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An Analysis of Productivity Gaps among Smallholder Groundnut Farmers in Uganda and Kenya

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An Analysis of Productivity Gaps among Smallholder Groundnut Farmers in Uganda and Kenya

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DEDICATION

This thesis is dedicated to my little friends Leah, Peter Jr., Patrick and Lydia. May God's light and blessings shine upon you.

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LIST OF ACRONOMS

ATE	Average Technical Efficiency
FAO	Food and Agriculture Organization
FAOSTAT	FAO Statistics
GDP	Gross Domestic Product
GoU	Government of Uganda
KARI	Kenya Agricultural Research Institute
MAAIF	Ministry of Agriculture Animal Industry and Fisheries
MTE	Mean Technical Efficiency
NAADS	National Agricultural Advisory Services
NARO	National Agricultural Research Organization
NaSARRI	National Semi Arid Resources Research Institute
NRF	Non-Research Farmers
PCRSP	Peanut Collaborative Research Support Program
RF	Research Farmers
SPF	Stochastic Production Frontier
SSA	Sub-Saharan Africa
TE	Technical Efficiency
UCONN	University of Connecticut
US	United States
USAID	United States Agency for International Development

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CHAPTER ONE

INTRODUCTION

1.1 Background

The agricultural sector plays a significant role in the economies of many developing countries, especially in sub Saharan Africa (SSA). Despite such importance, productivity has remained low and this is no exception in Kenya and Uganda, which are the two countries of interest in this thesis (World Bank 2008). Agriculture contributes 24% and 19% to Gross Domestic Product and occupies 69.9% and 48.1% of the arable land area in Uganda and Kenya, respectively (World Bank 2010). Furthermore, over 60% of the total population in both Uganda and Kenya live in rural areas and depend entirely on agriculture as the main source of employment and income (World Bank 2010).

In Uganda, studies have shown that most farm yields are lower than the potential yield attainable with adequate farm management (NARO 2009). The evidence shows yield gaps of 67% for maize, 78% for groundnut, 67% for sorghum and 40% for egg production. Earlier evidence revealed that most rice varieties were not achieving their potential yields on farmers' fields in many developing countries (FAO 2004). Yields of 4 to 6 tons per hectare for rice were being obtained compared to a potential of 10 to 11 tons per hectare. Biophysical factors, cultural practices, socio economic conditions, institutional and policy constraints as well as inadequate efforts to transfer technologies and poor market linkages were identified as some of the key reasons for these yield gaps.

Rockström, Barron and Fox (2003) noted that suboptimal performance of rain-fed agriculture is not necessarily due to low physical potential, but primarily to management related issues. Thus, the majority of smallholder farmers remain engaged in subsistence agriculture using traditional methods as most modern technologies and innovations are not accessible and thus highly irrelevant to them.

Increases in food production in the recent past in SSA are a result of more land being brought into production rather than higher output per unit area. According to 2011 estimates, the population growth rate was at 3.6% for Uganda and 2.4% in Kenya with fertility rates of 6.65 and 3.98 children born per woman, respectively (World Fact book 2012). With the increasing population, cultivable land is becoming the limiting factor in meeting the growing food demand implying that farm output growth needs to be achieved through higher productivity (Rockström, Barron and Fox 2003; Govereh, Jayne and Nyoro 1999; World Bank 2008).

According to the World Bank, agricultural based economic growth requires a productivity revolution in smallholder farming (2008). Over 68% of the total agricultural output and marketed agricultural produce is dominated by small-scale farmers in Kenya. Between 2002 and 2007, smallholder farmers produced over 70% of Kenya's maize, 65% of the coffee, 50% of the tea, 80% of the milk, 85% of the fish, and 70% of the beef and related products.

Despite, the significant contribution of smallholder farmers to the agricultural sector and the economy as a whole, they have limited access to services such as extension and credit. Limited market information compromises the bargaining power of smallholders, while they also face high transport costs as well as high input costs associated with using commercially supplied inputs such as improved seeds and inorganic fertilizer. These factors make small scale producers especially vulnerable to external shocks that are outside their control (MAAIF 2009; Republic of Kenya 2010).

Groundnut (*Arachis hypogaea* L.) is one of the most agronomically important food legumes grown in the drier areas of Uganda and Kenya. Many farmers and urban consumers rely on this crop, which is highly adapted to tropical and sub-tropical climates, for their livelihood and nutritional well-being (Rachie 1974; Summerfield et al. 1983). Much of this crop is grown by small scale farmers and many of them operate at the margin of subsistence. In East Africa, groundnut production is characterized by low productivity, low-input cultivation and limited market access (Giliomee 1994; Carr 2001). Therefore, groundnuts play a critical role in attaining food security among poor rural households. For most of these farmers, increased production will translate directly into higher consumption and better nutrition. As the family consumption needs are met, a larger share of production may be traded on regional markets. Thus, higher production and productivity should lead to improved household incomes.

Despite the economic, social and cultural importance of groundnuts, its productivity is severely constrained by both biotic and abiotic factors, resulting in depressed yields of about 700 kg/ha compared to potential yields of 2,000 kg/ha and above achievable with improved cultivars (Okello, Biruma and Deom, 2010). According to Okoko e al. (1998), average yields in Western Kenya, a major groundnut growing region, varied depending on the farming system and type of seed farmers used. Higher yields were observed in farms that used improved varieties as compared to those that used local varieties. Similarly, groundnuts grown in pure stands gave better yields than those in mixed stands. Farmers obtained 30% to 50% lower yields than their potential.

Pests and diseases, lack of appropriate production technologies, inadequate markets and information, and poor post harvest handling practices among others are some of the major factors that influence the low production and profitability of groundnuts in East Africa (Mutegi 2010; Okello et al. 2010; Masette and Candia 2011). Collectively, these challenges adversely affect groundnut productivity limiting the potential contribution of the crop towards improved livelihoods of resource-constrained households. However, there is a major potential for improving groundnut farmers' incomes by increasing productivity. This can be achieved by better access to improved groundnut varieties that are endowed with better disease resistance, better yields and good market acceptability. For maximum benefit, this must be coupled with adoption of improved crop husbandry techniques and accompanying market uptake pathways (Kassie, Shiferaw and Muricho 2010).

The Peanut Collaborative Research Support Program (PCRSP) in collaboration with the Kenya Agricultural Research Institute (KARI) and the National Semi- Arid Resources Research Institute (NaSARRI) in Uganda is addressing some of the constraints facing the groundnut industry in the two countries. The work reported in this thesis is part of this collaboration.

1.2 Problem statement

It is widely recognized that major investments in adopting improved technologies and crop management practices are required to raise agricultural productivity in SSA and various efforts have been made to support agricultural development programs. For example, during the past decade the government of Uganda has established several such programs including: Poverty Eradication Action Plan (PEAP); Local Governments Act and Decentralization; National Action Plan on Women (NAPW); National Agricultural Advisory Services (NAADS); and Plan for

Modernization of Agriculture (PMA) (G0U, 2000). The success of these programs depends to a significant degree on the effective adoption of appropriate technologies (Markham, 1998; 2002). In particular the PMA emphasizes the need to transform agriculture from subsistence to commercial production (GoU 2002). This call for the identification of suitable enterprises and technologies that will enhance agricultural productivity and profitability, and that will open up additional local and international market outlets. Groundnut is one of the priority enterprises identified for commercialization in East and Northern Uganda in response to the national development plan (PMA 2009).

Consequently, several efforts by governments and various partners have led to the development of technologies aimed at increasing groundnut productivity. In Kenya, an increase in the production of maize, beans, and root tubers was registered between 2002 and 2007 although the production of other food crops declined (Republic of Kenya, 2010). The growth in production was attributed to better technology transfer, adoption of high-yielding varieties, better agronomic practices and support from the extension services. Yields of medium-scale and large-scale farmers increased more than those for smallholder farmers. Medium-scale and large-scale farmers had better access to services (extension, credit), and tended to be more receptive to technological innovations than their smaller counterparts, which resulted in the productivity growth differentials just noted (Republic of Kenya, 2010).

Although, yield increases resulting from adoption of improved technologies have been reported in both Uganda and Kenya (ICRISAT 2012), these increases have not matched the yields obtained at on-station and on-farm research managed trials. Whether differences in managerial performance are the major cause of the yield gaps between the potential and actual farm yields remains to be examined.

Researchers also acknowledge that yield gaps span across many ecologies, regions, and countries (FAO 2004). The yield gaps in SSA are, however, higher than those reported elsewhere in the world. For groundnuts, the average yield recorded in SSA was 980 kg/ha in 2006, a level which is considerable lower than the world average of 1,690 kg/ha (Bucheyeki et al. 2008). Reducing yield gaps will increase productivity, improve land and labor use, reduce production costs, and increase sustainability (FAO 2004). It is this background that provided the motivation to undertake the current study aimed at analyzing productivity gaps among groundnut producers in Kenya and Uganda.

Productivity improvements through technological change and/or technical efficiency gains have an important role to play in groundnut farming. Technological progress relates to jumps in the production frontier originating from the adoption of modern technologies like improved seeds, and better machines. By contrast, technical efficiency (TE) refers to a firm's ability to achieve maximum output from a given amount of resources and available technology (Coelli, Rao and Battese 1998).

1.3 Objective of the study

The general objective of the study is to analyze 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. The specific objectives pursued in the study are:

1. To analyze productivity gaps stemming from the use of improved seed varieties versus local varieties; and
2. To examine productivity gaps associated with the managerial performance of research (RF) versus non research farmers (NRF), and of male versus female farmers.

The data include two groups of farmers in each country. One group consists of research farmers, defined as those who received direct support from researchers on groundnut farming and/or were engaged in on farm groundnut trials. The other group comprises non-research farmers defined as those who received no direct intervention from researchers and/or extension agents but cultivated groundnuts.

The degree to which the various productivity gaps are present would make it possible to suggest potential actions for achieving improvements in agricultural output and thus inform suitable policy recommendations. The resulting productivity gains would increase output and farm profits leading to improved farmer livelihoods.

1.4 Data and methodology

Farm level data was collected through a household survey that was conducted by the Kenya Agricultural Research Institute (KARI) and the National Semi- Arid Resources Research Institute (NaSARRI) in Uganda in cooperation with the University of Connecticut Peanut Collaborative Research Program (CRSP) between April and August, 2010 for the two cropping seasons of 2009. The survey covered the following nine districts in Uganda: Kumi, Amuria, Soroti, Pallisa, Budaka, Jinja, Kamuli, Pader and Lira, located in the regions of Teso, Busoga and Northern. The data for Kenya was collected in the Ndhiwa, Nyarongi, and Kobama divisions of the Ndhiwa district. These regions were selected mainly because some farmers in these areas had received groundnut research interventions, and also due to the importance of groundnut production in the corresponding farming systems.

The data collected in the surveys is used to estimate stochastic production frontiers that represent the best-practice technology against which individual farm efficiency is measured. The stochastic frontier model incorporates a composed error structure where a two sided symmetric term captures standard random variability and a one sided component captures inefficiency. The ratio of the observed output relative to the potential output defined by the estimated frontier, given inputs and the technology, provides an estimate of technical efficiency. The parameters of the stochastic production frontiers are estimated using maximum likelihood techniques, given suitable distributional assumptions of the error terms.

1.5 Organization of the thesis

The rest of the thesis is organized into four additional chapters. Chapter 2 gives a description of the geographical location of the study area, discusses the concepts of technological progress and technical efficiency and includes an overview of agriculture in Africa. Chapter 3 provides details concerning the conceptual framework, data and empirical model used in the analysis. Chapter 4 comprises the empirical results of the study and the final chapter contains a summary, conclusions and recommendations.

CHAPTER TWO

STUDY AREA AND REVIEW OF RELATED LITERATURE

This chapter gives a detailed description of the study area, discusses the concept of technological progress and technical efficiency and summarizes some of the key literature focusing on the productivity of African Agriculture and technical efficiency studies.

2.1 Study Area: Geographical location and agro ecological zones

Located in East Africa, Uganda is a landlocked country, about 800 kilometers inland from the Indian Ocean. It lies astride the Equator, between latitudes 4^o 12´ N and 1^o 29´ S and longitudes 29^o 34´ W, and 35^o 0´ E. Temperatures are in the range of 15^o to 30^o C. Precipitation is fairly reliable, varying from 750 mm in drier areas in the Northeast to 1,500 mm in the high rainfall areas around lake shores and in the highlands. The country has a tropical climate and is generally rainy with two dry seasons (December to February, and June to August). There is a semiarid region in the northeast (World fact book 2011). It has a total land surface of 241,038 square kilometers, 197,100 square kilometers of dry land and 43,938 square kilometers under water. Uganda is bordered by Tanzania and Rwanda to the south, Zaire to the west, Sudan to the north and Kenya to the east. The country is divided in to four regions North, South, East and West and each region is divided into districts (Wikipedia 2012).

Uganda is comprised of seven broad agro ecological zones that are similar in economic and social backgrounds and in which ecological conditions (soil types, topography, and rainfall), farming systems and practices are fairly homogeneous. This study covers three of the seven agro ecological zones: Busoga; Teso; and the Northern system.

The Busoga system, also known as the banana-millet-cotton system, receives bimodal rainfall that is less stable; therefore, there is greater reliance on annual food crops (millet, sorghum and maize). The soils are mainly sandy-loams of medium to low fertility. In the drier areas, livestock production is a main activity. The districts of Budaka, Jinja and Kamuli fall in this category (MAAIF 1995).

The Teso system also receives bimodal rainfall on sandy-loams of medium to low fertility. Its vegetation is characterized by short grasses which are ideal for grazing. The staple foods are millet, maize and sorghum. Oil seed crops (groundnuts, simsim and sunflower) are common. Cotton is the major cash crop. Mixed agriculture is practiced and cultivation by oxen is the main agricultural technology. Livestock are also kept. The use of crop residues as manure and animal feed is very common in this system. The districts of Pallisa, Kumi, Amuria and Soroti are part of the Teso agro ecological system (MAAIF 1995).

The Northern system has an annual rainfall of about 800 mm. The dry season is severe therefore drought tolerant annual crops are cultivated. These include finger millet, simsim, cassava and sorghum. Tobacco and cotton are the major cash crops. The districts of Lira and Pader belong to this category (MAAIF 1995).

Kenya is located east of Uganda, bordered by the Indian Ocean, Somalia and Tanzania to the east, north east and south, respectively. To the north and northwest, it is bordered by Ethiopia and Sudan. It lies on coordinates 1 00 N, 38 00 E. The country covers a total area of 580,367 km^2, of which 569,140 km^2 is dry land and 11,227 km^2 is water. The climate varies from tropical along the coast to arid in the interior (World fact book 2011). Administratively, Kenya is divided into eight provinces: Central, Coast, Eastern, Nairobi, North Eastern, Nyanza, Rift Valley, and Western provinces. These provinces are further subdivided into districts (Wikipedia 2012).

Kenya is divided into seven ecological zones: Tropical Alpine; Upper Highland; Lower Highland; Upper Midland; Lower Midland; Lowland; and Coastal Lowland. The Ndihwa district, where some of the data used in this study comes from, lies in the Lower Midland agro-ecological zone between Latitude 0.73°S and Longitude 34°E. It is situated at an altitude of 1,200 to 1,400 meters above sea level, between the lower Lake Victoria basin and western Kenya. It receives an average rainfall of about 1,300 mm annually, with two rainy seasons. The long rains come from February to June, with a peak in March–April and the short rains are from August to November, with a peak in October (Republic of Kenya 2010).

2.2 Factors affecting productivity

Productivity growth can be decomposed into technological change and technical efficiency (Nishimizu and Page 1982). Technical efficiency can be interpreted as a relative measure of managerial ability for a given technology, whereas technological change captures "jumps" in the production function stemming from the application of improved practices that come from research and development efforts (Ahmad and Bravo-Ureta 1995). Many productivity studies involve the use of production frontiers that describe the technical relationship between inputs and outputs and thus define the maximum output attainable from a given bundle of inputs and technology (Coelli, Rao and Battese 1998).

A given production frontier reflects the current state of technology used by a firm. Therefore, productivity improvements through technological change can be represented by an upward shift of the production frontier while productivity improvements through higher technical efficiency are reflected by firms operating closer to the frontier. The distance between the maximum or frontier output and the point where a firm actually produces reflects the level of inefficiency or the efficiency gap. The presence of inefficiency in production indicates that output could be increased without requiring additional inputs given the prevailing technology (Coelli 1995; Coelli, Rao and Battese 1998).

Technological change encompasses output and productivity growth that result from the application of scientific knowledge. Technological change could be achieved through changes in production methods, input quality or introduction of new processes and inputs. However, high and low rates of technological progress can co-exist with declining or improving technical efficiency levels. The driving forces behind the productivity components of efficiency and technological change are different. While research and development are the driving forces behind technological change, education and experience are essential for improving technical efficiency (Anderson and Feder 2007; Ahmad and Bravo-Ureta 1995). It is therefore important to decompose productivity growth into technological change and technical efficiency components when designing policies geared at improving performance (Antle and Capalbo 1988; Nishimizu and Page 1982).

Another way to visualize productivity improvements is by defining technological and managerial gaps. These gaps are defined by differences in production between farmers' actual practices and the best practices that exist at any point in time. Anderson and Feder (2007) defines best practices as an embodiment of the latest science-based developments designed to overcome the limitations imposed by traditional technology and practices and thereby enhance productivity. However, new technologies should be aligned with the agro-ecological and socioeconomic characteristics of the target area. Narrowing of both the technological and management gaps is needed in order to improve productivity.

Education may directly affect agricultural productivity through its cognitive and non cognitive effects or indirectly by its effects on output through interactions with institutional variables such as access to credit (Appleton and Balihuta 1996). Cognitive outputs of education include the transmission of specific information and the formation of general skills and proficiencies. Increasing literacy and numeracy may help farmers to acquire and understand information and to calculate appropriate input quantities in a modernizing or rapidly changing environment. Non-cognitive effects include changes in attitudes, beliefs and habits. Improved attitudes and changes in beliefs and habits may lead to a greater willingness to take risk, adopt innovations, save for investment and generally to embrace modern productive practices. Education may also lead to a greater openness to new ideas and modern practices thereby affecting agriculture negatively as the more qualified individuals leave farming to seek employment in other sectors of the economy (Appleton and Balihuta 1996).

Appleton and Balihuta (1996) found a positive relationship between education and agricultural productivity among Ugandan farmers. Four years of formal education raised production by seven percent. Education also increased productivity among neighboring farmers through spillover effects. They also noted that education raised productivity through increases in physical capital and purchased inputs. Weir and Knight (2004) concluded that household education positively influenced the level of technical efficiency. They found that there are substantial and significant benefits to education that increased average production, and shifted out the frontier.

Parikh et al. (1995), using stochastic cost frontiers in Pakistani agriculture in a two-stage estimation procedure, found that education, the number of working animals, credit per acre, and the number of extension visits significantly increased cost efficiency, while larger farms and a more subsistence orientation significantly decreased cost efficiency. Coelli and Battese (1996), Wang, Wailes, and Cramer (1996), and Seyouma et al. (1998) found that the farmer's level of education was positively related to technical efficiency, and suggested that this may be because educated farmers are more open to new ideas. They also found that older farmers are less technically efficient than younger farmers and that family size and per capita net income are both positively related with production efficiency. Off-farm employment was negatively related to efficiency, perhaps because households with off-farm employment have limited time to devote to managing their farms.

Another important theme is that for investments in research and technology to have an impact on agricultural productivity, appropriate information delivery mechanisms to reach farmers are essential and in this context well functioning extension services are very important. Extension involves transferring knowledge from researchers to farmers, guiding the farmers' decision-making process which enables them to clarify their own goals and possibilities and thus stimulate desirable agricultural development options. The information that can be delivered by extension ranges from estimates of future prices of farm products to the use of new technologies such as improved seeds and knowledge about how to apply modern or unfamiliar inputs (Byerlee 1998).

Extension helps to reduce technology gaps by accelerating technology transfer and efficiency gaps by helping farmers become better managers. By bridging communication channels between scientists and farmers, extension facilitates both adoption and adaptation of technology to local conditions. Technology adoption is facilitated by translating information from the store of knowledge and research to farmers while adaptation is facilitated by articulating farmers' problems and constraints to researchers (Anderson and Feder 2007).

It should be noted that extension has the greatest impact at the early stages of technology dissemination. As the number of farmers who become increasingly aware of a specific technology rises, the impact of such extension diminishes until the opportunity and need for more information-intensive technology arises. The way in which extension services are rendered and the circumstances under which recipients of extension services operate, will affect the extent of the impact observed (Anderson and Feder 2007). Seyouma (1998) added that farmers who have access to extension services tend to be more technically efficient than those who have no such access. This indicates the importance of extension services in improving productivity. Solis, Bravo-Ureta and Quiroga (2008) used data from 639 farms in El Salvador and Honduras to estimate a household input oriented stochastic distance frontier and then analyzed TE among peasant farmers participating in Natural resource programs. These authors found a positive relation between productivity and output diversification, and a positive relationship between TE and off- farm income, human capital and agricultural extension.

2.3 Productivity in African agriculture

Studies have shown a pattern of growth in productivity of African agriculture in the 1960s, regression in the 1970s, and an upturn in the early 1980s (Rezek, Campbell and Rogers 2011). FAO (2009) has reported an annual productivity growth rate of 0.6% for the years 2000–2007, and an annual growth in crop production equal to 2.9% from 1997 to 2007.

In terms of groundnut production, developing countries account for over 90% of the area devoted to this crop worldwide and about 95.5% of total groundnut production with average yields equal to 1,522 kg/ha. Production is concentrated in Asia and Africa, where the crop is grown mostly by smallholder farmers under rain-fed conditions with limited inputs. Africa accounts for 40% of the global groundnut area but only for 26% of production (ICRISAT 2012). The highest average groundnut yields have been observed in Southern Africa and the lowest in East Africa (Table 1). Within East Africa, the highest average yields have been observed in Kenya while Uganda is the major growing country in the region (Figure 1).

Nkamleu (2004) in his study of the agricultural sector of 16 African countries from 1970 to 2001 has argued that the 0.1% per annum productivity growth estimated was the result of an average increase in TE equal to 0.6% per year combined with a 0.5% annual decrease in technological progress. The technological change component was observed to fluctuate widely suggesting that its promotion had not been consistent during the period. Eleven out of the 16 countries analyzed increased efficiency more than technology. Uganda was among the five countries where technological change increased more than efficiency. It was noted that high technology investments often follow civil war and this could explain the better productivity performance observed in Uganda and Mozambique, which did experience civil wars.

In another cross country study, Lusigi and Thirtle (1997) reported an average productivity growth of 1.27% with efficiency improvements of 1.15% and technological progress at 0.9% per annum over a period of 30 years (1961 to 1991). A total of 47 countries were included in this study and five of them registered efficiency losses while 17 experienced technological regress. The authors argue that population pressure on land was the major explanation for faster growth, which is consistent with Boserup (1965), and with Hayami and Ruttan's (1985) induced innovation hypothesis.

De Janvry and Sadoulet (2001), using a general equilibrium model found that Africa benefitted significantly from the direct effects of technology adoption. Farmers who adopt technological innovations derive potential benefits from increased production for home consumption, and higher profits from sales as a result of lower production costs. Indirect effects of technology stem mainly from more generalized adoption which leads to lower commodity prices, employment and growth linkage effects.

2.4 Technical efficiency in sub-Saharan Africa

This section provides a review of farm level studies that have used frontier methods to examine TE in SSA, highlighting the few studies that have focused on TE of groundnut farming and on studies that looked at the connection between TE and gender.

Table 2 presents technical efficiency estimates for African farms reported in 29 studies that used farm level data, published from 1983 to 2012. The studies are categorized according to the methodology employed in the study and summarized by the last name of first author, year of publication, country, enterprise(s) analyzed, number of observations and the mean TE reported. For studies that reported more than one TE estimate with the same methodology, the number of observations and TE estimates is reported separately.

The 29 studies reviewed yielded a total of 40 technical efficiency estimates, where 36 are stochastic, 2 are parametric deterministic and 2 are non-parametric. The lowest mean TE reported was 35% for rice in Côte d'Ivoire, while the highest was 96% for cocoyam in Nigeria. The stochastic frontier methodology gave the highest mean TE equal to 71.2%, followed by non-parametric with 60.1% while the two parametric deterministic studies exhibited the lowest mean at 53.5%. The overall average TE for the 40 cases is 69.8% which is somewhat lower than the 73.7% overall average reported by Bravo-Ureta et al. (2007) for the 28 cases they analyzed for Africa. In sum, the studies show that there is considerable room to raise agricultural output given the prevailing technology and without additional conventional inputs.

Only two studies focusing on TE for groundnut farms were found. One of these studies, by Thiam and Bravo-Ureta (2003), reported an average technical efficiency of 70.3% for a sample of Senegalese groundnut producers. The second study is by Binam et al. (2004) who focused on a sample of 450 farmers that practiced slash and burn agriculture in Cameroon. These authors reported an average technical efficiency of 77% and 75% for groundnut mono crop and maize-groundnut farming systems, respectively. The differences in TE were explained by access to credit, soil fertility, and social capital, distance of the plot from the access road and access to extension services. Farmers with more than four years of schooling, better access to credit, located in fertile regions and with membership in a club or association were more efficient compared to their counterparts. The distance of the plot from the main access road and access to extension services had a negative relationship with technical efficiency.

The literature on groundnut in Africa shows that groundnuts were originally cultivated by women to supplement their families' diet with protein. The income from sales offers women a way to generate cash thereby increasing their agency and empowerment. A number of studies have focused on the role gender plays on agricultural productivity and here we provide an overview of a few of these studies that have special relevance for this thesis.

Kibaara (2005) and Msuya, and Hisano and Nariu (2008) examined the technical efficiency of smallholder maize farmers in Kenya and Tanzania, respectively. Both studies found male headed households to be more efficient than their female counterparts. Njuki et al. (2006) in their study of productivity differences between male and female managed farms in the Eastern and Central highlands of Kenya found that farms managed jointly by males and females had the highest TE at 77%, followed by those managed by males with a mean TE of 62% while farms managed by females had the lowest TE at 56%.

Quisumbing (1995) reviewed seven studies from Kenya, Burkina Faso, Nigeria, Korea and Thailand that used production frontiers to analyze TE by gender of the farm manager. The study found that women farmers exhibited lower yields but this was attributed to their low input use and lower levels of human capital compared to men which led to the conclusion that there was no gender related difference in management. The author also found significant returns to schooling for both men and women, and farmers with more education were more likely to adopt new technologies.

2.5 Conclusions

The literature on technical efficiency of groundnuts in Africa is scarce; however there is evidence of productivity gaps in African agriculture in general. Understanding the driving forces behind technical efficiency and technological change can guide policy decisions in improving productivity. Extension can play a major role in narrowing the technology gap by accelerating technology transfer and diminishing efficiency gaps by helping farmers become better managers. Although most studies argue that the productivity gaps in African agriculture are a result of both technical inefficiency and low levels of technological progress, others have argued that smallholder farmers are efficient and thus productivity gains need to come from technological progress.

The next chapter discusses the conceptual framework used to address the objectives of the study, and presents the data and empirical model used in the analysis.

Table1. Groundnut yields (kg/ha)

	2005	2006	2007	2008	2009	2010
World	1,609	1,553	1,654	1,579	1,531	1,564
Africa	996	1,080	909	930	932	889
Eastern Africa	590	667	674	659	670	637
Northern Africa	754	1184	1,232	945	1,169	830
Southern Africa	1,484	1,430	1,313	1,484	1,653	1,401
Western Africa	1,202	1,242	981	1,036	991	975

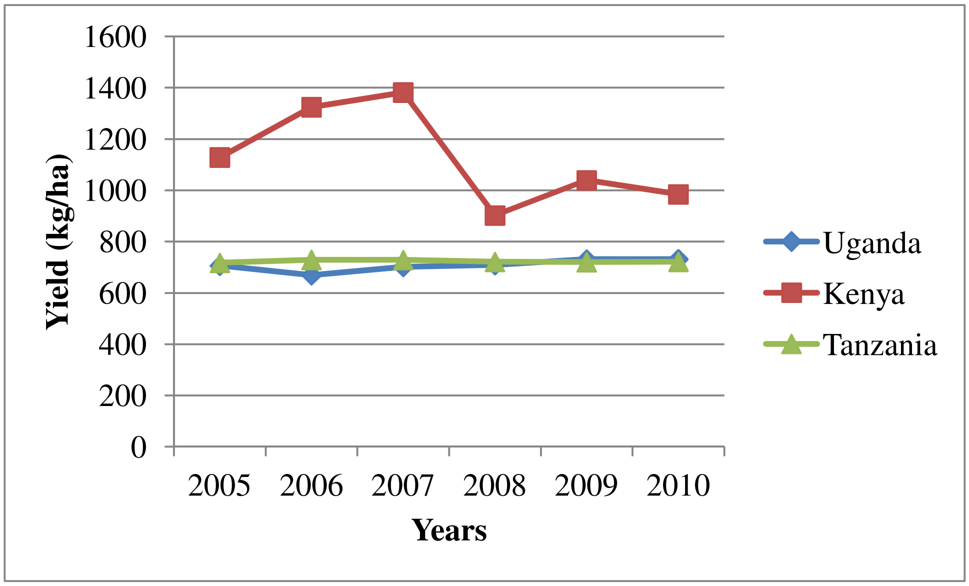
FAOSTAT | © FAO Statistics Division 2012 | 11 January 2012

Table 2. Technical efficiency estimates for African farms

First Author	Year of publication	Country	Enterprise(s)	Sample size	MTE
a). Parametric-Stochastic Frontiers					
Abdulai	2000	Ghana	Rice	120	73.0
Admassie	1999	Ethiopia	Crops	64	90.8
Aguilar	1993	Kenya	Crops	347	93.9
Ajibefun	2002	Nigeria	Crops	67	82.0
Ajibefun	1999	Nigeria	Crops	98	67.0
Amaza	2007	Nigeria	Crops	123	69.0
Amaza	2002	Nigeria	Crops	123	69.0
Audibert	1997	Mali	Rice	836	69.5
Binam	2004	Cameroon	Crops	150	75.0
Binam	2004	Cameroon	Groundnut	450	77.0
Heshmati	1996	Uganda	Plantain	144	65.3
Binam	2004	Cameroon	Maize	450	73.0
Binam	2004	Cameroon	Groundnut & Maize	450	75.0
Seyoum	1998	Ethiopia	Maize	20	86.6
Sherlund	2002	Côte d'Ivoire	Rice	464	43.0
Ofori-Bah	2011	Ghana	Cocoa mixed crop	161	86.0
Ofori-Bah	2011	Ghana	Cocoa	161	47.0
Djokoto	2012	Ghana	Agriculture		82.0
Binam	2010	Cameroon	Cocoa	824	65.0
Binam	2010	Ghana	Cocoa	861	44.0
Binam	2010	Nigeria	Cocoa	1041	74.0
Binam	2010	Côte d'Ivoire	Cocoa	1020	58.0
Mignoun	2012	Kenya	Maize	600	70.0
Maganga	2011	Malawi	Potatoes	200	83.0
Chirwa	2007	Malawi	Maize	156	46.2
Irz	2010	Botswana	Agriculture	342	85.0
Thiam	2003	Senegal	Groundnut	501	70.4
Obwona	2006	Uganda	Tobacco	65	78.4
Okoye	2007	Nigeria	Cocoyam	120	96.0
Lovo	2010	South Africa	Maize/Vegetables/Fruits	547	36.0
Ogundari	2010	Nigeria	Food crops	846	81.0
Uaiene	2009	Mozambique	Crops	4104	65.0
Iheke	2008	Nigeria	Cassava	160	77.0
Idiong	2008	Nigeria	Rice	112	77.0
Rao	2010	Kenya	Traditional market Vegetables	269	54.0

Rao	2010	Kenya	Super market Vegetables	133	80.0
ATE					**71.2**
Deterministic Frontiers					
Croppenstedt	1997	Ethiopia	Crops	344	41.0
Shapiro	1983	Tanzania	Cotton	37	66.0
ATE					**53.5**
b). Non parametric Frontiers					
Sherlund	2002	Côte d'Ivoire	Rice	464	35.0
Chavas	2005	Gambia	Food crops	120	85.2
ATE					**60.1**
Overall ATE					**69.8**

Figure 1. Average groundnut yields among East African Countries



CHAPTER THREE

CONCEPTUAL FRAMEWORK, DATA AND EMPIRICAL MODEL

This chapter discusses the conceptual framework used to address the study objectives, presents the data used, and gives an overview of the sample characteristics. The last section specifies the empirical model employed in the analysis.

3.1 Conceptual framework

The frontier methodology is classified into parametric and non parametric methods. Non-parametric methods, also known as data envelopment (DEA) analysis, use linear programming while parametric approaches use econometric or statistical methods (Coelli, Rao and Battese 1998). Unlike the parametric approach, non parametric methods do not impose a functional form or make assumptions about the error term.

Parametric frontiers can be categorized as deterministic and stochastic where the former assume that all deviations from the frontier are due to inefficiency. This makes the resulting TE estimates sensitive to outliers since measurement error and/or any other source of stochastic variation in the dependent variable is embedded in the one sided error component (Greene 1993). The stochastic frontier analysis on the other hand, acknowledges the fact that random errors outside the control of producers do affect output. This measurement error is accounted for by incorporating a composed error structure with a two sided symmetric term and a one sided component. In addition, in contrast with DEA, stochastic frontier analyses permit estimation of standard errors and make it possible to undertake various statistical hypotheses tests (Greene 2008).

The main criticisms of the stochastic frontier approach is the need to specify some arbitrary functional form for the frontier and that there is generally no *a priori* justification for the selection of any particular distributional form for the one sided inefficiency term. Specification of more general distributional forms for both the frontier and the one-sided error has partially alleviated the problem, but resulting efficiency measures may still be sensitive to the underlying assumptions (Coelli, Rao and Battese 1998).

The stochastic frontier production approach was initially proposed by Aigner, Lovell and Schmidt (1977), and Meeusen and van den Brock (1977). A key extension to the model was introduced by Battese and Coelli (1995) and their formulation can be expressed as:

(1) $Y_i = f(X; \beta) + v_i - u_i \qquad i = 1, 2 \ldots n$

where Y_i is the output of the i-th firm; X is a vector of inputs; β is a vector of parameters to be estimated; $f(.)$ represents the functional form; v_i is a two–sided random error term which is assumed to be identically and independently distributed (iid) with a normal distribution [N (0, σ_V^2)]; and u_i is a one–sided non negative random error that captures technical inefficiency in production. The terms v and u are assumed to be independent of each other. The inefficiency error term measures the shortfall in output from its maximum value given by the stochastic frontier while the random error captures stochastic effects outside the firm's control such as rainfall, drought, luck, measurement error and other statistical noise.

Battese and Coelli (1995) suggest that the technical inefficiency effects in equation (1) can be expressed as a linear function of explanatory variables reflecting farmer specific characteristics. The term u_i is assumed to be independently distributed and obtained by truncations at zero of the normal distribution with variance σ_u^2 and mean u_i defined as:

(2) $U_i = Z\delta + w_i$

where w_i is a random variable defined by the truncation of the normal distribution with a mean of zero and variance σ^2 such that the point of truncation is equal to $-Z\delta$, i.e. $w_i \geq -Z\delta$. The assumptions are consistent with u_i being a non-negative truncation of the N ($Z\delta$, σ^2) distribution. Z is a set of explanatory variables and δ is a vector of unknown coefficients.

The β and δ coefficients as well as the variance parameters σ^2_s and γ are estimated using the maximum likelihood method. The likelihood function is expressed in terms of the variance parameters as $\gamma = \sigma_u^2/\sigma_s^2$ and $\sigma^2_s = \sigma_u^2 + \sigma_v^2$. The parameter γ has a value between 0 and 1. A value of γ equal to 0 implies that deviations from the frontier are entirely due to noise while a value of 1 indicates that all deviations are due to technical inefficiency (Battese and Corra 1977).

The technical efficiency of the i- th firm is calculated relative to the estimated production frontier of a fully efficient firm using the same set of inputs and is defined as:

(3) $TE_i = \exp(-u_i) = \exp(- Z_i\delta - w_i)$

Following Jondrow et al (1982), Battese and Coelli (1988) suggest that technical efficiency can be predicted using its conditional expectation, given the composed error. Technical efficiency ranges between zero and one and is the inverse of technical inefficiency.

The variation of TE across firms can be explained using either a one stage or a two stage approach. The two stage approach involves first the specification and estimation of the stochastic frontier production function and the prediction of the technical inefficiency effects under the assumption that the inefficiency effects are identically and independently distributed. In the second stage, a regression model for the predicted technical inefficiency effects is specified as a function of farm specific factors. The two-step approach has received criticism because there is a contradiction in the assumption concerning the distribution of *u* between the first and the second stage (Coelli 1995). In the stochastic model, this problem can be overcome by using the single-step maximum likelihood approach of Battese and Coelli (1995). In this study, we adopt this one stage approach where parameters of the stochastic frontier and the inefficiency model are estimated simultaneously in one step.

3.2 Data

This study used data collected through a household survey that was conducted by the Kenya Agricultural Research Institute (KARI) and the National Semi- Arid Resources Research Institute (NaSARRI) in Uganda, in cooperation with the University of Connecticut Peanut Collaborative Research Program (CRSP), between April and August, 2010. The questionnaire was developed by the Peanut CRSP Project team and reviewed with different stakeholders. A pilot study was then conducted and adjustments made on the questionnaire based on enumerators' and farmers' input.

The survey was conducted in the districts of Kumi, Amuria, Soroti, Pallisa, Budaka, Jinja, Kamuli, Pader and Lira in the regions of Teso, Busoga and Northern in Uganda, and from Ndhiwa, Nyarongi, and Kobama divisions of Ndhiwa district in Kenya. These areas were selected mainly because of the importance of groundnut production prevailing in these areas and because it was known a priori that farmers had been selected to participate in on farm variety trials and thus had been exposed to groundnut research interventions. A stratified random sampling technique was used to select households within the various locations.

Some of the variables included in the models reported in Chapter 4 were obtained directly from the questionnaire and others were computed as follows: Total production was obtained by aggregating total output in first and second seasons in order to obtain annual production. The gardens where groundnuts were grown in pure stands and those that were intercropped were identified, and then the acreage devoted to groundnuts was computed in each case. This information allowed us to calculate the total land devoted to groundnuts. Total seed sown, in kilograms, was calculated by adding the amount of seeds purchased to that received as gifts. The expenditure on family labor was calculated by multiplying the number of labor days by wage per day. Total labor was then computed by summing hired and family labor. All inputs and output quantities are an aggregate amount for the two cropping seasons. Variables like education, farmer type and age are included in the model to capture the human capital aspects of the farmers.

The outliers from the sample were identified using Cook's D. This is a normalized measure of the influence of point i on all predicted mean values, and it is used to assess influence in regression. An observation is considered an outlier if it exceeds the Cook's D critical value given by 4/n-(k+1) where n is the sample size, and k is the number of parameters estimated (Chatterjee, Hadi and Price 2000). A simple regression model was run where total output was regressed on the amount of land, seed, labor and two dummies, one capturing regional differences and the other seed type. Critical values of 0.028 for Uganda and 0.021for Kenya were computed. Eight and 13 households from Uganda and Kenya respectively, had their values greater than the computed critical values, for a total of 21 outliers.

A total sample of 321 (141 from Uganda and 180 from Kenya) households were used in the analysis. Households with missing data of one or more variables and the 21 outliers identified using cook's D procedure were excluded from the final sample.

SPSS and STATA computer programs were used to compute summary statistics, run regressions, compute Cook's D values and run likelihood ratio tests for a number of hypotheses. The FRONTIER Version 4.1 software is used to compute the maximum likelihood estimates of the stochastic frontier (Coelli 1996).

3.3 Sample characteristics

Tables 3 and 4 present descriptive statistics, including means and standard deviations, of the key variables used in the analysis. Of the 141 farmers in Uganda, the overall average age was 49 years. Female managers were a year younger than the male managers whose average age was 50 years. When the sample was divided by farmer type, research farmers were relatively younger with an average of 48 years compared to NRF at 51 years. Overall, farmers in Uganda completed seven years of schooling with a difference of one year between males and females. RF completed eight years while NRF completed seven years of schooling. In Kenya, farmers were on average 44 years old, with male managers older than female managers by four years. Male managers also attained an extra year of schooling compared to female managers who completed 6 years. Both RF and NRF completed seven years of schooling and this was also the overall sample average for farmers in Kenya.

The proximity of households to the research station was comparatively shorter for farmers in Uganda than those in Kenya. The average distance to the nearest research station was

39.2 km in Uganda with RF and NRF located 32.9 km and 47.2 km away, respectively. In Kenya, the overall mean distance was 80.1km with 83.1km for RF and 77.5 km for NRF.

The average farm size was 2.8 hectares (ha) in both countries. Farmers in Uganda devoted a mean of 1.15 ha of land to groundnut farming compared to the 0.64 ha cultivated by producers in Kenya. More seeds were sowed in Uganda compared to Kenya. On average farmers used total labor equivalent to US $194.2 and US $113.5 in Uganda and Kenya, respectively.

Average yields were lower in Uganda compared to Kenya (685 kg/ha versus 907 kg/ha, respectively). Higher yields were observed among households who planted improved varieties as compared those that planted only local varieties in Uganda and Kenya. Similarly RF obtained higher yields compared to NRF in both countries. In Uganda, households where females managed the gardens had an average yield of 623 kg/ha while male-managed gardens had a mean yield of 758 kg/ha. A similar pattern was observed in Kenya where female-managed gardens had an average yield of 867 kg/ha while male managed gardens had a mean yield of 933 kg/ha.

3.4 Empirical model

Both the Cobb-Douglas and the translog functional forms are used to fit the stochastic production frontiers that will be discussed in Chapter 4. The Cobb-Douglas functional form is preferred in most empirical estimations of frontier models because of its simplicity. However, the input elasticities and returns to scale are the same for all firms in the sample and elasticity of substitution is assumed to equal one. More flexible functional forms like the translog impose relatively fewer a *priori* restrictions on the structure of production but may suffer from degrees of freedom and multi-collinearity problems (Coelli 1995; Greene 1993).

The output and input variables in the translog function are expressed as deviations from their sample means, so the first-order coefficients can be interpreted as partial elasticities of output evaluated at the mean of the data (Coelli et al. 2003). The Cobb-Douglas and the translog production frontiers to be estimated are expressed in equation (4) and equation (5) respectively:

(4) $\ln Y_i = \beta_0 + \beta_1 \ln X_{1i} + \beta_2 \ln X_{2i} + \beta_3 \ln X_{3i} + \beta_4 T_D + \beta_5 locD_i + v_i - u_i$

(5) $\ln Y_i = \beta_0 + \beta_1 \ln X_{1i} + \beta_2 \ln X_{2i} + \beta_3 \ln X_{3i} + \beta_4 T_D + \beta_5 locD_i + 0.5\ \beta_6 \ln (X_1)^2 + \beta_7 \ln X_{1i}X_{2i} + \beta_8 \ln X_{1i}X_{3i} + 0.5\ \beta_9 \ln (X_{2i})^2 + \beta_{10} \ln X_{2i}X_{3i} + 0.5\ \beta_{11} \ln (X_{3i})^2 + v_i - u_i$

where the subscript *i* refers to the i-th farmer in the sample and ln to natural logarithm and:

Y is the output of groundnuts measured in kilograms;

X_1 is the amount of land under groundnut cultivation in hectares;

X_2 is the quantity of groundnut seeds sowed in kilograms (Kg);

X_3 is the value of the sum of family and hired labor in US dollars;

T_D is a dummy equal to 0 if only local seed varieties are used and 1 otherwise;

LocD is the dummy that captures regional differences (D = 1 if farmer is located in Northern region in Uganda and Ndihwa division in Kenya; 0 otherwise).

The variables used in the inefficiency effects model for both the Cobb-Douglas and the translog functions are defined as follows;

(6) $U_i = \delta_0 + \delta_1 Z_{D1i} + \delta_2 Z_{D2i} + \delta_3 Z_{3i} + \delta_4 Z_{4i} + \delta_5 Z_{5i} + w_i$

Z_1 = dummy for gender of the garden manager (D = 1 if female; 0 otherwise);

Z_2 = farmer type (D = 1 if research farmer and D = 0 if NRF);

Z_3 = age of the household head in years;

Z_4 = education of the household head in years of schooling completed;

Z_5 = distance to the nearest research institute in kilometers (km).

As mentioned in chapter one, the two key objectives of the study are: to analyze productivity gaps stemming from the use of improved seed varieties versus local varieties; and to examine productivity gaps associated with the managerial performance of research (RF) versus non research farmers (NRF), and of male versus female farmers. Consequently, three null hypotheses (H_0) are tested:

$H_0$1: The parameter of β_4 (for type of seed T_D) = 0

$H_0$2: Mean TE_{RF} = Mean TE_{NR}; and

$H_0$3: Mean TE_{MALE} = Mean TE_{FEMALE}

Farmers that used improved seed varieties are expected to operate on a higher production frontier compared to those that used local varieties. Cultivating improved seeds increases output relative to local seeds thereby shifting the production function upwards. In this study, this difference in output between improved and local varieties holding all other inputs constant reflects the technological gap. In addition, we expect the average level of TE for the RF to be higher than the average for the NRF because the former received technical support on production of groundnuts from researchers and/or extensionists. The expectation is that such support would translate into better management by RF relative to NRF which in turn would be captured by a higher level of TE.

The first two hypotheses are depicted graphically in figure 2 below. The distance between Y_2 and Y_4 represents the jump in the production frontier due to technological improvements associated with cultivating the improved varieties, holding other inputs constant. The distance Y_1 to Y_2 and Y_3 to Y_4 correspond to technical efficiency gaps for NRF and RF respectively, again holding other inputs constant.

3.5 Summary

This chapter provided the conceptual and empirical framework used to address the objectives of the study. Both parametric and non parametric methods of efficiency analysis were discussed along with the advantages and limitations of each. The stochastic production frontier (SPF) approach of Aigner, Lovell and Schmidt (1977) is used to estimate technical efficiency and the output effect of improved seeds which representing an improved technology. The SPF model incorporates a composed error structure where a two sided symmetric term captures standard random variability and a one sided component captures inefficiency. Technical efficiency is given by the ratio of the observed output relative to the potential output defined by the estimated frontier, with a given input vector. The extension of this approach by Battese and Coelli (1995), which specifies the one-sided error term as a function of explanatory variables that reflect farmer specific characteristics, is used as well.

The chapter also described the data collection process including sample size and data cleaning. The empirical model was specified both as a Cobb-Douglas and translog production frontiers. Based on the objectives of the study, hypotheses to be tested were formulated. The chapter ends with a detailed illustration of the research hypotheses of the study. The next chapter provides a detailed analysis and discussion of the results.

Table 3. Socio-economic characteristics of groundnut farmers in Uganda and Kenya

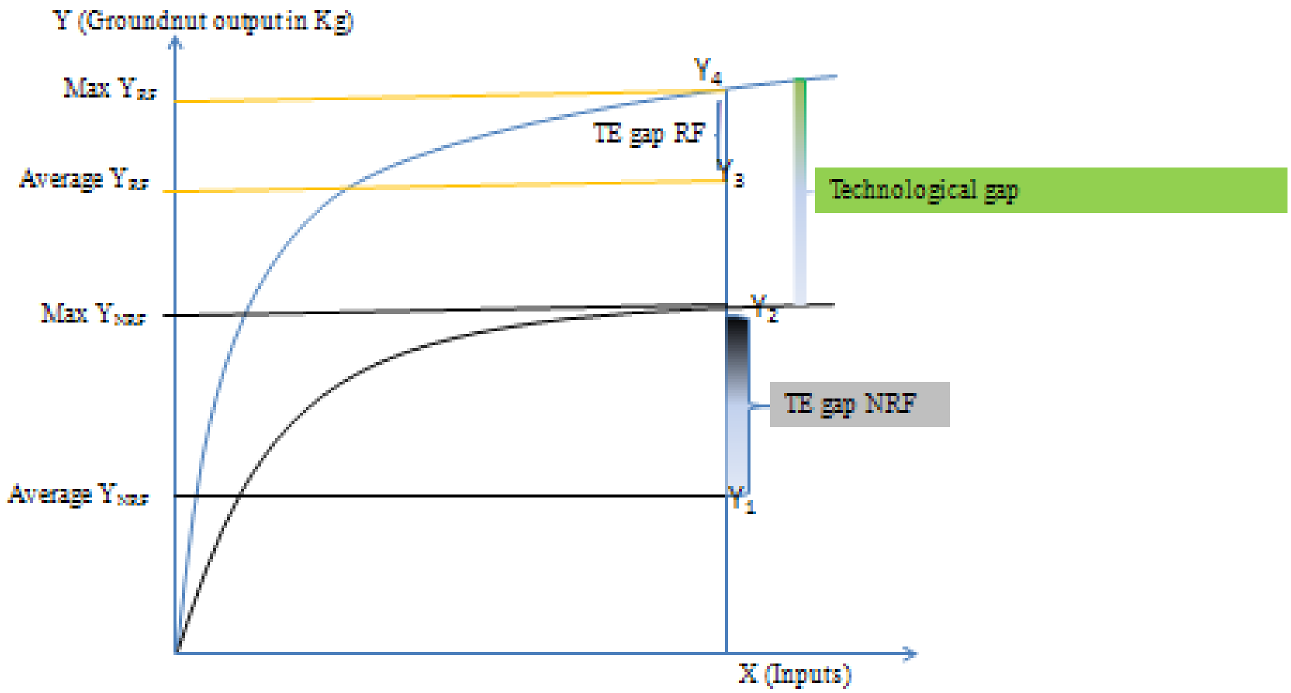
	Uganda			**Kenya**		
Variable	N	Mean	Std. Dev	N	Mean	Std. Dev
Overall sample						
Age of household head (years)	141	49.8	12.6	180	44.8	14.2
Education of household head(years completed)	141	7.4	4.1	180	7.2	3.4
Distance to nearest research station(km)	141	39.2	25.2	180	80.1	14.5
Female headed households						
Age of household head (years)	76	49.5	12.7	70	42.4	12.7
Education of household head(years completed)	76	7.4	4.5	70	6.3	3.5
Distance to nearest research station(km)	76	38.4	26.5	70	81.2	12.2
Male headed households						
Age of household head (years)	65	50.2	12.5	110	46.3	15.0
Education of household head(years completed)	65	7.6	3.7	110	7.7	3.2
Distance to nearest research station(km)	65	40.1	23.8	110	79.4	15.9
Research Farmers						
Age of household head (years)	79	48.7	11.5	84	44.7	14.1
Education of household head(years completed)	79	7.6	4.0	84	7.4	3.3
Distance to nearest research station(km)	79	32.9	27.6	84	83.1	16.3
Non Research Farmers						
Age of household head (years)	62	51.3	13.7	96	44.8	14.4
Education of household head(years completed)	62	7.3	4.2	96	6.9	3.5
Distance to nearest research station(km)	62	47.2	19.2	96	77.5	12.3

Table 4. Descriptive statistics of production variables used in the model

	Uganda			Kenya		
Variable	**N**	**Mean**	**Std. Dev**	**N**	**Mean**	**Std. Dev**
Groundnut land (ha)	141	1.15	0.87	180	0.64	0.71
Labor([1])	141	194.2	165.5	180	113.5	105.9
Seed(kg)	141	45.4	43.7	180	31.0	33.0
Farm size (ha)	141	2.8	1.8	180	2.8	1.3
Yield (kg/ha) by variety type						
D =1 if farmer planted improved variety	120	749.5	771.4	174	918.5	542.5
D = 0 if farmer planted local variety only	21	319.7	231.7	6	588.3	166.9
Yield(kg/ha) by farmer type						
D=1 if RF	79	776.8	778.3	84	925.9	561.2
D=0 if NRF	62	569.1	658.3	96	891.3	518.1
Yield (kg/ha) by gender of manager						
D = 1 if female	76	623.6	664.3	70	867.2	521.1
D = 0 otherwise	65	757.8	804.8	110	933.1	548.3
Productivities						
Total Yield (kg/ha)	141	685.5	732.8	180	907.5	537.4
Seed/ha	141	48.4	47.2	180	58.0	77.7
Labor/ha	141	250.9	281.6	180	284.0	713.0

Note: [1] Expressed in US dollars computed using the IMF 2009 average exchange rates of 2,030.5 Ugandan shilling and 77.4 Kenyan shilling per US$. Source: World Development Indicators (WDI) and Global Development Finance (GDI) 2010.

Figure 2. Illustration of the technological and management gap



CHAPTER FOUR

RESULTS AND DISCUSSION

This chapter gives a detailed description and discussion of the findings of the study. It begins with an explanation of estimates of individual country frontier models estimated both as Cobb-Douglas and translog functions. Then, several tests are performed to assess the suitability of the models with the data, followed by a presentation of the analysis and a discussion of the results based on the most robust model. The chapter ends with a summary of the key findings and conclusions.

4.1 Assessment of different models

The first step is the estimation of individual country stochastic frontier models. The frontier is specified using both the Cobb-Douglas and the translog functional forms as described in the previous chapter. In addition to the base model (referred herein as model I), two additional models II and III were estimated. Model I, as specified in the earlier chapter, incorporates the inefficiency effects component following Battese and Coelli (1995), while model II and III are of the Aigner, Lovell and Schmidt (1977) type.

Models I, II and III can be specified in general terms as in equations (7), (8) and (9), respectively:

(7) $Y_i = f(X; \beta) + \nu_i - g(Z;\delta)$ Model I (Base)

(8) $Y_i = f(X, Z; \beta, \delta) + \nu_i - u_{i,}$ Model II

(9) $Y_i = f(X; \beta) + \nu_i - u_{i,}$ Model III

Model I includes five variables in the stochastic frontier (X) and another five (Z) in the inefficiency effects component, while models II and III include 10 (X, Z) and five (X) variables in the stochastic frontier model, respectively. The explanatory variables included in the inefficiency component in Model I are farmer type (research or non-research), gender, years of schooling, age of the household head and distance to the nearest research station. These variables were already presented and defined in Tables 3 and 4 in Chapter 3.

Cobb-Douglas and translog production frontiers were estimated for the three models (I, II and III) separately for each country and, as will be discussed shortly, the Cobb-Douglas specification was chosen. The maximum-likelihood (ML) estimates of the parameters for models I, II and III for the Cobb-Douglas specification are presented in Table 6 for Uganda and in Table 7 for Kenya. None of the variables in the inefficiency effects component were significant in models I, four out the 10 variables were significant in model II while most of the coefficients in model III were significant in both countries. The ML estimates for the translog production function for Kenyan farmers are presented in Appendix 1. ML estimates that were inconsistent with theory were obtained for the translog for models II and III for Ugandan farmers therefore, only estimates for model I are reported in Appendix 2.

Next, a likelihood ratio test is performed to investigate the adequacy of the Cobb-Douglas functional form relative to the less restrictive translog. The likelihood ratio test requires estimation of the model under both the null (restricted) and alternative (unrestricted) hypothesis. The test statistic is calculated as $LR = -2[\ln L(H_0) - \ln L(H_A)]$ where $\ln L(H_0)$ and $\ln L(H_A)$ are values of the log likelihood functions under the null and alternative hypotheses respectively. The degrees of freedom for the chi-square statistic are given by the difference between the number of parameters estimated under H_A and H_0 (Coelli, Rao and Battese 1998; Battese, Rao and O'Donnell 2004).

In this test, if the second order and interaction parameters of the translog are zero (i.e., H_0 is not rejected), then the Cobb-Douglas is considered an adequate representation of the data. Table 5 presents the results of the LR test of the restricted *versus* the unrestricted translog. In Uganda and Kenya, the LR test did not reject the null hypothesis therefore, the Cobb-Douglas was chosen over the translog production specification.

Another likelihood ratio test was conducted to verify if the same Cobb-Douglas production frontier for models I, II, and III is shared by farmers from Uganda and Kenya. In other words, this test is to determine if the two groups of farmers share the same technology. A pooled sample was obtained by combining the data from Uganda and Kenya and joint Cobb-Douglas frontiers for models I, II, and III were estimated. The log likelihood function values of these stochastic functions were used to compute the test statistic. The results of the LR test presented in Table 5 rejected the pooled stochastic frontier in favor of separate frontiers. This implies that Ugandan and Kenyan groundnut farmers do not share the same technology. Consequently, separate stochastic frontiers were estimated for each country. The results of the pooled models are presented in Appendix 3.

Having settled on separate Cobb-Douglas production frontiers for each country, the null hypothesis that the one-sided error distribution is half normal (H_0: $u_i = 0$) was investigated. The half normal distribution has its mode at zero which implies that there is a high probability that the inefficiency effects are in the neighborhood of zero. This in turn, would imply relatively high technical efficiency (Coelli, Rao and Battese 1998). More general distribution forms like the truncated-normal (Stevenson 1980) have partially addressed the problem. Model III was therefore, estimated using both the half normal and the truncated-normal distributions and the two models were contrasted using likelihood ratio (LR) tests. The LR test (probability > χ^2 critical value = 0.523) failed to reject the null hypothesis in Kenya and the truncated-normal distribution did not converge for the Ugandan data. Therefore, the half-normal distribution is adopted.

The robustness of the three estimated models (I, II and III) was also tested. Based on the LR test described in Table 8, model III was preferred to both models I and II in the two countries. In sum, model III was the most robust and thus is used in the analysis and discussion that follows for each country.

4.3 Coefficients of the production frontier

As shown in Table 6 (Uganda) and Table 7 (Kenya), all coefficients of the inputs included in model III in both countries had the expected positive signs. In addition, all of these coefficients are statistically significant with only one exception, the parameter for labor in Uganda.

The coefficients of the Cobb-Douglas production frontier can be interpreted directly as partial elasticities of production. These partial elasticities measure the percentage change in output when the respective input is changed by 1%. In addition, the sum of all these partial elasticities, known as the function coefficient, gives the returns the scale for the model (Beattie, Taylor and Watts 2009). In Kenya, land had the highest partial elasticity equal to 0.603, followed by the quantity of seeds with 0.287 and labor had the lowest elasticity (0.111). A similar trend was observed in Uganda, where land registered the highest partial elasticity at 0.442, followed by seed with 0.252 and then labor had the lowest value at 0.023. For example, the partially elasticity for land for Uganda and Kenya indicate that a 1% increase in hectares would increase output by 0.442% and 0.603%, respectively. Moreover, the value of the function coefficient for Kenya is 1.001 which denotes constant returns to scale, while for Uganda it is 0.717 revealing decreasing returns to scale.

The dummy that captures regional differences among farmers in Uganda has a value of 0.533 and is significant at the 1% level. This result indicates that farmers in Pader and Lira in the Northern region of the country have a higher groundnut output compared to those in Teso and Busoga, holding all else constant. To calculate this effect in percentage terms for the Cobb Douglas it is necessary to take the antilog of the estimated parameter for the dummy variable, subtract one from it and multiple the difference by 100 (Halvorsen and Palmquist 1980). Therefore, *ceteris paribus*, farmers in Northern can produce 70.4% ($[(e^{0.533}) - 1]*100$) more output than those from other regions. This result is consistent with the fact that the land in the Northern region had been under fallow from late 1980s to about 2007 when the population in the area had been displaced to camps due to the rebel insurgence. A similar geographical variable is introduced in the models for Kenya, and in this case the coefficient for Ndihwa was negative but statistically insignificant and thus no location effect is present.

4.2 Hypothesis tests for model III

Continuing with the most robust model (III) for both countries, several additional hypotheses are evaluated. The first of these hypotheses involves a t-test and a likelihood ratio test to determine the significance of γ, which, as indicated in the previous chapter, is equal to the ratio of the variance of the one sided term (sigma u) divided by the variance of the composed error. Thus, gamma is bounded between 0 and 1 and the closer to 1 the more significant is the output shortfall associated with inefficiency (Battese and Corra 1977; Coelli, Rao and Battese 1998). The γ parameter is significant at the 10% level in Uganda and at the 1% in Kenya. This implies that technical inefficiency is indeed present and therefore the frontier specification is preferable over the average function that would be estimated using ordinary least squares.

In Kenya, the γ parameter value of 0.949 indicates that 95% of the variation in groundnut output is due to technical inefficiency. This result is consistent with that of the one-sided generalized likelihood-ratio test in which H_0 was rejected (LR = 16.68 > critical value of 2.71) leading to the conclusion that groundnut farmers in Kenya are inefficient. However, this was not the case in Uganda where the significance of gamma contradicted the results obtained from the LR ratio test which suggested failure to reject the null hypothesis that technical inefficiencies are absent from the model. In such a case, the one-sided LR test is a better option because it has a higher power than the t-test (Coelli 1995). These results need to be interpreted with caution given the inconsistency of the two tests; the data might have extra noise since the farmers do not keep records and rely mainly on memory.

Next, the presence of a technological gap is investigated. In this study, technological gap is defined by the difference in output between farmers using improved and local varieties holding all other variables constant. This is captured by the coefficient β_4 of Model III in Tables 6 and 7. The null hypothesis that there is no technological gap ($\beta_4 = 0$) among groundnut farmers was rejected at the 1% and 5% significance levels in Uganda and Kenya respectively. This result indicates that the output is higher for farmers using improved varieties compared to those using local varieties. The coefficient for β_4 is equal to 0.888 for Uganda and 0.461 for Kenya, which indicates, respectively, that farmers who planted improved groundnut varieties enjoyed a 143.03% and a 58.6% output advantage over those that planted only local varieties.

The results concerning the technological gap are comparable with findings from other studies. Farmers that used la Fleur II, an improved groundnut variety in Senegal obtained a higher output than those that used the traditional variety (Thiam and Bravo-Ureta 2003). Kassie, Shiferaw and Muricho (2011) also found a positive and significant relation between adoption of improved groundnut varieties and crop income and poverty reduction in Uganda. In a related study, Kipkoech et al (2007) using a Cobb-Douglas production frontier estimated the average TE of adopters and non adopters of fertilizers in Kenya. The authors found that although, adoption of fertility enhancing technologies improved profitability assessed by cost benefit analysis, it did not necessarily improve the TE of the farmers). In Ethiopia, the TE of resource use in the production of irrigated potatoes was estimated using cross sectional data from 80 randomly selected farmers. Farmers that used modern irrigation schemes were found to have a higher average level of technical efficiency compared to those that used traditional irrigation schemes (Bogale and Ayalneh 2005).

Lastly, the null hypothesis of constant returns to scale is performed again involving LR ratio tests. The LR test rejected the null hypothesis (probability > χ^2 critical value = 0.039) in Uganda and failed to reject (probability > χ^2 critical value = 0.89) in Kenya. This confirms the returns to scale measures reported above at 0.717 for Uganda and 1.001 for Kenya. Groundnut farmers therefore, exhibited decreasing and constant returns to scale in Uganda and Kenya, respectively.

4. 4 Technical Efficiency

Again, going back to the most robust model (III), TE efficiency measures are calculated as summarized in Table 9. The results indicate that the predicted average TE of groundnut farmers was 54.6% in Uganda and 54.4% in Kenya. In other words, on average farmers in Uganda and Kenya incur about a 46% loss in output due to technical inefficiency. This implies that farmers in the study area could increase production by 46% utilizing the existing resources and technology.

Groundnut farmers had efficiency scores ranging from 11.7% to 77.9% in Uganda and from 9.8% to 92% in Kenya. If an average farmer in the sample was to achieve the TE of its most efficient counterpart, then the average farmer could increase production by 29.9% (1- [54.6/77.9]) and 40.9% (1- [54.4/92]) in Uganda and Kenya, respectively. Similarly, if the least efficient farmer in the sample was to achieve the TE of its most efficient counterpart, then this farmer could increase production by 85.0% (1- [11.7/77.9]) in Uganda and 89.4% (1- [9.8/92]) in Kenya.

The distribution of individual efficiency levels of the farmers is demonstrated using the histogram in Figure 3 for Uganda and Figure 4 for Kenya. The majority (61%) of farmers in Uganda have efficiency scores less than 60% while the other 39% have TE scores between 60% and 79.9%. In Kenya, 50% of the farmers had scores below 60% while the other half had TE scores greater than 60%. The efficiency scores just discussed are compared with estimates reviewed from other studies from Africa. The mean TE from this study for both Uganda and Kenya are in the range of mean TE values (35% to 96%) reported from African studies and summarized in Table 2 in Chapter two. However, these TE scores are lower than the stochastic frontier average of 71.2% and the overall mean TE of 69.8% computed for all African farms. The mean TE of 54.6% in Uganda and 54.4% in Kenya is also lower than the average of 70.3% and 77% reported for groundnut farmers in Senegal (Thiam and Bravo-Ureta 2003), and Cameroon (Binam et al. 2004).

Comparing the 10% most efficient farmers with the 10% of farmers clustered around the average TE point shows that the first group tended to plant more improved seeds and be closer to the research station than the second group. Specifically, 86% (100%) of the most efficient farmers in Uganda (Kenya) planted improved varieties compared to 79% (89%) of those in the average TE group. The mean distance for all Ugandan farmers in the sample to the nearest research institute was 29.3 km. However, this distance was 35 km for the most efficient group and 44.2 km for those in mid TE level. A similar trend was observed in Kenya where the mean distance of 75.1 km was lower and of 84.7 km was higher than the sample average of 80.1 km for high and medium efficiency households, respectively.

Table 10 reports the means for two groupings of farmers for the Uganda and Kenya samples along with statistical test of mean differences. One group is divided according to gender and the results show no difference in the average TE of male and female managed gardens or plots. Similar results were reported by Kinkingnihoun-Medagbe et al (2010) who found female rice farmers in Central Benin to be as technically efficient as male farmers. However, other studies have found male farmers to be more efficient than female farmers (Kibaara 2005; Njuki et al. 2006; Msuya, Hisano and Nariu 2008).

The other grouping is to investigate the difference in the mean level of technical efficiency between RF and NRF. The hypothesis here is that farmers that received support from extension and research personnel and obtained improved seeds would also get additional information that would help to increase their overall performance measured by technical efficiency. However, the results showed no difference in the mean TE level between the two groups of farmers, which suggest that NRF are equally as efficient as RF. This finding is consistent with the presence of spillover effects where non research farmers learn management techniques from their neighbors who had access to researchers and extension workers.

4.5 Summary

Cobb-Douglas and translog production frontiers were estimated for Uganda and Kenya separately and jointly following three alternative options referred to as model I, II and III. Various statistical tests were performed to obtain the best model for the data under analysis and these tests led the following conclusions.

The Cobb-Douglas functional form was chosen over the translog based on the appropriate LR test result, and economic theory results from published studies (Koop and Smith 1980; Ahmad and Bravo-Ureta 1996). Next, the Cobb-Douglas production frontiers for models I, II, and III for a pooled sample of farmers from Uganda and Kenya was estimated and again a likelihood ratio test was performed to investigate if the groundnut farmers from the two countries exhibited the same technology. The pooled stochastic frontier was rejected in favor of individual frontiers which implied that Ugandan and Kenyan groundnut farmers did not share the same technology; therefore, separate stochastic frontiers were estimated.

A comparison of the distributions of the error term for model III using likelihood ratio tests rejected the truncated-normal distribution in favor of the half normal distribution for Kenya, and the results of truncated-normal distribution did not converge for the Ugandan data. Thus, the half-normal distribution was adopted. The robustness of the estimated models I, II and III was also tested. The LR test rejected models I and II in favor of model III in both countries. Hence, the analysis was based on the most robust specification, i.e., model III defined by a separate

Cobb-Douglas production frontier for each country, with a half normal distribution for the one-sided efficiency term.

The results demonstrated that farmers that used improved varieties increased their outputs significantly relative to those that used local varieties. Groundnut farmers exhibited decreasing and constant returns to scale in Uganda and Kenya respectively. Overall, groundnut farmers in the study area were found to be inefficient. There were no significant differences found in the mean TE of RF and NRF, and between male and female managed gardens. The next and last chapter provides an overall summary of the thesis along with conclusions and recommendations stemming from the analysis.

Table 5. Likelihood ratio tests for comparisons across frontier models

	LR-statistic	$\chi^2_{0.05\ (df)}$	Decision
Functional form(Restricted vs. Unrestricted)			
Model IU	5.037	11.911(6)	Do not reject H_0
Model IIU	5.137	11.911(6)	Do not reject H_0
Model IIIU	4.582	11.911(6)	Do not reject H_0
Model IK	4.483	11.911(6)	Do not reject H_0
Model IIK	3.899	11.911(6)	Do not reject H_0
Model IIIK	3.149	11.911(6)	Do not reject H_0
Pooled vs. individual frontiers			
Model I	64.902	23.069(14)	Reject H_0
Model II	76.728	21.742(13)	Reject H_0
Model III	73.082	14.853(8)	Reject H_0

Note: U = Uganda, K = Kenya; df = degrees of freedom

Table 6. Estimated production frontier models for Uganda (U)

		Inefficiency effects		No inefficiency effects				
		Model IU		Model IIU			Model IIIU	
Stochastic frontier model		coefficient	std.error	coefficient	std.error		coefficient	std.error
Constant	β_0	5.827***	0.796	5.171***	0.716	β_0	4.894***	0.575
LnLand(ha)	β_1	0.421***	0.122	0.444***	0.116	β_1	0.442***	0.117
LnSeed(kg)	β_2	0.299***	0.103	0.275***	0.092	β_2	0.252***	0.092
LnLabor(US$)	β_3	0.053	0.085	0.034	0.082	β_3	0.023	0.081
Seed variety(local=0; 1 otherwise)	β_4	0.925***	0.249	0.965***	0.25	β_4	0.888***	0.252
Location(North=1; 0 otherwise)	β_5	0.484**	0.25	0.554***	0.209	β_5	0.533***	0.200
Constant	δ_0	1.671*	0.967					
Garden manager(female=1; 0 otherwise)	δ_1	0.017	0.205	-0.03	0.169	β_6		
Farmer type(RF=1;0 otherwise)	δ_2	-0.116	0.225	0.055	0.18	β_7		
Age	δ_3	-0.002	0.008	0.003	0.007	β_8		
Education	δ_4	0.028	0.025	-0.027	0.021	β_9		
Distance to research station(km)	δ_5	0.005	0.004	-0.006*	0.004	β_{10}		
Variance parameters								
Sigma-squared	σ^2	1.124***	0.237	1.811***	0.532	σ^2	1.546***	0.506
Gamma	γ	0.906***	0.165	0.715***	0.202	γ	0.548*	0.296
Log-likelihood function		-197.865		-197.75			-200.134	

Note: *** Significant at 1% level, ** significant at 5% level, and *significant at 10% level

Table 7. Estimated production frontier models for Kenya (K)

		Inefficiency effects		No Inefficiency effects				
		Model IK		**Model IIK**			**Model IIIK**	
Stochastic frontier model		coefficient	std.error	coefficient	std.error		coefficient	std.error
Constant	β_0	5.354***	0.346	5.308***	0.469	β_0	5.323***	0.333
LnLand(ha)	β_1	0.596***	0.061	0.619***	0.061	β_1	0.603***	0.059
LnSeed(kg)	β_2	0.285***	0.057	0.257***	0.06	β_2	0.287***	0.054
LnLabor(US$)	β_3	0.107**	0.05	0.123**	0.05	β_3	0.111**	0.047
Seed variety(local=0; 1 otherwise)	β_4	0.482**	0.201	0.541***	0.204	β_4	0.461**	0.204
Location(Ndihwa=1; 0 otherwise)	β_5	-0.049	0.079	-0.093	0.08	β_5	-0.062	0.073
Constant	δ_0	0.996	0.725					
Garden manager(female=1; 0 otherwise)	δ_1	0.038	0.236	-0.057	0.076	β_6		
Farmer type(RF=1;0 otherwise)	δ_2	0.032	0.2	-0.027	0.076	β_7		
Age	δ_3	0.002	0.008	0.001	0.003	β_8		
Education	δ_4	-0.052	0.035	0.018	0.013	β_9		
Distance to research station(km)	δ_5	-0.005	0.008	-0.002	0.003	β_{10}		
Variance parameters								
Sigma-squared	σ^2	0.678***	0.244	0.864***	0.12	σ^2	0.893***	0.124
Gamma	γ	0.942***	0.032	0.945***	0.026	γ	0.949***	0.025
Log-likelihood function		-147.238		-148.255			-149.971	

Note: *** Significant at 1% level, ** significant at 5% level, and *significant at 10% level

Table 8. Comparison of the estimated models for Uganda (U) and Kenya (K)

Restricted vs. Unrestricted	LR-statistic	$\chi^2_{0.05\ (df)}$	Decision
Estimated Models			
Uganda			
Model IIIU vs. Model IIU	4.768	10.371(5)	Do not reject H_0; hence choose model IIIU
Model III U vs. model IU	4.538	11.911(6)	Do not reject H_0; hence choose model IIIU
Kenya			
Model IIIK vs. Model IIK	3.432	10.371(5)	Do not reject H_0; hence choose model IIIK
Model IIIK vs. model IK	5.182	11.911(6)	Do not reject H_0 ; hence choose model IIIK

Note: df = degrees of freedom

Figure 3. Distribution of TE scores in Uganda

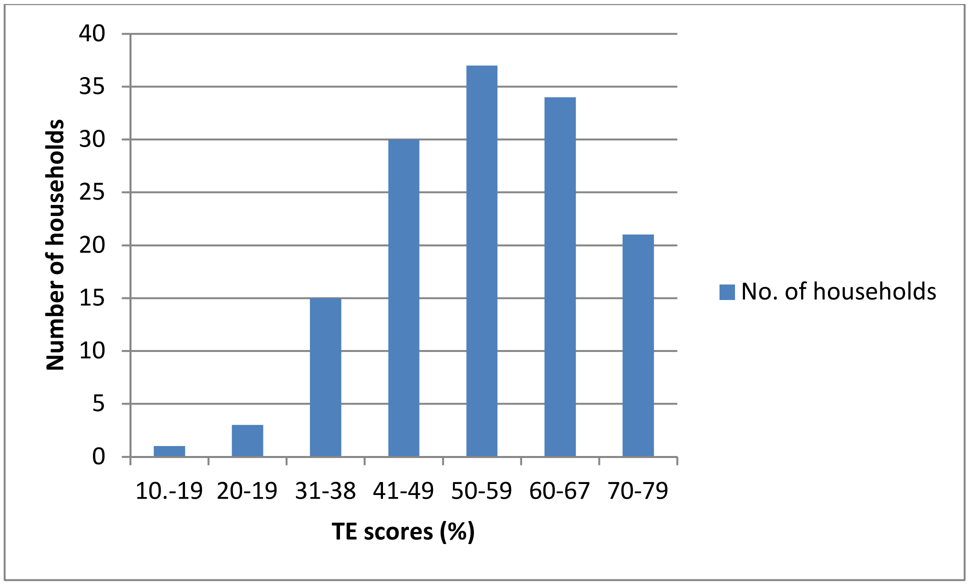


Figure 4. Distribution of TE scores in Kenya

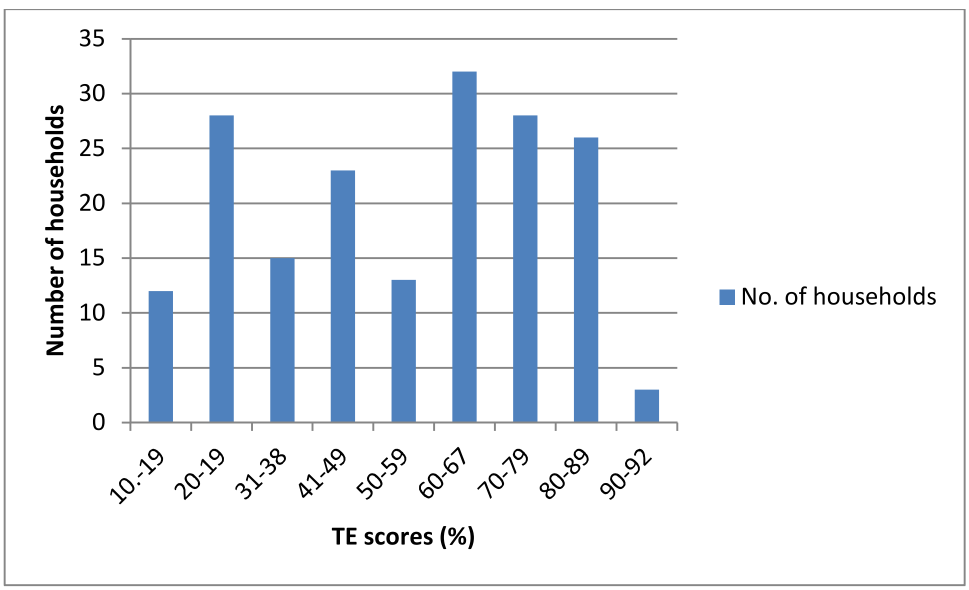


Table 9. Frequency distribution of TE scores in Uganda and Kenya

	Uganda			Kenya		
TE scores (%)	**Frequency**	**%**	**Cumulative %**	**Frequency**	**%**	**Cumulative %**
10.-19	1	0.7	0.7	12	6.7	6.7
20-19	3	2.1	2.8	28	15.6	22.2
31-38	15	10.6	13.5	15	8.3	30.6
41-49	30	21.3	34.8	23	12.8	43.3
50-59	37	26.2	61.0	13	7.2	50.6
60-67	34	24.1	85.1	32	17.8	68.3
70-79	21	14.9	100.0	28	15.6	83.9
80-89	0	0.0		26	14.4	98.3
90-92	0	0.0		3	1.7	100.0
Total	**141**	**100.0**		**180**	**100.0**	

Table 10. Mean sample tests for two groupings of Ugandan and Kenya groundnut farmers

	Uganda				Kenya			
	N	mean	Diff[2]	**t-value**	N	mean	diff	**t-value**
Gender of garden manager								
Female	65	0.55	0.005	**0.238**	110	0.553	0.23	**0.659**
Male	76	0.543			70	0.53		
Type of farmer								
NRF	62	0.534	-0.02	**-0.922**	96	0.541	-0.007	**-0.202**
RF	79	0.555			84	0.548		

Note: [2] Difference in the mean TE level between the groups

CHAPTER FIVE

SUMMARY, CONCLUSION AND RECOMMENDATIONS

This chapter first provides a summary of the study objectives and the methodology used. It then gives the main findings, draws the major conclusions stemming from the results and analysis, and ends with some recommendations.

5.1 Summary

This study analyzed productivity gaps stemming from the use of improved seed varieties versus local varieties, and examined productivity gaps associated with the managerial performance of research (RF) versus non research farmers (NRF), and of male versus female farmers.

Alternative specifications were tested and the stochastic production frontier (SPF) model developed by Aigner, Lovell and Schmidt (1977) was chosen to examine if productivity gaps existed. The SPF incorporates a "composed" error structure, consisting of a two-sided error term and a one-sided error component. The two-sided error term captures random variability while the one-sided error term captures inefficiency measured as a shortfall in output from its maximum value given by the SPF. The extension of this approach by Battese and Coelli (1995) specifies the one-sided error term as a function of explanatory variables that typically capture farmer specific characteristics.

The data used for the study was collected through a survey conducted by the Kenya Agricultural Research Institute (KARI) and the National Semi-Arid Resources Research Institute (NaSARRI) in Uganda in cooperation with the University of Connecticut Peanut Collaborative

Research Program (CRSP). The data was collected between April and August, 2010 for the two cropping seasons of 2009. The survey covered the nine districts of Kumi, Amuria, Soroti, Pallisa, Budaka, Jinja, Kamuli, Pader and Lira, located in the Teso, Busoga and Northern regions in Uganda and the Ndhiwa, Nyarongi, and Kobama divisions of Ndhiwa district in Kenya. A total sample of 141 and 180 households from Uganda and Kenya respectively was used after households with missing data on one or more key variables and a few outliers were excluded from the final sample. Inputs and output quantities were expressed as the sum for each variable for the two 2009 cropping seasons.

Cobb-Douglas and translog specifications were fitted to estimate stochastic production frontiers for three alternative models (I, II and III). Model I incorporates the inefficiency effects component following Battese and Coelli (1995), while model II and III are of the Aigner, Lovell and Schmidt (1977) type. The FRONTIER Version 4.1 software was used to compute the maximum likelihood estimates for all models (Coelli 1996). These models were estimated separately for each country and as a pooled sample for the two countries.

Likelihood ratio (LR) tests were conducted to select the most suitable model, and this led to the following conclusions. First, the Cobb-Douglas was chosen over the translog specification and the null hypothesis that groundnut farmers from the two countries operate on the same production frontier was rejected. This implies that Ugandan and Kenyan groundnut farmers did not share the same technology; therefore, separate stochastic frontiers were estimated. Next, the robustness of models I, II and III was also tested and the first two were rejected in favor of model III in both countries.

A comparison of the distributions of the error term for model III rejected the truncated-normal distribution in favor of the half normal distribution for Kenya, and the results of the truncated-normal distribution did not converge for the Ugandan data. Thus, the half-normal distribution was adopted for both countries. Therefore, analyses and results presented in this study are based on the most robust specification, i.e., model III defined as a Cobb-Douglas production frontier estimated for each country separately, with a half normal distribution for the one-sided efficiency term in both cases.

All coefficients for the inputs included in model III in Uganda and Kenya had the expected positive sign. In addition, all estimated coefficients were statistically significant except for the parameter for labor in Uganda and the location dummy in Kenya. Land had the highest partial elasticity, followed by seeds while labor had the lowest in both countries. This shows that the use of additional inputs will increase groundnut output. However, farmers exhibited decreasing and constant returns to scale in Uganda and Kenya, respectively.

Regional differences were significant among farmers in Uganda where, *ceteris paribus*, those located in the Northern part of the country produce 70.4% more output than their counterparts from the Teso and Busoga regions. This location differential amounts to 197.8 kg/ha for the average groundnut land cultivated. A similar geographical parameter was negative and statistically insignificant in Kenya implying that no location effect is present.

Of interest to this study is the null hypothesis that there is no technological gap among groundnut farmers in Uganda and Kenya. This was rejected in both countries and therefore, the output for farmers using improved varieties is significantly higher compared to those using local varieties. The coefficient for the dummy for improved varieties was equal to 0.888 for Uganda and 0.461 for Kenya. The values of these parameters indicate that on their corresponding frontiers, farmers who planted improved groundnut varieties enjoyed a 143% and a 58.6% output advantage over those that planted only local varieties for Uganda and Kenya, respectively. On average this implies, *ceteris paribus*, an increase in farm output from 133.5 kg to 324.4 kg in Uganda and from 205 kg to 325.1 kg in Kenya. In terms of yields and considering that the average farmer cultivates 1.15 ha in Uganda and 0.64 ha in Kenya, this amounts to a change from 116.1 kg/ha to 282.1kg/ha and from 320.3 kg/ha to 508 kg/ha. Therefore, this is equivalent to a yield gain of 166 kg/ha and 187.7 kg/ha for Uganda and Kenya, respectively.

The results for Model III are also used to analyze the technical efficiency (TE) levels for farmers in both countries. The analysis reveals that the predicted mean TE for the two countries is very similar reaching 54.6% in Uganda and 54.4% in Kenya. These TE estimates are in the range of mean TE values (35% to 96%) and lower than the overall mean TE of 69.8% reported from African studies summarized in Table 2 in Chapter 2. These mean TE scores are also lower than the average of 70.3% and 77% reported for groundnut farmers in Senegal (Thiam and Bravo-Ureta 2003), and Cameroon (Binam et al. 2004), respectively.

The statistical tests performed failed to reject the null hypotheses that there were no differences in mean TE between RF and NRF and between male and female managers of groundnut plots or gardens as they are called in Uganda. This means that the average TE for the two groups is the same in both Uganda and Kenya. RF received technical support on the production of groundnuts from researchers and/or extension personnel. This support was expected to translate into better management by RF relative to NRF which in turn would be captured by a higher level of TE. The findings suggest the presence of spillover effects where NRF learn management techniques from their neighbors who had access to researchers and extension services. Alternatively, this finding could suggest that the extension systems in Uganda and Kenya were not effective in helping farmers to increase their efficiency.

In many regions in Africa, groundnuts are predominately grown by women to supplement their families' diet with protein and the income from sales offer women a way to generate cash. The results of this thesis show that the mean TE of female managers was not significantly different from that of male managers suggesting that the vast experience that women have in cultivating groundnuts did not translate in better outputs and thus higher TE.

5.2. Conclusions and Recommendations

Overall, two main empirical findings emerge from this study. First, farmers who planted improved groundnut varieties enjoyed a 143% and a 58.6% output advantage over those that planted only local varieties in Uganda and Kenya, respectively. This shows that cultivating improved varieties shifts the production frontier outwards. With the increased output, households are expected to become more food secure and any excess output can be sold off to earn income thereby leading to improved farmer livelihoods.

Hence, these findings suggest that research work devoted to the generation of improved varieties coupled with extension work designed to promote the adoption and diffusion of such varieties can have high returns. A related implication is that suitable varieties need to be generated so that they are well adapted to different agro-ecological zones. This is even more relevant now as climate change remains a major issue affecting agricultural productivity across the globe. A well-functioning agricultural extension system will help facilitate the dissemination of the new technologies to farmers and provide researchers with feedback from producers on the most marketable groundnut attributes that the breeding programs should target in addition to disease and drought resistance.

Policy makers at both the national and international level should work with the relevant institutions to ensure that research is facilitated and researchers are motivated to develop new technologies. Smallholder farmers on the other hand, might need special support to plant improved seed varieties. Groundnuts have a high seed rate of about 90 to 100 kg/ha under rain fed conditions (ICRISAT 2012), which may make it difficult for farmers to acquire the seed quantities required to establish the recommended plant populations if incentives are not provided.

It should be noted that the average quantity of seeds used by the Uganda and Kenyan sampled farmers is 48 kg/ha and 58 kg/ha, respectively. These low seeding rates combined with the positive partial elasticities for seeds in both countries calls for the need to promote higher plant densities. In turn, this will require the promotion of seed multiplication to make improved varieties readily available to farmers so that higher groundnut productivity can be achieved.

It is interesting to note that there is a sharp effect on yields coming from improved varieties observed in Northern Uganda compared to the Teso and Busoga regions. Most farmers from the Northern region received seeds as part of the resettlement kits after the Lord Resistance Army (LRA) rebel insurgence ended (PRDP 2007). The August, 2006 signing of the cessation of hostilities between the government of Uganda and the LRA brought relative peace to the region. As a consequence, the focus of development agencies changed from emergence to recovery as the population began to return to their homeland after over 20 years in internally displaced people's (IDP) camps (Oxfam 2008). The returning population was supported with basic household items and inputs such as hoes, machetes, axes and seeds. The output advantage of farmers in Northern Uganda could, therefore, be a result of the input support received and the relatively fertile land that had been under fallow when the population was in IDP camps.

Secondly, it can be deduced from the study that there is considerable room to raise the groundnut output of farmers in Uganda and Kenya without additional conventional inputs and technology. Specifically, the results show that on average farmers incur a 46% loss in output due to technical inefficiency; thus, groundnut output could be increased by that percentage utilizing the existing resources and technology.

Fifteen percent of households in Uganda and 32% of the households from Kenya had average TE values greater than 70%. The productivity of these households could be improved by a more intensive further use of improved varieties that shift the frontier outwards, since these farmers are operating close to their production frontier. In contrast, the productivity of households with low efficiency scores could be improved by addressing the management issues that prevent them from making better use of their existing technology and thus move closer to their frontier.

The apparent spillover effect of the technical support that research farmers received on NRF calls for more support to extension since farmer education has a multiplier effect on other farmers. However, an improvement in the delivery of the extension services could address the possibility of the extension systems in both countries not being effective in improving the managerial abilities of RF. Interestingly, the results indicate that the most efficient farmers in both countries are on average situated closer to the nearest research institute. This suggests that access to information coming from these institutes plays a role on farm productivity.

Further research is needed in order to understand the underlying causes as to why the vast experience that women have in cultivating groundnuts did not translate in improved efficiency. Improved efficiency of women in groundnut production will help to reduce malnutrition, increase income, and empower female heads of households.

Having established that improvements in technical efficiency could contribute significantly to increases in farm output, it is necessary to look at issues that have implications on the measurement and potential improvement of farm efficiency. Understanding the determinants of the TE gaps and factors that can narrow this gap is very crucial. Surprisingly, most of the variables included in the inefficiency component of the estimated models were not statistically significant. This will necessitate more research to better understand the factors affecting TE of groundnut farmers in both Uganda and Kenya.

Finally, if the drivers of productivity growth at the farm level are to be better understood then significant improvements are needed in the methods used to collect and generate farm level data. Both KARI and NaSARRI need to undertake surveys on a regular basis to monitor the performance of farmers using their services and technologies. This information and findings should be made more readily available to all stakeholders including farmers.

APPENDICES

Appendix 1. Parameter estimates for Translog production frontiers for Kenyan groundnut farmers

Parameter		Model IK coefficient	Model IK std-error	Model IIK coefficient	Model IIK std-error		Model IIIK coefficient	Model IIIK std-error
Constant	β_0	0.297	0.254	0.177	0.364	β_0	0.27	0.232
lnLand(x1)	β_1	0.652***	0.068	0.684***	0.07	β_1	0.648***	0.067
lnSeed(x2)	β_2	0.246***	0.063	0.204***	0.073	β_2	0.262***	0.063
lnLabor(x3)	β_3	0.16**	0.069	0.174***	0.067	β_3	0.143**	0.066
$0.5(x_1)2$	β_4	-0.112	0.134	-0.076	0.133	β_4	-0.106	0.131
x_1x_2	β_5	0.142	0.088	0.134	0.09	β_5	0.129	0.087
x_1x_3	β_6	0.043	0.069	0.015	0.073	β_6	0.032	0.067
$0.5(x_2)^2$	β_7	-0.126	0.098	-0.14	0.099	β_7	-0.094	0.093
x_2x_3	β_8	-0.02	0.063	-0.011	0.064	β_8	-0.023	0.061
$0.5(x_3)^2$	β_9	0.076	0.086	0.071	0.085	β_9	0.049	0.082
Seed variety(local=0; 1 otherwise)	β_{10}	0.458**	0.212	0.523***	0.216	β_{10}	0.463**	0.223
Location(Kenya=1; 0 otherwise)	β_{11}	-0.041	0.082	-0.096	0.087	β_{11}	-0.059	0.075
Constant	δ_0	1.166	0.764					
Garden manager(female=1; 0 otherwise)	δ_1	0.038	0.239	-0.048	0.078	β_{12}		
Farmer type(RF=1; 0 Otherwise)	δ_2	0.053	0.195	-0.043	0.078	B_{13}		
Age	δ_3	0.001	0.008	0.001	0.003	B_{14}		
Education	δ_4	-0.061*	0.037	0.023*	0.014	B_{15}		
Distance to research station(km)	δ_5	-0.006	0.008	-0.002	0.003	B_{16}		
Variance parameters								
Sigma-squared	σ^2	0.67***	0.232	0.855***	0.122	σ^2	0.89***	0.124
Gamma	γ	0.946***	0.032	0.948***	0.028	γ	0.953***	0.025
Log Likelihood Function		-144.995		-146.304			-148.394	

Note: *** Significant at 1% level, ** significant at 5% level, and *significant at 10% level

Appendix 2.Parameter estimates for Translog production frontiers for Ugandan groundnut farmers

		Model IIIU	
Parameter		**coefficient**	**std-error**
Constant	β_0	-0.769	0.631
lnLand(x1)	β_1	0.688***	0.158
lnSeed(x2)	β_2	0.233**	0.127
lnLabor(x3)	β_3	-0.158	0.114
0.5(x_1)2	β_4	0.188	0.274
x_1x_2	β_5	-0.048	0.153
x_1x_3	β_6	-0.183	0.132
$0.5(x_2)^2$	β_7	0.102	0.135
x_2x_3	β_8	0.09	0.09
$0.5(x_3)^2$	β_9	-0.061	0.112
Seed variety(local=0; 1 otherwise)	β_{10}	0.659***	0.232
Location(North =1; 0 otherwise)	β_{11}	0.368**	0.188
Constant	δ_0	-0.28	0.337
Garden manager(female=1; 0 otherwise)	δ_1	0.118	0.226
Farmer type(RF=1; 0 Otherwise)	δ_2	-0.243	0.144
Age	δ_3	0.007	0.004
Education	δ_4	0.024	0.001
Distance to research station(km)	δ_5	0.004	0.002
Variance parameters			
Sigma-squared	σ^2	0.765***	0.037
Gamma	γ	0	0.013
LLF		-180.416	

Note: *** Significant at 1% level, ** significant at 5% level, and *significant at 10% level

Appendix 3. Estimated models for pooled data for Uganda and Kenya

		Inefficiency effects		No inefficiency effects				
		Model I		**Model II**			**Model III**	
Stochastic frontier model		coefficient	std.error	coefficient	std.error		coefficient	std.error
Constant	β_0	5.416***	0.316	5.307***	0.399	β_0	5.03***	0.336
LnLand	β_1	0.555***	0.059	0.556***	0.065	β_1	0.537***	0.065
LnSeed	β_2	0.273***	0.052	0.251***	0.056	β_2	0.27***	0.054
LnLabor	β_3	0.11**	0.046	0.116**	0.05	β_3	0.114**	0.05
Seed variety(local=0; 1 otherwise)	β_4	0.657***	0.155	0.742	0.156	β_4	0.707***	0.158
Location(Kenya=1; 0 otherwise)	β_5	-0.272	0.118	0.2	0.152	β_5	0.069	0.144
Constant	δ_0	0.591	0.793					
Garden manager(female=1; 0 otherwise)	δ_1	0.228	0.24	-0.058	0.088	β_6		
Farmer type(RF=1;0 otherwise)	δ_2	-0.358	0.26	0.082	0.088	β_7		
Age	δ_3	0.014	0.01	-0.001	0.003	β_8		
Education	δ_4	0.005	0.033	-0.004	0.012	β_9		
Distance to research station(km)	δ_5	-0.019	0.007	-0.004	0.002	β_{10}		
Variance parameters								
Sigma-squared	σ^2	1.688***	0.424	1.578	0.252	σ^2	1.526	0.28
Gamma	γ	0.939***	0.029	0.885	0.065	γ	0.861	0.087
Log Likelihood Function (LLF)		-377.551		-384.369			-386.646	

Note: *** Significant at 1% level, ** significant at 5% level, and *significant at 10% level

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