have the greatest importance in the production technology of Douro farms.

5.2.4 Productivity studies in Uganda

Analysis of agricultural productivity in Uganda has attracted a reasonable number of studies, most especially in the area of land productivity (Okoboi, 2010). Using the Uganda Integrated Household survey data of 1992/3 and 1993/94, Deininger and Okidi (2001) in Okoboi, 2010 show that increase in value of farmers' output was positively associated with the value of land, labour and fertiliser used in production. Years of experience and the level of education were also found to play a positive role in increasing household output. In an earlier study, Appleton and Balihuta (1996) had also found a positive relationship between education level and household agricultural output. Nabbumba and Bahiigwa (2003), in a study of agricultural productivity constraints and their implications for investment use household data from four rural districts selected from two agro-ecological zones to explore profitability and productivity of two technologies; improved maize varieties and improved cattle breeds. Regression analysis is used to identify the determinants of both maize and cattle profitability. Maize productivity is measured as quantity produced per unit of land (tons per hectare) differentiated by improved and local varieties, while cattle productivity is measured as milk produced per lactating animal (litres per animal) differentiated by improved and indigenous cattle breeds. The findings indicate that growing improved maize was more profitable than local maize across all farm sizes, and improved cattle breeds, both exotic and cross breeds, are more profitable and more productive than indigenous cattle. The main constraints to increased maize production across the four districts during the season under study were pests and diseases, followed by low and fluctuating prices and inadequate capital to invest in production. Pests and diseases were also the main constraints to livestock production, followed by inadequate pasture, high cost of inputs and lack of capital (Nabbumba and Bahiigwa, 2003).

Pender *et al.* (2003) estimate a structural econometric model of household decisions regarding income strategies, participation in programs and organizations, crop choices, land management, labour use, and their implications for agricultural productivity and land degradation. Several factors were found to contribute to increased value of crop production without significant effects on land degradation. These include specialized crop production, livestock, non-farm income strategies and irrigation. Okello and Laker-Ojok (2005) using the least-squares method found that farmer productivity was significantly influenced by land topography, level of rainfall, incidence of pests and diseases, and infrastructural developments. Other factors found to significantly affect farmer productivity included the value of investment in agricultural production inputs such as seeds and fertiliser. Hyuha *et al*. (2007) analysed farmer productivity from the profit viewpoint using the SFA method in 3 rice growing districts of Tororo, Pallisa and Lira in eastern and northern

Uganda. Lack of extension services and low educational levels were found as the major factors that amplified the profit inefficiency of rice farmers in the areas where the study was conducted.

Okoboi (2010) examined the productivity of improved inputs used by small holder maize farmers in Uganda using the UNHS dataset of 2005/06. Yield and gross profit functions were estimated with the stochastic frontier production model of the Cobb-Douglas function. Results revealed a significant effect of improved input use on yield but not gross profit. Farmers who planted recycled seed of improved variety, without fertilizer obtained lower yield but the highest gross profit. Overall farmers were found to make economic losses when the opportunity cost of own land and labour inputs in maize production were imputed. The study concluded that maize cultivation in Uganda in 2005/06 was found to be of no economic consequence other than food at household level (Okoboi, 2010).

5.3 The Model

Following from the stochastic frontier production function specified for the farming households in the study sample in equation (3.4), returns to scale (RTS) are obtained as the summation of the β coefficients; $\beta_1,.......\beta_5$ such that;

$$RTS = \beta_1 + \beta_2 + \beta_3 + \beta_4 + \beta_5 \qquad (5.4)$$

The interpretation of the RTS is as discussed in section 5.2.2 above.

5.4 Returns to Scale of the food crop farming households

The resultant RTS computed from Model 3.4 and using equation 5.4 are presented in Table 5.1 below. The results show that there were increasing RTS among households participating in maize, and cassava farming in the study period, and decreasing RTS among the beans and banana farming households. Increasing RTS present the opportunity for households to expand their scale of production by increasing input use as well as crop acreages. For example, intensified use of organic fertiliser and both family and hired labour would still be beneficial in enhancing maize yield, while intensified use of organic and inorganic fertiliser, hired and family labour would enhance cassava yield. The coefficients of these inputs were highly significant as shown in section 3.9.

Table 5.1 Returns to Scale (RTS) among the food crop farming households

	Food Crops (Coefficient)			
Inputs	**Maize**	**Beans**	**Bananas**	**Cassava**
Organic fertilizer (β_1)	0.3323	‘-0.2537	0.0269	0.8252
Inorganic fertilizer (β_2)	-0.0121	-0.0781	0.2571	0.3475
Pesticide/Herbicide (β_3)	-0.0841	-0.0943	-0.0453	-0.2585
Hired Labour (β_4)	0.3181	-0.2228	-0.1067	0.1847
Family Labour (β_5)	1.733	-0.546	-0.2846	1.2399
Returns to Scale (RTS)	**2.2872**	**-1.1949**	**-0.1526**	**2.3388**

(Source: Extracted from Table 3.9, 3.12, 3.13, and 3.14 in Chapter 3)

Intensified use of organic and inorganic fertiliser would enhance banana yield, while results show that further increases of the selected input values would not be beneficial in bean production. Sibiko *et al.*, (2013) found the use of certified bean seed and top-dressing fertiliser to be significantly associated with bean productivity. In their study in the eastern region where bean production is high, the authors found that although certified seed and top-dressing fertiliser were significantly associated with bean productivity, farmers found the seed costly and for those who used it, they failed to accompany it with enough fertiliser and crop husbandry to warrant better productivity (Sibiko *et al*., (2013). A decreasing RTS among the bean farming households is a signal for households not to expand the use of resources in bean farming especially if current practice is that they use saved seed with no soil fertility enhancement. Facilitated access to improved seed and other purchased inputs would enable bean farmers improve productivity and exploit better RTS.

Bagamba *et al*. (2004) observe for banana production that limited access to factor markets especially land, labour and credit, are key constraints to improving production and productivity. At the same time, they observe that while education is important in improving management skills, farmers with higher levels of education had a tendency of finding non-farm employment, which would reduce productivity. However the education level of housewives and women farmers, was found to contribute to raising banana productivity (Bagamba *et al*, 2004; Bagamba *et al*., 2007). The findings of this study concur with their observation that investment in technology improvement would enhance banana productivity, and that education of both men and women farmers would enhance the human capital in banana production. Both of these improvements would have the effect of improving returns to scale in banana production.

CHAPTER SIX

SUMMARY, CONCLUSIONS AND IMPLICATIONS FOR POLICY AND RESEARCH

6.1 Summary

The agriculture sector in Uganda, like many other developing countries, has potential for the economic development of the country. This however can only be achieved through raising the productivity of the sector. The Government of Uganda has in the recent past focused on many interventions to raise agricultural productivity. It is however important to have evidence that tracks the performance of the sector over time, highlighting what factors have led to favourable positive impacts and those that have led to under-performance in agricultural productivity. The overall goal of this study was to examine technical efficiency, technological change and the returns to scale among selected food crops in Uganda for the period between 2005 and 2010. Specifically, the study estimated and investigated technical efficiency, technological change, and established the returns to scale among four of the country's food crops; maize, beans, banana, and cassava.

The study utilizes the Uganda National Panel Survey (UNPS) data sets of the years 2005/06, and 2009/10 collected by the Uganda Bureau of Statistics (UBOS). The UNPS data set between the two waves consisted of 2,556 households, out of which the food crop farming households were selected. A translog stochastic frontier production function is used to estimate technical efficiency, technological change, and returns to scale, while a robust ordinary least squares regression is used to find the determinants of technical efficiency. The method of maximum likelihood is used for the estimation of the parameters of the stochastic frontier, in STATA version 13. Technical efficiency scores are predicted using the Battesse and Coelli (1995) function in STATA.

Technological change is obtained from the coefficient of the *year* variable of the stochastic frontier model, and returns to scale of the farming households are obtained as a summation of the output elasticities of the inputs included in the stochastic frontier model.

The food crop farming households were on average found to be technically inefficient with a mean TE 22%, 15%, 15% and 14% for the maize, beans, bananas and cassava farming households respectively over the study period. These results imply that there would still be a possibility to produce 78%, 85%, 85%, 86% more output of maize, beans, banana, and cassava respectively, using the same resources and at the existing technology. Moreover technical efficiency declined in all the four crops during the study period, and significantly so in beans and banana, at the 1% level.

The factors found to determine technical efficiency across the food crop farming households included the education, number of extension visits, location of the household whether rural or urban, and housing index which was used as a measure of the well-being of a given household. Other factors that had influence on technical efficiency in specific food crops included age and sex of household head for cassava, household size for beans and maize, and off-farm income for banana and maize.

The model used in the study assumes the presence of Hicks-neutral technical change where a single time trend variable is included in the stochastic production frontier model to capture the effect of technological change on crop yield. The study finds that although there were no significant changes in the use of technologies by the food crop farming households during the study period, there was intensified use of both family and hired labour to influence crop production and productivity, and hence technical change. The *year* variable was highly significant and positive in all the four food crops indicating significant technical change during the study period.

The study finds increasing RTS in maize and cassava, and decreasing RTS in beans and banana production. An increasing RTS implies the need to expand the use of purchased inputs, labour, as well as crop area in order to improve productivity. On the other hand, a decreasing RTS implies, not necessarily expansion of scale, but further technical and technological change to expand production possibilities even at the existing scale of production.

6.2 Conclusions and Policy Implications

Food crop production in Uganda is technically inefficient and at the existing technology, there is still plenty of room for expanding efficiency. Although purchased inputs were expected to increase food crop productivity, improvement in productivity among the farming households, between 2005/6-2009/10, was propelled more by technical change, resulting more from intensified use of both family and hired labour, than technical efficiency. In terms of policy, the results underscore the need for government to promote the use of purchased farm inputs through market interventions that will enable input and output prices to motivate investment by the farming households. Government should pursue a land reform policy that will support farming households to secure and expand food crop area in rural areas, provide market supportive road and physical infrastructure, education and extension support for household heads and spouses, specifically on market dynamics of purchased inputs and food crop output, in order to enhance food crop productivity.

6.3 Further research

- The model used in the study does not incorporate certain factors which might be important in describing the variations in technical efficiency and technical change across regions. For example nutrient depletion from the soils of central and western Uganda, floods in eastern Uganda. Further research would be required in order to confirm their impact on technical efficiency and technical change among the food crop farming households.

- The study utilizes the first two data sets of the UNPS collected by UBOS. A study that incorporates subsequent data sets that are now available would be able to track changes in the productivity of the food crop sector in Uganda.

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Annex 1

Education level of the household heads in the sample households in 2009-10

	Food Crop				
	Maize	**Beans**	**Cassava**	**Banana**	**Average**
N	2,343	2, 307	2, 664	1, 954	2,317
Education level			**(%)**		
None	22.0	22.3	20.9	23.3	22.1
Primary	50.9	51.4	49.1	54.3	51.4
Secondary	18.5	19.1	20.6	13.0	17.8
Tertiary	8.5	7.2	9.4	9.4	8.6

(Source: Author computation from UBOS data, 2009/10)

Annex 2: COMPUTATIONS OF THE CONTRIBUTION OF PURCHASED INPUTS CONSIDERING INTERACTIONS AMONGST THEM

A. 2.1 The contribution of hired and family labour to maize yield.

(i) Family Labour

The contribution of family labour to maize yield is given by:

$$\beta_5 + 0.5\,\beta_{11} \ln\,(famlb.sq) + \beta_{27}\ln\,(famlb.time) \ldots\ldots\ldots\ldots\ldots\ldots\ldots.(A\ 2.1.1)$$

The value of *ln(famlb)* is obtained at its mean value from the data to be 1.522, while time=1. The values of β_5 ,$\beta_{11,}$ and β_{27} are obtained from Table 3.9, so that;

1.733 - 0.2308 (0.5 x 1.522 x 1.522) – 0.1917(1.522 x 1)= 1.174

This means that a 1% increase in family labour days resulted in an increase in maize yield of about 1.2% during the study period.

(ii) Hired Labour

Similarly, the contribution of hired labour to maize yield is given by;

$$\beta_4 + \beta_{25} ln(val.hrdlb)\ln\,(famlb) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..(A\ 2.1.2)$$

The values of *ln(val.hrdlb) and ln(famlb)* are obtained at their mean values from the data to be 1.48 and 1.522 respectively, and β_4 and β_{25} are obtained from Table 3.9 so that;

0.3181 – 0.0751 (1.48 x 1.522) = 0.149

A 1% increase in the value of hired labour resulted in a 0.15% increase in maize yield during the study period.

Annex 2.2 The contribution of hired labour, farm chemicals and family labour to bean yield

(i) The contribution of hired labour to bean yield is given by;

$$\beta_4 + \beta_{10} 0.5\ \ln(val.hrdlb)^2 + \beta_{26}\ln(val.hrdlb.time) \ldots\ldots\ldots\ldots\ldots\ldots.(A\ 2.2.1)$$

The value of ‘ln(*val.hrdlb)’* used is its mean value from the data (1.804), and the coefficients

$\beta_4, \beta_{10}, \beta_{26}$ are obtained from Table 3.12, so that;

-0.2228 + 0.0407 (0.5)(1.804 x 1.804) + 0.0291(1.804 x 1) = -0.104

Therefore a **1% increase in the value of hired labour was associated with a reduction of about 0.1% in bean yield during the study period.**

(ii) The contribution of farm chemicals to bean yield is given by;

$$\beta_3 + 0.5\ \beta_9 ln(val.chem)^2 + \ \beta_{24} \ln(val.chem)\ time \dots\dots\dots\dots\dots\dots\dots\dots..(A\ 2.2.2)$$

The value of *ln(val.chem)* used is its mean value from the data (0.2142), and the values of $\beta_3, \beta_9, \beta_{24}$ are taken from Table 3.12, so that;

-0.0943 + (0.5 x 0.0701 x 0.2142 x 0.2142) + 0.1164 (0.2142 x 1)= -0.0677

Therefore a **1% increase in the value of farm chemicals is associated with a reduction of about 0.1% in bean yield during the study period**.

(iii) The contribution of family labour to bean yield is given by;

$$\beta_5 + 0.5\ \beta_{11} \ln(famlb)^2 + \ \beta_{16} \ln(val.org.famlb) \dots\dots\dots\dots\dots (A\ 2.2.3)$$

The values of *ln(famlb)* and *ln(val.org)* used are their mean values from the data; (1.7897) and (0.0705) respectively, while the values of $\beta_5, \beta_{11}, \beta_{16}$ are obtained from Table 3.12, so that;

-0.546 + (0.5 x 1.7897 x 1.7897 x 0.0892) + (0.0341 x 1.7897 x 0.0705) = -0.3989

Therefore, **a 1% increase in the number of family labour days is associated with a reduction of about 0.4% in bean yield during the study period.**

Annex 2.3: Computing the contribution of inorganic fertiliser, hired and family labour to banana yield.

(i) The contribution of inorganic fertiliser is given by:

$$\beta_2 + 0.5\ \beta_8 \ln\ (val.inorg)^2 + \beta_{20} \ln(val.inorg) \ln(famlb) + \beta_{21} \ln(val.inorg)\ (time) \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots..(A\ 2.3.1)$$

The values of *ln(val.inorg)* and *ln(famlb)* used are their mean values from the data; 0.0918 and 3.352 respectively, time=1, and the coefficients $\beta_2, \beta_8, \beta_{20,}\beta_{21}$ are obtained from Table 3.13. Hence;

0.2571+(0.5 x 0.0603 x 0.0918 x 0.0918) + (0.0286 x 0.0918 x 3.352) – (0.2945 x 0.0918 x 1)

= 0.2571 + 0.00025 + 0.0088 – 0.027 = 0.239

Therefore a 1% increase in the value of inorganic fertiliser is associated **with 0.2% increase in banana yield during the study period.**

(ii) Hired Labour

$$\beta_4 + 0.5\,\beta_{10}\ln(val.hrdlb)^2 \ldots\ldots\ldots\ldots\ldots..(A\ 2.3.2)$$
$$-0.1067 + 0.5(0.0448\ x\ 1.1153\ x\ 1.1153) = -0.078$$

A 1% increase in the value of hired labour is associated with a **reduction of about 0.1% in** banana yield.

(iii) Family labour

$$\beta_5 + 0.5\,\beta_{11}\ln\,(famlb)^2 + \beta_{20}\ln(val.inorg)\ln(famlb) + \beta_{27}\ln(famlb)(time)\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.(A\ 2.3.3)$$

-0.2846 + (0.5 x 0.0422 x 3.352^2) +0.0286(0.0918 x 3.352) + (0.4236 x 3.352 x 1)=

-0.2846 + 0.2371 + 0.0088 + 1.4199= 1.3812

A 1% increase in family labour days is associated with **an increase of 1.4% in banana yield** during the study period.

Annex 2.4 The contribution of organic fertiliser, hired and family labour to cassava yield

(i) Organic fertiliser

$$\beta_1 + \beta_{17}\ln(val.org)(time)\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.(A\ 2.4.1)$$

0.8252 – (0.3947 x 0.0372 x 1)= **0.8106**

(ii) Hired labour

$$\beta_4 + \beta_{25}\mathit{ln(hrdlb)\ ln(famlb)} + \beta_{26}\ln(val.hrdlb)\,(time)\ldots\ldots\ldots\ldots\ldots\ldots(A\ 2.4.2)$$

0.1847 – 0.0499(1.1044 x 1.2707) – 0.0474(1.1044 x 1) = **0.0624**

(iii) Family labour

$$\beta_5 + 0.5\beta_{11}ln(famlb)^2\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(A\ 2.4.3)$$

1.2399 - 0.0224 – 0.1424 = **1.0751**