A COMPARATIVE ANALYSIS OF THE STRUCTURE AND PERFORMANCE OF AGRICULTURAL SCIENCE AND TECHNOLOGY POLICY SYSTEM IN KENYA AND UGANDA

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DEDICATION

To Moses, Joshua and Ruth; let this work be an inspiration to you. May you grow up to serve and honour God.

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ABSTRACT

Despite the acknowledged importance of agricultural science and technology (AS&T), little is known about the structure and performance of AS&T policy system in developing countries. The structure and performance of this policy system in Kenya and Uganda was analysed using a preliminary 'system components-shift effects' framework. The *system components* comprised of agricultural research, extension, education and transboundary technology transfer. The impact of these components was modified by three-levels of *shift-effects*: policy environment, institutional arrangements and micro-conditions to give a 3x4 matrix of potential determinants of system structure. The structure was hypothesised to exist in three different generations: first, second and third. Uganda was presumed a first generation system and Kenya second. The potential system structure was separately related to three performance indicators, namely; technical efficiency, technical change and efficiency change using different econometric techniques in order to delineate important determinants of structure. The results indicated that the preliminary three-level framework can be used as an effective tool for delineating the structure of AS&T policy system in developing countries. Furthermore, the structure of the policy system differed between the first and second generation systems. At policy level, transboundary technology transfer was significant and positive only in second generation systems whereas agricultural education and research expenditures were important in both. At institutional level, intellectual property rights regulatory system had impact only in second generation systems, agricultural extension decentralisation had negative effect in first generation systems, whereas agricultural research coordination had no impact in both systems. At micro-level, literacy within the agricultural labour force was significant in second generation but not in first. However, domestic research outputs had significant impact in first generation systems but not second. The same applied to policies geared towards reducing transaction costs in accessing technologies. These results imply that generation specific AS&T policies should be encouraged instead of collective generic policies for all developing countries. Although lack of data precluded effective application of the three-level framework, this study offers opportunities for further research in this area, which has previously been driven by data and not ideas.

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LIST OF ABBREVIATIONS

ASTI	Agricultural Science and Technology Indicators
CEPA	Centre for Efficiency and Productivity Analysis
DEA	Data Envelopment Analysis
FAO	Food and Agriculture Organisation
FTE	Full Time Equivalent
GDP	Gross Domestic Product
IFPRI	International Food Policy Research Institute
ISNAR	International Service for National Agricultural Research
LBP	Labour Productivity
MDGs	Millennium Development Goals
NAADS	National Agricultural Advisory Services
NEPAD	New Partnership for Africa's Development
PMA	Plan for Modernisation of Agriculture
PME	Planning Monitoring and Evaluation
R&D	Research and Development
S&T	Science and Technology
SRA	Strategy for Revitalising Agriculture
SSA	Sub Saharan Africa
TFP	Total Factor Productivity
UN	United Nations
UNEP	United Nations Environmental Programme
WHO	World Health Organisation

CHAPTER ONE: INTRODUCTION

1.1 Background to the study

Kenya and Uganda like most developing countries are dependent on their agricultural sectors[1] for provision of citizen's livelihoods. The sectors employ about 80% of the labour force and are dominated by small-scale farmers (Uganda, 2004; Kenya, 2007). These farmers operate in an environment of increasing population pressure, rapid natural resource degradation and low and declining levels of agricultural productivity – all which contribute to increased poverty levels. In order to reduce the high levels of poverty, it is important to, among other factors, implement strategies that increase agricultural productivity. Instituting effective agricultural science and technology (AS&T) interventions is one such strategy (Dasgupta and David, 1994; IAC 2004). This is because the level of development of AS&T of a country influences the acquisition of new technologies through investments in research and human resource development (Alston et al, 2000; Evenson 2003; Thirtle et al, 2003). In this regard, AS&T needs to be guided by effective public policy framework to facilitate unlocking its potential.

The rationale for public policy in AS&T in developing countries is well documented (Thirtle, 1986; Byerlee and Alex, 1998; Alston et al, 1995). AS&T has been referred to as comprising those factors that bear public good characteristics and whose provision is neither excludable nor rivalrous. In essence, this has made it difficult for the private sector to fully recover investment costs or make profits from such goods. Therefore, they have tended to under-invest and undersupply such goods. To mitigate such outcomes, appropriate private incentives need to be put in place to make markets for such science and technology products and services not to fail. Public roles in science and technology therefore rests on providing incentives to enable the private sector undertake welfare-enhancing investments, and where appropriate, fill the gaps left by market failure. These arguments form the basis for investigations into AS&T policy (Omamo et al, 2005).

However, despite the acknowledged importance of AS&T, little is known about its structure and performance in developing countries. More surprising is the fact that the definition

[1] This study conceptualises agriculture in the context in which it is defined in policy documents of the study countries. It encompasses the production and utilization of plants, animals and fishes and the management of the environment in which they are raised for producing food, drink, fibre and wood (Uganda 2003).

of AS&T policy system (or simply 'system') is still obscure. Garfield (1988) provides a review of some conceptual considerations of what might comprise this system. First, it can contentedly be interpreted as the use of science and its products to ensure economic futures and security and pursuit of development goals. Second, it can be depicted as narrow as the planning and programming of public science and technology investments. Third, it can be viewed as whatever the government of the day wants science and technology to do. Fourth, it can be visualised squarely as the public policy affecting scientific and technical activities; and, lastly it can be taken to be composed of the various impacts of science and technology investments.

In order to contribute to this discourse, this study adopted the definition of AS&T policy system in developing countries first suggested by Omamo et al (2005). This policy system is taken to encompass '*the structures and processes for setting priorities, financing, organising, delivering, monitoring, evaluating and assessing the impacts of agricultural research, extension, education and transboundary technology acquisition and exchange*'. This definition is still preliminary and yet to be widely acknowledged and this study intends to contribute to empirical evidence to enable its entrenchment in literature. The definition formed the basis of this study because of its comprehensive conceptualisation of the policy system by identifying four independent yet related components that comprise the system (*viz*. agricultural research, agricultural extension, agricultural education and agricultural transboundary technology transfer).

Besides building upon the above definition, this study was based on a preliminary proposal for categorising AS&T policy systems in developing countries as originally suggested by Omamo et al. (2005). This classification is founded on the stages (or 'generations') of development of the policy systems. The systems are categorised as first, second or third generation. The key differentiating features between these generations are as presented in Table 1.

Table 1: Generations of agricultural science and technology policy systems in developing countries

Generation	Illustrative countries	Illustrative issues
First	• Most African countries including Uganda • Small countries of Central America and the Caribbean • Less-developed countries in Eastern Europe, South Asia, Southeast Asia, and West Asia	• Capacity development • Priority setting - crop and resource management versus varietal improvement • Public financing • External acquisition of basic technologies (for example, machinery, seed)
Second	• Mid-size Latin American countries like Bolivia, Chile, Colombia, Peru • Mid-size Asian countries like Pakistan and Thailand • North African countries • Few sub-Saharan countries like Kenya and Nigeria	• Capacity maintenance • Priority setting - high-value versus food crops • Increasingly important private financing • External acquisition of more advanced technologies (for example, biotechnologies)
Third	• Large countries like Mexico, Brazil, Argentina, China, India, South Africa	• Capacity adjustment • Priority setting - options for biotech research • Largely private financing • External acquisition and exchange of advanced technologies and methods (for example, biotechnology development techniques)

Source: Omamo et al. (2005).

This taxonomy recognises that the AS&T policy systems structure and functioning are likely to differ across generations. Initial analysis suggests that each potential determinant of structure is likely to manifest itself differently depending on a particular system's stage of development. For instance, a first-generation system of a country like Uganda likely reflects the relatively small size of the economy, the relatively large share of agriculture in the overall economy, the prominence of diversified subsistence-oriented practices, the relatively large role of the public sector in research and development (R&D) funding and delivery, the relatively small roles of the private and civil society sectors in R&D, the relatively high dependence on donor funds, the relatively low level of development of its legal system supportive of the AS&T initiatives, and the relatively low level of implementation capacity in the public sector.

On the other hand, a third-generation system of a country like South Africa would reflect opposite conditions—e.g., the large size of the economy, the relatively small share of agriculture in the overall economy, the relatively low profile of diversified subsistence-oriented practices, and the relatively small role of the public sector in R&D funding and delivery. The other conditions are the relatively large roles of the private and civil society sectors in R&D, the low dependence on donor funds, the relatively high level of development of its legal system, and the relatively high level of implementation capacity in the public sector.

Second-generation systems of countries like Kenya have features of both first- and third-generation systems—e.g., large segments of agricultural sectors featuring diversified subsistence-oriented livelihood strategies but also large segments pursuing highly commercialised agriculture, steadily falling public funding but rapidly rising private financing. It is important to point out that this categorisation of AS&T policy systems is preliminary, and one of the aims of this study is to provide empirical evidence towards its deepening.

Based on the foregoing conceptualisation of AS&T policy, two sets of policy questions rendered themselves open to enquiry in this study. The first set was related to system structure and functioning. How have the four key policy components of agricultural S&T policy—(i.e., research, extension, education and technology and information acquisition and exchange)—fitted together in the policy systems in Kenya and Uganda or of developing countries for that matter? Has each component been at a similar level of development? Which of the four components has been the strongest (weakest), and why? How well integrated have been the components with each other, and which institutions have governed that integration? This study aimed at shedding light to some of these concerns by investigating the structure of the policy system in Kenya and Uganda.

The second area of policy concern related to system dynamics. For example, how might Uganda's first-generation system develop into one like Kenya's second- or even a third-generation one of a country like South Africa? What might cause a second-generation system to regress to a first-generation condition? Which institutions are likely to be most appropriate at given stages of system development? One would anticipate that there is more at play than mere system size or capacity. How, then, might a small country with a first-generation AS&T system become a small country with a second- or third-generation S&T system—i.e., which combination of policies and institutions matter the most, and why? This study endeavoured to redress these questions by evaluating the performance of the policies and institutions of policy systems in Kenya and Uganda.

The perceived differences in the potential structure of AS&T policy systems across countries provided fertile ground to identify important determinants of system structure and performance. This required undertaking a comparative case study analysis of selected national system types, where Kenya and Uganda were considered. Based on insights from Aoki (2001), it was envisaged that undertaking a historical and comparative institutional analysis would help uncover how these systems (and their underlying institutions) have emerged over time, whether their arrangements have been robust, and why they have had to change or not. The objective was to build an understanding of the details and origins of key system institutions, and the factors that have rendered them self-enforcing.

Assessment of performance of the case study policy systems was dependent first on identifying and estimating suitable performance indicators. Subsequently, it was necessary to develop a framework to delineate the policy system structure determinants that would encompass policies and institutions (Garfield, 1988). Omamo et al (2005) argued that while developing the said framework, the relevant institutions—such as property rights regimes, market information systems, grades and standards, farmer collective action—should entail appropriate quantification and integration into the framework. Finally, the performance indicators were then related to the potential determinants of system structure. It was envisaged that these analyses would yield the sorely needed information about the agricultural S&T policy design and implementation in developing countries across the globe.

Such approaches have proved to be extremely useful for industrial policy design and implementation (see Edquist et al., 2000; Ergas, 1987) but are still lacking in agriculture. Specifically, the information generated from this study will offer insights into how AS&T policy systems can be improved for increased productivity and poverty alleviation. This is particularly so since AS&T policy systems influence the rate of agricultural sector productivity growth through their influence on social, economic and technical innovations (Weaver et al., 2005).

1.2 Statement of the Problem

Despite the existence of different modes of innovations in AS&T policy systems in developing countries, and availability of a variety of lessons from which approaches can be designed to strengthen agricultural science and technology policy formulation, very little is known about the structure and performance of AS&T policy systems in developing countries. First, a clear-cut definition of AS&T policy is difficult to locate in literature, making it hard to concisely analyse the structure and performance of the policy system in developing countries. Second, there is limited knowledge in methodological approaches for analysing the system structure. Third, the structure of the policy system appears not to be homogenous, but presumed to vary across countries and regions in a form not well understood. These limitations have led to a scenario where there is limited systematic and internationally comparable information about the structure and performance of AS&T policy systems in developing countries. The absence of this information has contributed to the inability to formulate specific AS&T policies, institutional reorganisation and investment options that would increase agricultural productivity and growth. This study aimed at addressing these important gaps by using Kenya and Uganda as case studies.

1.3 Objectives

The broad objective of this study was to undertake a comparative analysis of the structure and performance of agricultural science and technology policy system in Kenya and Uganda between 1970 and 2002. The specific objectives were to:

1. Develop and employ a framework to analyse the structure and performance of AS&T policy systems in Kenya and Uganda;

2. Evaluate the trends and identify policy reforms and institutional innovations that have improved performance of AS&T policy systems in Kenya and Uganda;—i.e., system-specific best practices; and,
3. Suggest appropriate policy interventions for enhanced performance of AS&T policy system in Kenya and Uganda.

1.4 Hypotheses

The following hypotheses were tested:

1. The potential determinants of AS&T policy system structure (individually and collectively) significantly influence the performance of the policy system.
2. Countries can be grouped based on the stage of development of their agricultural S&T policy systems i.e. generation stage. This hypothesis implied that the structure of the policy system differs between Kenya (second generation) and Uganda (first generation).

1.5 Justification

The argument that agricultural science and technology is central to the process of reversing sluggish growth of the agricultural sector has been expounded in various important international policy initiatives. For example, the United Nation's Millennium Report on Science, Technology and Innovation has described approaches to applying science, technology and innovation in achieving the Millennium Development Goals (MDGs), with applications in agriculture viewed as crucial and warranting special attention (UN, 2004). The World Bank, FAO, WHO, and UNEP have recently launched an international assessment of the role of AS&T in reducing hunger, improving rural livelihoods and stimulating economic growth (World Bank, FAO, WHO, UNEP, 2003). In Africa, the New Partnership for Africa's Development (NEPAD) has launched the Comprehensive Africa Agriculture Development Program in which investments in AS&T are adjudged to be crucial to sustainable agricultural and overall development on the continent (NEPAD, 2004). All these initiatives advocate for agricultural science and technology policy intervention to enhance agricultural productivity, but action has largely been constrained by limited empirical evidence on what needs to be done, and how.

This study applied a preliminary framework to explore and provide empirical information on the structure and performance of AS&T policy systems in two sub-Saharan countries, Kenya and Uganda. Uganda represented a first generation system, whereas Kenya was second. Both countries are found in East Africa and have economies dependent on agriculture. Their important agricultural produce includes tea, coffee, sugarcane, horticulture, cereals, sisal, pyrethrum and livestock. Horticultural products, tea and coffee account for the bulk of export revenues.

It was anticipated that the findings in this study would stimulate debate and perhaps lead to more comprehensive investigations that would be useful in guiding implementation of targeted productivity enhancing AS&T policies and investments, for increased agricultural output, incomes and food security, and in essence contribute to attainment of MDG 1 of eradicating extreme poverty and hunger.

1.6. Limitations of the study

Limitation in data meant that not all appropriate variables representing the potential determinants of structure of AS&T policy could be quantified. In this case proxies were used or such variables omitted altogether. Furthermore, frontier methods were used to estimate performance indicators. Frontier functions assume that all inputs have been taken into consideration. However, in this study, it is possible to raise questions about whether all inputs were actually accounted for. In addition, some concerns have been raised about Food and Agriculture Organisation data (that is used in this study) since it does not take into account quality of inputs (especially for land, labour and capital), all which might have affected the estimated performance indicators.

CHAPTER TWO: LITERATURE REVIEW

This chapter focuses on five areas. First, a review of work related to AS&T policy with emphasis on developing countries is provided and inherent gaps identified. In an effort to set the stage for a more in-depth investigation into the policy system in developing countries, part two of the review describes a framework that can be applied to systematically investigate the functioning of the policy system. This framework requires the use of appropriate performance indicators, which are identified in part three. This section also describes how these indicators are linked to AS&T policy system structure. Part four elaborates on the different approaches that can be applied in estimating these indicators. Part five discusses the different methodologies that can be used to link the performance indicators and the potential policy system structure. The review concludes with a choice of appropriate models that are subsequently employed in this study.

2.1 Review of studies focussing on agricultural science and technology in developing countries

At the moment, there is limited literature on empirical work on agricultural science and technology policy system in developing countries. Perhaps, this has been due to lack of consensus on what comprises the policy system. As a starting point, Garfield (1988) provides a collection of interpretations of AS&T policy. These range from the much wider view that regards this policy as entailing the use of science and technology and its products to ensure human prosperity, to a much narrower perspective encompassing the planning of public science and technology investments. Omamo et al (2005) have argued that more often than not, perceptions on what comprises AS&T policy are derived from a deeply held historical and cultural viewpoint that sees science as the responsibility of the state and which should be supported by citizens that are beneficiaries of its outcomes. Although the argument that AS&T always brings benefits is contested, what remains lucid is that a sure outcome of AS&T is change. Intuitively, such a change may be positive or negative, and any empirical enquiry into AS&T policy needs to involve investigations into the form of change induced by the policy.

Based on the foregoing and building on (i) earlier work on agricultural research policy by Pardey et al (1991); (ii) a definition of agricultural research policy provided by Omamo et al (2000); and, (iii) various works on agricultural science policy[2], Omamo et al (2005) proposed a definition of AS&T policy system which they stated would drive further empirical work in this area. They defined AS&T policy system or just 'system' as '*the structures and processes for setting priorities, financing, organising, delivering, monitoring, evaluating and assessing the impacts of agricultural research, extension, education, and transboundary technology acquisition and exchange*'. Two salient features are inherent within this definition. First it recognises that agricultural science and technology is a system that encompasses four components, *viz*. agricultural research, agricultural extension, agricultural education and agricultural transboundary technology transfer[3]. Second, it recognises the need to investigate impact (change) brought about by innovations within these key components.

This review could not obtain any studies that have assessed the collective effect of the four components of the policy system on agricultural productivity. However, several studies have investigated the individual impact of some of these components of AS&T policy system on agricultural productivity in developing countries. Since the current study is a two-country comparative analysis, this review will be limited to studies that have focused on multi-country comparative analyses.

Since the 1970's, a number of analyses of cross-country differences in agricultural productivity have been conducted. This perhaps was out of the realisation that productivity growth in the agricultural sector was essential if agricultural output was to grow at a sufficiently rapid rate to meet the rising demands for food, feed and raw materials. Coelli and Rao (2003) observed that this increase could also have arisen because of a number of factors. First, there has been an increase in availability of some new panel data sets, like FAO database, making such studies possible. Second, there has been progressive development of new empirical techniques to analyse this type of data. Thirdly, there has arisen a desire to assess the degree to which intervention programs (like green revolution or specific policy interventions) have improved agricultural productivity in developing countries. Most of these studies have covered several countries, the highest being 115 by Wiebe et al. (2000) (Table 2). Of the studies listed in Table 2, this review will elaborate only on six that are more relevant to this study. These include those that have gone further to investigate factors

[2] Some of these works that have focused on agricultural science policy include Alston et al (1998) and Alston et al (2001). The broad focus of these studies has been on identification of how investments in and policies for improving agricultural education, research, and extension can efficiently promote agricultural productivity.
[3] The earlier works have not included transboundary transfer as a source of technologies, where technology in the sense used by economists encompasses the means by which resources are transformed into commodities that have value.

influencing differences in agricultural productivity between countries, some of which are components of AS&T policy system as conceptualised in this study.

Table 2: Studies on inter-country agricultural productivity growth, 1993-2005

Study	Method$^{\psi}$	Years	Countries
Fulginiti and Perin (1993)	CD	1961-85	18 LCD
Block (1994)	DEA	1973-88	39 SSA
Bureau, Fare and Grosskopf (1995)	DEA & Fisher	1973-89	10 CD
Frisvold and Ingram (1995)	CD	1973-75	28 SSA
Thirtle, Hadley and Townsend (1995)	DEA	1971-86	22 SSA
Fulginiti and Perin (1997)	DEA	1961-85	18 LCD
Craig, Pardey and Roseboom (1997)	CD	1961-90	98 World
Lusigi and Thirtle (1997)	DEA	1961-91	47 Africa
Fulginiti and Perin (1998)	CD (VC)	1961-85	18 LCD
Rao and Coelli (1998)	DEA	1980-95	97 World
Arnade (1998)	DEA	1961-93	70 World
Fulginiti and Perin (1999)	DEA & CD	1961-85	18 LCD
Martin and Mitra (1999)	Translog	1967-92	49 World
Wiebe et al. (2000)	CD	1961-97	110 World
Chavas (2001)	DEA	1960-94	12 World
Ball et al. (2001)	Fisher (EKS)	1973-93	10 DC
Suhariyanto, Lusigi and Thirtle (2001)	DEA	1961-96	65 Asia/Africa
Suhariyanto and Thirtle (2001)	DEA	1965-96	18 Asia
Trueblood and Coggins (2003)	DEA	1961-91	115 World
Nin, Arndt and Preckel (2003)	DEA	1961-94	20 LCD
Fulginiti, L.E., Perrin, R.K., and Yu, B. (2004)	Fourier	1960-99	41 Africa
Rao, D.S.P., Coelli, T.J., and Alauddin, M. (2004)	DEA	1970-2000	111 World
Tonini (2005)	Translog	1993-2002	10 DC

Source: Updated from Coelli and Rao, 2003 (SSA=Sub-Saharan Africa)

$^{\psi}$The suitability of these methodological approaches is discussed later in this thesis

Frisvold and Ingram (1995) examined land productivity in 28 countries in four regions of SSA from 1973-75 and 1983-85. Land productivity was estimated to have grown at an annual rate of 1.5-1.8 percent in most regions over the period principally due to increased use of agricultural labour. They concluded that substantial increases in land productivity should not be expected until land becomes relatively scarce, echoing sentiments from Binswanger and Pingali (1988) and Boserup (1965). Growth in the stock of *conventional inputs* (such as labour and machinery) accounted for more than two-thirds of growth in land productivity, which in turn accounted for most of the growth in agricultural output. *Nonconventional inputs* (such as land quality and historic calorie availability) were significant in explaining land productivity variation across countries, but did not contribute significantly to land productivity growth over time in most regions. No significant relationship was found to exist between agricultural research expenditures and land productivity.

More investigations into labour productivity was undertaken in a study of 67 developing countries, including South Africa and 24 other SSA countries (including Kenya and Uganda) by Craig, et al. (1997). They found that conventional inputs explained nearly three quarters of the variation in labour productivity across countries. Variables that adjusted for quality differences in land and labour (rainfall, share of land that is arable, share of land that is irrigated and life expectancy) were significant in explaining cross-sectional differences in productivity. Unlike earlier work of Frisvold and Ingram, this study established significant relationship between publicly provided infrastructures such agricultural research expenditures with labour productivity.

Lusigi and Thirtle (1997) estimated an average rate of total factor productivity (TFP) growth of 1.3 percent per year for 47 African countries from 1961-91. They found that conventional inputs, land quality and research expenditures together explained almost three-quarters of variation in production across the countries studied. Like Frisvold and Ingram (1995), Lusigi and Thirtle stressed the contribution of population pressure to faster growth, arguing that land abundance depressed farmer incentives to increase land productivity by adopting yield increasing technologies.

Block (1994) found rates of growth in agricultural TFP in 39 SSA countries increasing from -0.5 percent per year (for 1973-78) to 1.6 percent per year (for 1983-88). Block suggested that expenditures for agricultural research and improved economic incentives (through improved macroeconomic policies) together explained two-thirds of measured productivity growth in SSA from 1983-88. This finding questioned the then on-going reductions in public spending on agricultural research in SSA.

Thirtle, et al. (1995) decomposed the low but positive TFP growth rate they estimated for 1971-86 in 22 SSA countries they studied into technical progress and efficiency change. Investments in infrastructure, agricultural extension and the level of real protection in international agricultural markets were shown to be significant in explaining efficiency change, while tractors, labour/land ratio, agricultural research and secondary education explained the variation in technical progress. Population density (labour/land ratio) was found to be the single most important explanatory variable, again suggesting that productivity growth will accelerate in land-abundant countries as population density increases. This study was different from the rest in that it disaggregated TFP growth into constituent elements and also included agricultural extension and indicators of international trade as some of the determinants of differences in productivity growth.

Lastly, Rao et al. (2004) estimated TFP indexes for 111 countries around the world for a period of thirty years between 1970 and 2000. Two issues were addressed in this study. First, was the identification of factors that influenced agricultural productivity levels and trends, and second, whether institutional factors were important. This study covered countries from all regions and from low-, middle- and high-income countries. In this regard, explaining productivity level differences was quite tricky. For purposes of econometric analysis, two levels of analysis were conducted. First a simple cross-sectional regression analysis for all countries covered in the empirical analysis for the years 1980 and 2000 was undertaken. Second, a more complex and rich econometric analysis that was based on the full data set consisting of a panel of all the countries in North Africa and the Middle East, Asia, Latin America and sub-Saharan Africa over the period 1970-2000 was done. The main reason for restricting the second analysis to developing countries was to identify the institutional, climatic and other factors that influenced productivity in agriculture. These factors include literacy rate, government expenditure, investments in irrigation, foreign direct investments, political openness and economic openness. With the exception of irrigation investment and political openness, all the other institutional factors were found to significantly influence agricultural productivity. The results of this study suggested that avenues through which developing countries may increase TFP in their rural sector included: investment in human capital, attracting foreign direct investment and promoting trade, and through improving physical infrastructure for the rural sector. It is important to point out that this study did not consider investments in research and extension, nor institutions relevant to these key areas.

While the precise effects of the different components of AS&T policy on various measures of agricultural productivity have varied from one study to the next, one broad pattern is clear. The studies have been nearly unanimous in attributing most historic productivity growth to increases in the use of conventional inputs, especially labour. Policy reforms, infrastructure, agricultural research and trade have also been shown to make important contributions to productivity, although the estimated magnitude of these contributions has been sensitive to, first, the precise ways in which these variables have been measured and analysed, and second to how productivity itself has been construed. What is lacking in these studies is a consistent approach or framework for delineating the structure of AS&T policy system and the choice and measurement of appropriate indicator of performance (measure of agricultural productivity).

Such a framework should include both the policies and institutional changes in each key sector. For example, Edwards (1983) observed that technological advances are accompanied with institutional changes citing the example of agricultural research and agricultural education institutions. However, he noted that the interaction between research technology generation and the accompanying institutions has been all too often overlooked in economic analysis of productivity in agriculture. He observed that the knack for building and rebuilding suitable institutional arrangements appears to have been lost and in essence most investigations have also overlooked such interactions. Some of the institutional changes that he considered characteristic of economic progress included property rights and improvement in skills of humankind among others.

This study endeavoured to fill this void by hypothesising that agricultural productivity was among other factors dependent on agricultural science and technology policy system. This study adopted a framework of delineating the structure of the system suggested by Omamo et al (2005). Furthermore, these systems were not assumed to be homogenous but differing with level of development of respective countries. This framework is discussed next.

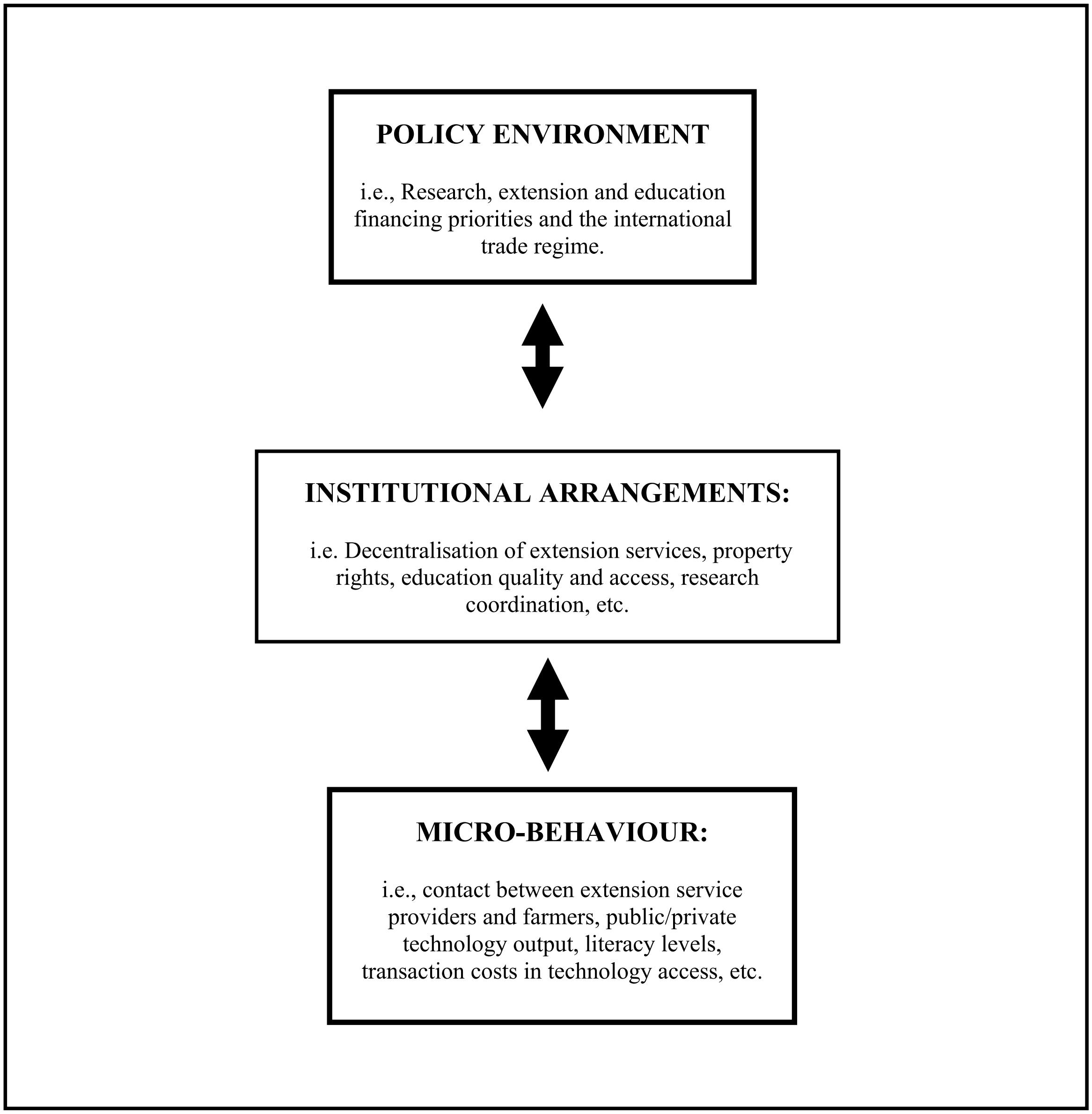
2.2 Theoretical framework for delineating the structure of AS&T policy system structure

The process of delineating the potential determinants of system structure is grounded in two conceptual underpinnings that are derived from posits of Omamo et al. (2005). First, the AS&T policy system is composed of four key functional areas, i.e. agricultural research, agricultural extension, agricultural education, and agricultural transboundary technology acquisition and exchange. These are taken to comprise the policy 'system-components'. The argument behind this categorisation is that these components are central to achieving the broad objective of agricultural productivity growth (FAO, 2000). They have also been shown to be unrivalled as generators of growth and yielders of poverty alleviating effects, being challenged only by investments rural transport infrastructure (Fan et al., 2005).

The influence of these system components on the performance of the policy systems is visualised to be modified by the second set of determinants, the 'shift effects'. These comprise of: (i) policy environment; (ii) the institutional arrangements; and (iii) the micro-level conditions. Based on the arguments of Davis and North (1971), Edwards (1983) and Williamson (1994), these shifts effects are related to one another as schematised in Figure 1. The interaction of the system components and the shifts effects give rise to the ***'system components-shifts effects'*** framework that can be presented as a 3x4 matrix as shown in Table 3. This matrix comprises the 'potential structure' of the AS&T policy system. This structure is visualised to exist either as first, second or third generation system, which in turn influence the systems' performance.

Within each policy system-component, the efficacy of alternative institutional arrangements varies, first, with the policy environment within which science and technology investments takes place, and, second, with the attributes of individuals and organisations at micro-level. Conditions (and changes) in policy environments thus define (and shift) the comparative costs of institutions, which, in turn, influence and reflect conditions and behaviour at the micro level. A detailed presentation of the elements of the potential shift effects as they occur within different AS&T policy system generations is presented in Table 4.

Figure 1: Policies, Institutions and Micro-behaviour – A Three - Level Schema



Source: Adapted with modification from Omamo et al. (2005)

Table 3: Potential S&T influences within different R&D functional areas

		Agricultural S&T Policy System Components			
		Research	**Extension**	**Education**	**Trans-boundary Technology Transfer**
Agricultural S & T Policy System Shift Effects	**Policy Environment**	Research financing priorities – Development of research capital	Extension financing priorities	Education financing priorities – Development of human resource capital	Degree of economic openness – Transboundary technology transfer
	Institutional arrangement	Coordination of research – level of public, private and civil society participation	Extension delivery systems, i.e., decentralization /privatised, etc	Education access and quality control systems	Regulatory framework for intellectual property rights
	Micro-conditions	Technologies developed, scientific information published, etc	Farmer-extension agent contact intensity; i.e., telephone contact; density of extension workers, etc	Literacy level within the agricultural labour force	Transaction costs in accessing technologies, i.e., road network, telephone access

Source: Adapted with modification from Omamo et al. (2005)

Table 4: Variation of potential 'shift effects' determinants in different AS&T policy system generations

Potential shift effects determinant	*First generation*	*Second generation*	*Third generation*
Policy environment			
Degree of political openness	Low	Moderate	High
Degree of economic openness	Low	Moderate	High
Agriculture's share of economy	Large	Moderate	Small
Size of economy	Small	Medium	Large
Donor role	High	Moderate	Low
Institutional arrangements			
Public involvement in agricultural R&D	High in funding; High in delivery	High in funding Low in delivery	Moderate in funding; Low in delivery
Private-sector involvement in agricultural R&D	Low	Low-to-moderate	Moderately high
Civil society involvement in agricultural R&D	Low in funding Low in delivery	Low in funding; Moderate in delivery	Low in funding; Moderately high in delivery
Level of development of legal and regulatory system	Low	Low-to-moderate	Moderately high
Public-sector implementation capacity	Low	Moderate	High
Micro-conditions/behaviour			
Nature of agriculture	Primarily diversified subsistence-oriented	Diversified subsistence-oriented and commercial segments	Large and prominent commercial sector
Transaction costs in exchange	High	Moderate	Low

Source: Omamo et al. (2005).

The potential determinants of the policy system structure can be related to the estimated performance indicators through a functional relationship. At the onset, this functional relationship can be conceptualised as a simple production function summarising the process of conversion of factors into a particular commodity as first suggested by Wicksteed (1894), thus:

$$P = f(X_i; Y_i) \tag{2.1}$$

where P is the performance indicator; X_i is a vector of policy system structure indicators; and Y_i is a vector of non-policy variables that may influence performance.

The two categories of performance-influencing determinants i.e., the "system components" and the "shift effects" can then be incorporated into equation 2.1 to become:

$$P = \alpha_i + \beta_i(System\ Effects) + \delta_i(Shift\ Effects) + \Phi_i(non\text{-}policy\ variables) + e \tag{2.2}$$

where α_i, β_i, δ_i, and Φ_i are vectors of estimated parameters, and e is vector of error terms.

Four progressively disaggregated estimation scenarios can be envisaged as being discernible from equation 2.2, and the choice of the scenario to apply in the analysis of structure and performance will depend on data available. These include:

a) Undifferentiated system and shift variables;
b) Functionally specific system effects with undifferentiated shift variables;
c) Functionally specific system effects with differentiated shift variables; and
d) Functionally specific system effects interacting with differentiated shift variables.

(a) Undifferentiated System and Shift effects:

Under this scenario, it is anticipated that there is no differentiation between the AS&T system components and consideration is not given to the implication of the shift effects. Thus, under such circumstances, sector-wide system variables (like aggregate public expenditure) together with non-policy variables (e.g., rainfall) can be regressed on performance indicators. In effect, Table 3 would thus collapse to a single box—i.e., no columns or rows. In retrospect, most of the past studies investigating the influence of AS&T policy have applied this scenario.

(b) Functionally Specific System Effects with Undifferentiated Shift Effects:

The second scenario is envisaged to recognise the four AS&T policy system components—research, extension, education, and transboundary technology acquisition and exchange—but disregard the impact of the shift effects. Thus under this scenario, the functionally specific policy system components (like research expenditures, education expenditure, etc) together with non-policy variables can be regressed on agricultural productivity measures. In this scenario, Table 3 would have four columns but only one row. The study by Thirtle et al (1995) fits under this scenario.

(c) Functionally Specific System Effects with Differentiated Shift Effects:

The third scenario is thought to explicitly capture not only the functional aspects of policy systems components, but also their modification by the shift effects – policy, institutional, and micro features. Table 3 would therefore have four columns and three rows, but in this case, the column- and row-effects would be captured independently of each other.

(d) Functionally Specific System Effects Interacting with Differentiated Shift Effects:

The fourth scenario is thought to assume a similar degree of disaggregation in system and shift dimensions as in the third scenario, but also allows for interaction between these aspects. Table 3 would therefore have four columns and three rows, but now with each of the column- and row-effects captured in an integrated manner.

Expressed mathematically, model development would proceed as follows:

$$\boldsymbol{P = f(Ag, Z, N)} \qquad (2.3)$$

where, $\boldsymbol{P}$ is the performance, $\boldsymbol{f(.)}$ is the associated technology parameter, which is hypothesized to be a function of the country's undifferentiated system effects ***(Ag),*** undifferentiated shift effects ***(Z)*** and non-policy variables **(*N*)**. ***Ag*** represents agricultural research and development encompassing agricultural research, extension, education and transboundary technology transfer.

By adding a random disturbance term ***e***, we obtain a rudimentary 'Undifferentiated System and Shift Effects' econometric model of system performance:

$$\boldsymbol{P = a_0 + a_1(Ag) + a_2(Z) + a_3(N) + e} \qquad (2.4)$$

Expanding the model to include the functionally specific system effects with undifferentiated shift effects we obtain:

$$\boldsymbol{P = a_0 + a_{11}(AgRes) + a_{12}(AgExt) + a_{13}(AgEduc) + a_{14}(Trans) + a_m(Z) + a_n(N) + e} \tag{2.5}$$

When the 'functionally specific system effects with differentiated shift effects' are added we get:

$$\boldsymbol{P = a_0 + a_{11}(AgRes) + a_{12}(AgExt) + a_{13}(AgEduc) + a_{14}(Trans) + a_{z1}(Policy) + a_{z2}(Inst) + a_{z3}(Micro) + a_z(Z) + a_n(N) + e} \tag{2.6}$$

When the functionally specific system effects interacting with differentiated shift effects are finally added we obtain:

$$\begin{aligned}\boldsymbol{P = a_0} &\boldsymbol{+ a_{111}(AgRes)*Z_{11}(Policy) + a_{121}(AgRes)*Z_{12}(Inst)\ \ a_{131}(AgRes)*Z_{13}(Micro) +} \\ &\boldsymbol{a_{121}(AgExt)*Z_{12}(Policy) + a_{122}(AgExt)*Z_{22}(Inst) + a_{123}(AgExt)*Z_{23}(Micro) +} \\ &\boldsymbol{a_{131}(AgEduc)*Z_{13}(Policy) + a_{132}(AgEduc)*Z_{23}(Inst) + a_{133}(AgEduc)*Z_{33}(Micro) +} \\ &\boldsymbol{a_{141}(Trans)*Z_{14}(Policy) + a_{142}(Trans)*Z_{24}(Inst) + a_{134}(Trans)*Z_{34}(Micro) + a_m(Z) +} \\ &\boldsymbol{a_nN + e}\end{aligned} \tag{2.7}$$

where ***'P'*** represents the indicators of performance (i.e., agricultural productivity growth), $\boldsymbol{a_i}$, $\boldsymbol{a_{ij}}$, and $\boldsymbol{a_{ijk}}$ are parametric effects of structures and processes governing agricultural research (***AgRes***), agricultural extension (***AgExt***), agricultural education (***AgEduc***), and agricultural transboundary technology transfer (***Trans***), $\boldsymbol{Z_{lm}}$ represent shift variables within policy environments (***Policy***), institutional arrangements (***Inst***), and micro-conditions (***Micro***), $\boldsymbol{a_z}$ and $\boldsymbol{a_{zl}}$ are parametric shift effects associated with $\boldsymbol{Z}$, and $\boldsymbol{e}$ are error terms.

The framework presented in equation 2.7 was applied in the analysis of the structure and performance of the policy system. It is important to point out that the effectiveness of this framework is based upon selection of a suitable performance indicator. Several options exist, and before they are discussed, it would be important to give a brief background review on the genesis of the systems components-shifts effects framework as used in this study.

2.2.1 A review of the genesis of the theoretical framework for delineating the structure of the AS&T policy system structure

The three-level system component – shifts effects framework used in this study is related to the other system oriented frameworks that have been widely used to investigate the innovation system in African agriculture. The systems perspective—that is, the study of sets of interrelated actors who interact in the creation, exchange and application of agriculture-related technologies under varying social, economic and institutional contexts that conditions their actions and interactions has become an important method of analysing policy systems. The systems approach has evolved to encapsulate the dynamics of developing-country agriculture. Three distinct forms of systems frameworks can be traced in literature, *viz*. the National Agricultural Research Systems (NARS), the Agricultural Knowledge and Information Systems (AKIS) and the Agricultural Innovation Systems (AIS) frameworks.

The NARS framework was developed during the 1970s. It was informed by neoclassical economics and the inherent failures in the market for agricultural research in developing countries. Numerous studies had empirically demonstrated that agricultural research generated high social rate of return in developing countries (Alston et al. 2000), but the private benefits of such research were often limited by poor market infrastructure in rural areas and weak purchasing power among farmers leading to undersupply of research products. Therefore, this required that public investment in research be undertaken to address the chronic undersupply (see among other studies Echeverría 1990; Huffman and Evenson 1993; Anderson, et al 1994; Alston, et al 1998; and Alston, et al 1999). The NARS framework thus focused on ways of optimising the investment in public research organisations as a means of developing technologies to foster agricultural transformation and development.

Limitations inherent within the NARS approach led to the evolution of a broader approach in the study of drivers of agricultural productivity growth – i.e. the agricultural knowledge and information systems (AKIS) framework of the 1980s[4]. Initially, the AKIS framework was applied in a narrower sense, recasting agricultural research as one point of a "knowledge triangle" which also included agricultural extension and education, and placed the farmer at the centre. The AKIS framework succeeded in refocusing the study of

[4] AKIS was defined as "a set of agricultural organizations and/or persons, and the links and interactions between them, engaged in such processes as the generation, transformation, transmission, storage, retrieval, integration, diffusion and utilization of knowledge and information, with the purpose of working synergistically to support

agricultural productivity growth on the dissemination and diffusion of knowledge and information, emphasising specifically the importance of knowledge and information flows between researchers, extension agents, educators, and farmers.

The NARS and AKIS frameworks were largely focused on the role of education, research, and extension as sources of new knowledge and technology to the farmer. This predisposition was found limited leading to development of the agricultural innovation system (AIS) approach at the end of the 1990s[5]. The AIS has therefore developed to include the farmer as part of a complex network of heterogeneous actors engaged in innovation processes, along with other institutions (formal and informal) and the policy environment that influence these processes.

The AIS drew from the concept of "national system of innovation," which emerged in evolutionary economics in the 1980s (see Lundvall 1985, 1988; Freeman 1987, 1988; Nelson 1988; Dosi et al. 1988; and Edquist 1997). The approach was introduced in the analysis of developing-country agriculture as a critique of the "linear" or "pipeline" model of agricultural research that was prominent in the NARS framework (Clark 2002). However, this framework shared important features with the original AKIS concept (see the rather similar definitions of AKIS and AIS).

Empirical studies that have been based on the AIS framework have highlighted on ways in which heterogeneous actors interact in generation, exchange and use of information and knowledge; how actors learn and change; and how social and economic institutions condition these interactions and processes. Such studies have continued to provide new insights into ways of increasing both the efficiency and effectiveness of innovation processes as the driver of productivity growth by identifying and exploiting comparative advantages of different actors; reducing transaction costs in the exchange of knowledge and technology; and achieving economies of scale, exploiting complementarities, and realising synergies in innovation (Davis et al. 2007). This has particularly been important given the changing nature of developing-country agriculture that has experienced increased knowledge intensity of

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decision-making, problem solving and innovation in a given country's agriculture or domain thereof" (Röling 1990, 1).

[5] A recent application of this approach by the World Bank (2006) defines an innovation system as "a network of organizations, enterprises, and individuals focused on bringing new products, new processes, and new forms of organization into economic use, together with the institutions and policies that affect their behavior and performance. The innovation systems concept embraces not only the science suppliers but the totality and interaction of actors involved in innovation. It extends beyond the creation of knowledge to encompass the factors affecting demand for and use of knowledge in novel and useful ways" (World Bank 2006, vi–vii).

agricultural production, and expanding number of actors in technology generation and delivery (World Bank 2006).

Spielman and Birner (2008) have observed that applications of the AIS framework to date have been primarily used to describe innovation processes that underlie the introduction of a given technology (for example, zero tillage cultivation (Ekboir and Parellada 2002); post-harvest technologies and value chain development (Clark et al. 2003); organisational learning and change in research institutes (Hall et al. 1998) among other studies). Investigations that describe and assess entire national agricultural innovation systems have been scarce in literature to date, particularly in developing countries of Africa. One reason for this would perhaps be the limitations of applying the AIS to a national innovation system. This gap in knowledge is one of the focus of this study.

2.2.2 Components of the agricultural innovation system framework and relationship to the 'systems components-shifts effect' framework

The essential elements of the AIS include (a) the knowledge and education domain, (b) the business and enterprise domain, and (c) bridging institutions that link the two domains. The knowledge and education domain is composed of agricultural research and education systems. The business and enterprise domain comprises the set of value chain actors and activities that both use outputs from the knowledge and education domain, and also innovate independently. Between these domains are the bridging institutions—extension services, political channels, and stakeholder platforms—that facilitate the transfer of knowledge and information between the domains. The framework also includes reference to the frame conditions that foster or impede innovation, including public policies on innovation and agriculture; informal institutions that establish the rules, norms, and cultural attributes of a society; and the behaviours, practices, and attitudes that condition the ways in which individuals and organizations within each domain act and interact.

Implicit throughout the system are farmers, who operate firstly as consumers and producers of knowledge and information, secondly, as producers and consumers of agricultural goods and services, thirdly as bridging institutions between various components, and lastly as value chain actors. Beyond the borders of the system, though nonetheless important, are influencing factors such as linkages to other sectors of the economy (manufacturing and services); general science and technology policy; international actors, sources of knowledge, and markets; and the political system (Spielman and Birner, 2008).

The rationale behind this study is to apply a modified version of the AIS framework that is referred to as the 'system components-shifts effect' framework to assess the structure and performance of national AS&T policy systems in developing countries using Kenya and Uganda as case studies. One additional component – transboundary technology transfer is added as a contributor to agricultural knowledge and technologies. In addition, the farmer ceases to be implied in the framework, but rather a focal player. This is achieved through incorporation of indicators that capture the interface between the developed knowledge and technologies and the farmer at micro-level.

2.3 Identifying suitable performance indicators for AS&T policy system – A review of potential indicators

Agricultural S&T is linked to agricultural production through its influence on agricultural productivity. It may be for this reason that most studies that have analysed the functioning of various elements of the AS&T policy system (Table 1) have used agricultural productivity as the performance indicator. Lovell (1993) defines agricultural productivity of a decision making unit (DMU) as the ratio of its outputs to its inputs.

Agricultural productivity measurement indicators have evolved over time (Hauver, 1989; Ball et al., 1997; Ahearn, et al., 1998). In the past, economists have developed and used productivity measures that are based on the relationship between one or more outputs relative to a single key input, alternatively called partial productivity indicators. The commonly used partial productivity measures in agriculture are labour and land productivity. Some of the studies that have used these indicators include Frisvold and Ingram (1995) and Craig et al (1997). These measures are referred to as partial because when considered in isolation, they may sometimes provide misleading indications of overall productivity. For example, it is possible to achieve increased land productivity by the utilisation of extra labour (or fertiliser), which may or may not result in improved overall productivity. Studies that have used these indicators of performance have found limited relationship between potential indicators of AS&T policy system with performance indicators.

Besides these partial indicators, productivity can also be estimated by overall productivity measures, also known as total productivity indicators. These measures compute the aggregate output per aggregate input used in production. However, it is not feasible to measure aggregate input and output levels. In such cases, index number methods are used to construct output and input indices, which are in turn used in the construction of productivity index numbers. The most common productivity index number is the total factor productivity (TFP) index. Simply put, a TFP index derives change in total output relative to change in all inputs. This makes it more suitable than partial productivity measures which may at times provide misleading results especially when countries are characterised by asymmetric changes in inputs (Rozelle and Swinnen, 2003). Several studies have used TFP as the performance indicator (e.g. Lusigi and Thirtle, 1997; Thirtle et al, 1995; Block, 1994).

When one has panel data (like envisaged in this study), it is possible to measure productivity change (TFP change) and decompose it into technical change (TC) and efficiency change (EC)[6]. These two measures (including TFP change) are derived from technical efficiency estimates (Coelli, 1996). Only one study by Thirtle et al (1995) has investigated the effect of AS&T policy system components on efficiency and technical change estimates in multi-country productivity analysis.

By definition, technical efficiency of a DMU is defined as the degree to which it is able to convert its inputs efficiently into outputs – relative to best practice, where best practice is defined by the production frontier (Rao et al., 2004). The true production frontier is rarely known but is generally estimated using data from a number of DMUs. There are two types of TE measures: input-oriented and output-oriented. Input-oriented TE measure the extent to which input usage can be reduced, while maintaining the same level of outputs. The output-oriented measure considers the expansion in outputs for a given set of input quantities. Efficiency change captures the change in technical efficiency between two time periods. It is important to observe that the rate at which a DMU can efficiently convert inputs into outputs is largely dependent on among other factors, the prevailing policy environment.

When productivity is compared over time, an additional source of possible productivity improvement is TC, or alternatively called technology growth. Technical change measures the extent to which the production frontier, representing the state of technology in a particular time period, shifts upwards over time, in essence reflecting application of new innovations and technology. Such shifts thus represent technical progress and are a product of the existing AS&T policy system and the prevailing socio-economic and political circumstances (Freeman 1995).

This conceptualisation of agricultural productivity as comprising of technical and efficiency change is in tandem with the arguments of both Nishimizu and Page (1982; p. 992), who typify productivity growth as 'the net change in output due to change in efficiency and technological change, where the former refers to change in how far an observation is from the frontier of technology and the latter is understood to be shifts in the production frontier'. This is also reinforced by Lovell (1993) who further stated that productivity of an individual DMU is dictated by differences in production technology and differences in the efficiency of the process, as well as on differences in the environment when and where production occurs. Because of these three factors, productivity changes over time. Under any given scenario, when technology and the production environment are essentially the same, DMUs may exhibit different productivity due to differences in their production efficiency. With these considerations, Bitran and Chang (1984) noted that in order to achieve valid productivity measures, a DMU must be compared to itself at different time points as well as to other DMUs at the same point in time. This study uses this approach in the measurement of agricultural productivity.

Agricultural science and technology contributes to improved technical efficiency and to progress in technical and efficiency change in a number of ways. First, it leads to production of technologies and knowledge, either through research within a country or from transboundary acquisition; and secondly, it creates an environment that fosters learning by firms/farms in application of these technologies, thereby leading to improved technical and efficiency change. This nested technology generation-cum-learning conceptual approach is closely linked to Malerba's general framework on incremental technical change arising from the learning process (Malerba, 1992). This framework presupposes that DMUs learn in a variety of different ways and these learning processes yield enhancements in the stock of knowledge and technological capabilities of the DMU. Therefore, the prevailing AS&T policy will promote learning by production units that in turn generate a whole range of trajectories of efficiency and technological advances leading to increased productivity.

The apparent direct relationship between AS&T policy system with technical efficiency and technical and efficiency change made them suitable indicators of performance to be applied in this study. However, there are several approaches that can be used to measure technical efficiency (which in turn is used to derive technical and efficiency change). The appropriateness of each of these methods for use in this study is discussed in the next section.

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[6] Technical efficiency change can further be decomposed into two components, namely scale efficiency and pure technical efficiency.

2.4 Measuring technical efficiency and technical and efficiency change

Technical efficiency can be estimated by using frontier methods. Two main categories of frontier approaches exist, i.e.:

(i) The deterministic frontier approach (or non-parametric) represented by Charnes et al. (1978) data envelopment analysis (DEA) and Deprins et al. (1984) free disposal hull (FDH); and,

(ii) The stochastic approach (or parametric) that was pioneered by Aigner et al (1977) and Meeusen and van den Broeck (1977) and which allows for random shocks in the production process. It includes the stochastic frontier approach (SFA), the thick frontier approach (TFA) and the distribution-free approach (DFA).

Other less widely used approaches include the corrected ordinary least squares[7] and the stochastic non-parametric envelopment of data[8] (Figure 2).

The five most commonly used frontier approaches (DEA, FDH, SFA, TFA and DFA) differ in three key areas:

(i) the assumptions they make regarding the shape of the frontier;

(ii) the existence of random error; and,

(iii) If random error is allowed, the distribution assumptions imposed on the inefficiencies and random error in order to disentangle one from the other (Fare et al, 1985; Coelli et al, 1998; O'Neill and Mathews, 2001).

This section discusses these techniques focussing not only on the underlying concepts and assumptions, but also on the technical details of the estimation process and its relevance to this study.

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[7] Winsted (1957) as quoted in (Kumbharka and Lovell, 2000) suggested that a deterministic production frontier model could be estimated in two steps. In the first step, ordinary least squares (OLS) is used to obtain consistent and unbiased estimates of the slope parameters and a consistent but biased estimate of the intercept parameter. In the second step the biased OLS intercept is shifted up (corrected) to ensure that the estimated frontier bounds all data from above. The COLS technique is easy to implement and generates an estimated production frontier that lies on or above the data. The frontier is parallel to the OLS and has the undesirable restrictive property of not allowing the structure of the best practice to bind the data from above as closely as possible, since it is required to be parallel to the OLS regression (Kumbharka and Lovell, 2000: pp 70). MCOLS is a modified version of COLS.

[8] StoNED is an estimation technique that combines the virtues of SFA and DEA in a unified framework. The study by Kousmanen (2006) is by no means the first to attempt to combine the features of DEA and SFA, but contributes to a long series of works that have pursued similar aims, e.g. Park and Simar (1994) explored semi-parametric estimation in the context of panel data, whereas Henderson and Simar (2005) presented the first fully non-parametric frameworks based on local maximum likelihood and kernel regression.

Figure 2: Classification of the frontier estimation literature

Model Type / *Specification*	*Parametric*	*Non-Parametric*
Deterministic	**<u>COLS and MCOLS</u>** (Corrected Ordinary Least Squares) • Winsted (1957) • Aigner and Chu (1968) • Timmer (1971)	**<u>DEA (FDH)</u>** (Data Envelopment Analysis) • Farrell (1957) • Charnes, Cooper, Rhodes (1978)
Stochastic	**<u>SFA (TFA & DFA)</u>** (Stochastic Frontier Analysis) • Aigner, Lovell, Schmidt (1977) • Meeusen and van den Broeck (1977)	**<u>StoNED</u>** (Stochastic Non-parametric Envelopment of Data) Kuosmanen (2006)

2.4.1 Deterministic frontiers

2.4.1.1 Data envelopment analysis (DEA)

DEA is a nonparametric approach which uses linear programming techniques to measure efficiency. DEA models are flexible, albeit primarily deterministic unless some sort of stochastic modifier is used. During the estimation process, one linear program needs to be generated and solved to compute the efficiency score of each DMU. DMUs are identified for which no other DMU or linear combinations of DMUs can produce as much or more of every output (for a given combination of inputs) or use as little or less of every input (for a given combination of all outputs).

The DEA efficient frontier is composed of these un-dominated DMUs and the piecewise linear segments which connect the set of input/output combinations of these DMUs, yielding a convex production possibility set. The efficient frontier is defined by certain convex combinations of these un-dominated DMUs; since these composite DMU do not have an observable instance, they create DMUs with composite levels of input and output. These composite DMUs are called virtual producers.

The linear program decides the weighting of the efficient DMUs to construct a virtual DMU for the purposes of determining the efficiency of the DMU under evaluation. If the virtual DMU is better than the DMU being evaluated by either making more output with the same or less input or making the same output with less input, then the evaluated DMU is inefficient. Take for example the case where a virtual DMU can make the same output with less input than DMU A, it is then said a proportional contraction of all resources, also called an equi-proportional contraction, can occur. The size of this contraction (call this b) relative to the distance function measured to the point representing DMU A (call this a), can be used to calculate the efficiency of DMU A by the equation $1-\frac{b}{a}$.

DEA can be classified into three separate subsets based on the assumption on returns to scale. These are:

(i) **constant** return to scale (CRS)

(ii) **variable** returns to scale (VRS)

(iii) **non-increasing** return to scale (NRS)

The difference in the linear programming formulations of these three forms of DEA is a single constraint, often referred to as the convexity constraint. This constraint forces the weights assigned to construct the virtual unit to sum to one. This in essence precludes a very small DMU from being scaled up several times with a weight greater than one, and forces the virtual DMU to be composed of at least one DMU producing more output than the DMU under evaluation. This is illustrated below.

DEA measures efficiency by the distance between a production plan and the production frontier. Assuming that:

$$B^t = \{(u^t, x^t)\} \cup \{(0^M, 0^N)\}, \tag{2.8}$$

such that (u^t, x^t) is feasible and where u are the m = 1, 2, ...,M outputs, x are the n = 1, 2, ..,N inputs and t are the t = 1, 2, ...,T time periods that represent a set of real or actual production plans. A production plan in the interior of the production frontier is considered inefficient, while a point on the frontier (the 'best practice' point) is considered efficient.

To be able to construct this production frontier, three assumptions need to be fulfilled, namely:

(i) Every observed production plan should belong to the production set. This is what makes the DEA analysis a deterministic one.

(ii) Any unobserved production plan that is weakly dominated by another production plan is also part of the production set. This assumption allows for free disposability.

(iii) The third assumption concerns the issue of combinations of production plans and has several different forms, where this form determines the assumed returns to scale.

If the returns to scale are assumed to be **constant** then the third assumption will state that: '***every unobserved production plan that is a linear combination of production plans is itself part of the output-possibility set***'. This, in conjunction with the first two assumptions, gives the panel data output-possibility set as:

$$P^t_{CRS}(x^t \big| M^t, N^t) = \{u^t \in \Re^M_+ \big| u^t \leq z^t M^t \wedge z^t N^t \leq x^t, z^t \in \Re^N_+\}, \tag{2.9}$$

where z^t are the slack variables.

Similarly, if the returns to scale are assumed to be **non-increasing**, then the third assumption states that: '***every unobserved production plan which is a convex combination of production plans, including the origin, also belongs to the output-possibility set***'. The new output-possibility set is thus defined as:

$$P^t_{NRS}(x^t \big| M^t, N^t) = \{u^t \in \Re^M_+ \big| u^t \leq z^t M^t \wedge z^t N^t \leq x^t, z^t \in \Re^N_+ \wedge \sum_n z^t \leq 1\} \tag{2.10}$$

The final variation of the returns to scale assumption is that of **variable** returns. In this case, the third assumption will be similar to the non-increasing scenario, except that the origin is no longer included in the output-possibility set. The output-possibility set becomes:

$$P^t_{VRS}(x^t \big| M^t, N^t) = \{u^t \in \Re^M_+ \big| u^t \leq z^t M^t \wedge z^t N^t \leq x^t, z^t \in \Re^N_+ \wedge \sum_n z^t = 1\} \tag{2.11}$$

Having explored the different forms of returns to scale assumptions, it is important to explain the numerical measurement of technical efficiency under each of these scenarios. Under the DEA CRS output-possibility set, determination of the degree of output efficiency (λ^{t*}) first needs one to obtain the optimal λ^{t*}, which is derived by solving the following linear problem:

$$\min_{Z^t, \lambda^t} \lambda^t$$

$$\begin{aligned} \textit{subject to} \quad & \frac{u^t}{\lambda^t} \leq z^t M^t \\ & z^t N^t \leq x^t \\ & z^t \geq 0. \end{aligned} \tag{2.12}$$

The value of λ^{t*} is usually less than one, but it is feasible that λ^{t*} may equal one. When the equality situation holds, the DMU is said to be efficient. Under the NRS output-possibility set, the condition $\sum_n z^t \leq 1,$ is added to the linear problem, whereas under the VRS, the final line of the maximization problem is replaced by $\sum_n z^t = 1$. The technical efficiency estimates are then used to derive efficiency and technical change values.

How then do these three forms of DEA differ from FDH? This is explained next.

2.4.1.2 Free Disposable Hull (FDH)

The third assumption in the DEA framework has been the borne of contention in its application. Convexity and returns to scale assumptions have been argued to be too restrictive. This has been the genesis of FDH that has nearly identical modelling features and properties as DEA, with the exception of the third assumption. Even though linear programming techniques can be used to solve for efficiency estimates using FDH model, FDH uses a min/max formulation which solves much faster. By definition, FDH is the smallest free disposal set containing all observations in a sample of producers. Free disposal implies if a DMU producing a particular level of output *y* with a particular level of input *x*, was given more of any input the producer could freely give away or destroy the extra input and still produce the same level of output (Johnson, 2006). Although DEA also makes this assumption, it is different from FDH where DEA also assumes convex combinations of any observed production possibilities can be achieved. Therefore, FDH production possibility set is typically non-convex. The FDH output-possibility set for panel data is thus given as:

$$P^t_{FDH}(x^t \big| M^t, N^t) = \{u^t \in \Re^M_+ \big| u^t \leq z^t M^t \wedge z^t M^t \leq x^t, \sum_n z^t = 1 \wedge z^t \in \{0,1\}\}. \qquad (2.13)$$

Just like DEA, the FDH production set is deterministic and also allows for free disposability.

When determining output efficiency from the output-possibility set, the process is nearly identical to DEA measures except that an additional line, i.e., $z^t \in \{0,1\}$, is added to the maximization problem. This measure is less than or equal to one. Again, a value of one deems a particular DMU to be totally efficient.

2.4.1.3 Assessment of the suitability of DEA and FDH to this study

The three forms of DEA are quite similar, but they collectively differ from FDH. The main difference between the two approaches lies in how they define an efficient production set. The linear programming technique used in DEA attempts to measure the distance from the frontier of a convex envelope of the data. While the first two assumptions deal with dominance, the third may deem an un-dominated production plan inefficient because it does not lie on the convex envelope. In contrast, the FDH is more concerned with dominance than with distance. It only deems production plans which are dominated by other production plans to be inefficient. Thus, the number of DMUs deemed efficient by the FDH is greater than or equal to those by each of the DEA models.

The difference between these formulations is also important from a managerial point of view. Some authors (e.g., De Borger and Kerstens, 1996; Vanden Eeckaut et al., 1993) argue that DEA calls inefficient too many observations because of the convexity assumptions. They argue that the assumptions, which often have no a priori support, fail to recognise local non-convexities. Further, they attempt to discredit DEA models by stating that their comparison technique is flawed. Specifically due to the convexity assumptions, an inefficient observation is often compared to an unobservable and fictitious linear combination of efficient observations. Hence, it is illogical to claim that a DMU can be dominated by another which does not exist. In contrast, FDH reference technology is not vulnerable to this critique. It relates each inefficient observation to a single dominating observation.

However, there is a general consensus that FDH allows far too many efficient observations. For instance, an observation with epsilon amount less of a particular input and a substantial amount less of output than an efficient DMU may be deemed efficient, whereas that DMU would be considered to be highly inefficient by DEA. This shortcoming of FDH lends its application in this study undesirable leaving DEA as the suitable non-parametric approach.

2.4.1.4 Choosing appropriate model orientation and return to scale assumptions in application of DEA

The choice of DEA model orientation and return to scale assumptions are some of the key decisions that need to be taken into consideration in application of DEA. Regarding returns-to-scale assumptions, these may be either variable or constant returns-to-scale (VRS or CRS) envelopment surfaces. On the other hand, the choice of model orientation determines the path of inefficient production units to the efficient frontier. It may be non-oriented or oriented (input or output). In non-oriented cases, output slack and input excess are considered comparable, in that neither pre-empts or receives greater scrutiny than the other. In the oriented cases, either inputs or outputs pre-empt the other, in that proportional movement toward the frontier is first achieved in input or output space, respectively. Therefore, in an output orientation model, the objective is to produce the maximum amount of outputs with a given set of inputs, such that efficiency frontier is constructed through proportional augmentation of all inputs. In an output orientation model, the objective is to produce desired output with a minimum of inputs.

Most productivity analysis studies have used an output orientation because it is believed that in agriculture, one endeavours to maximise output from a given set of inputs rather than the converse. Specifically, Tonini (2005) supports this argument by emphasising that for a country level analysis an output orientation is the proper choice, where it is assumed that the production technology looks for maximal proportional expansion of an output vector given an input or resource vector. Similarly, most studies have preferred the application of the CRS technology. This is because of two reasons. First, in instances where aggregate country-level data is used, it may not appear sensible to consider a VRS technology. The use of a VRS technology may be appropriate when the summary data is expressed on an 'average farm' basis. In such a situation, one can then discuss the scale economies of the ‘average farm’, but when dealing with aggregate data, the use of a CRS is the most sensible option (Coelli and Rao, 2003).

A second argument for the use of a CRS technology is that performance may not be correctly measured when VRS is assumed for the technology (Grifell-Tatjé and Lovell, 1995). It is therefore important that CRS be imposed upon any technology that is used to estimate distance functions for computation of performance. Otherwise, the resulting measures may not properly reflect the gains or losses emanating from scale effects (Coelli and Rao, 2003).

2.4.1.5 Constraints anticipated in application of DEA

Having observed that DEA offers a more appropriate deterministic estimation approach, it is prudent to mention some of the expected constraints to be encountered in its application. The first constraint involves the problem of ‘self-identifiers’ and ‘near-self-identifiers’. Under the usual radial forms of DEA, each DMU can only be compared to DMUs on the frontier or their linear combinations with the same or more of every output (given inputs) or the same or fewer of every input (given outputs). In addition, other constraints are often imposed on DEA problems which require comparability with linear combinations of other DMUs. Having to match other DMUs in so many dimensions is likely to result in DMUs being as highly efficient solely because no other DMUs or few other DMUs (and their linear combinations) have comparable values of inputs or outputs. This implies that DMUs may be self identified as 100% efficient not because they dominate any other DMUs, but simply because no other DMUs or linear combination of DMUs are comparable in so many dimensions. Similarly, other DMUs may be measured as 100% efficient or nearly 100% efficient because there are only a few other observations with which they are comparable.

The problem of self-identifiers and near-self-identifiers is more likely to occur when there are a small number of observations relative to the number of inputs, outputs and constraints, so that a large proportion of the observations are difficult to match in all dimension. This will require that DEA be applied in a way that it minimises the self-identifier problem. One approach in which this can be attained is through the use of a relatively large number of observations relative to the small number of inputs and outputs. Charnes and Cooper (1990) noted that the ratio of the number of observations and the number of inputs and outputs should equal at least three, while Fernandez-Cornejo (1994) argued for a ratio of more than five. However, Smith (1997) noted that one can not rule out cases of overestimating efficiency levels even if this ratio exceeds thirteen.

Problems of DEA that are difficult to solve are that it usually does not allow for random error due to measurement problems (that may temporarily raise or lower inputs or outputs), it does not allow for specification error (such as excluded inputs and outputs) and it imposes the piecewise linear shape on the frontier. Any random error that exists may be counted as differences in efficiency by DEA, since the approach does not distinguish data noise and inefficiency (Lovell, 1993). Although stochastic DEA models that are able to deal with such problems have been developed (Desai and Schinnar, 1987; Sengupta, 1987), their empirical implications are extremely difficult due to rigorous data requirements. That is, in addition to input and output data, it is necessary to have information on expected values of all variables, variance-covariance matrices for all variables and probability levels at which feasibility constraints are to be satisfied. This study thus envisaged that DEA would lead to lower measurements of efficiency, and that there was likely to be more dispersion in the data, unless if there was some unusual statistical association between random error and 'true' efficiency. This effect may be quite large, since the random error in a single observation on the efficient frontier is likely to affect the measured efficiency of all of the DMUs that are compared to any linear combination on the frontier involving this DMU.

These weaknesses of DEA may warrant utilisation of other approaches for purposes of triangulating the findings. In this regard, parametric approaches become suitable candidates. Appropriateness of these methods is reviewed next.

2.4.2 Stochastic Frontiers

The stochastic frontier model was first specified by Aigner et al. (1977) and Meeusen and Van den Broeck (1977) and later modified for panel data by Pitt and Lee (1981) to become:

$$\begin{aligned} y_{it} &= f(x_{it};\beta) + v_{it} - u_{it} \\ & i = 1,.........., N \quad t = 1,..........T \end{aligned} \tag{2.14}$$

where t is time. For T=1 the model is a simple cross section stochastic frontier as specified by Aigner et al. (1977). These stochastic frontiers – Stochastic Frontier Analysis (SFA), Thick Frontier Approach (TFA) and Distribution-Free Approach (DFA) – require imposition of structure on the shape of the frontier by specifying a functional form. To elaborate more on this, let, for example, the imposed functional form $f(x_i;\beta)$ for (2.14) above take the log-linear Cobb-Douglas form, then the stochastic production frontier model can be written as:

$$\ln y_i = \beta_o + \sum_n \beta_n \ln x_{ni} + v_i - u_i, \qquad (2.15)$$

where v_i is the two-sided 'noise' component, and u_i is the non-negative technical inefficiency component, of the error term[9]. The stochastic frontier methods allow for random error, such that they are less likely to misidentify measurement error, transitory differences, or specification error as inefficiency. However, the primary challenge lies in determining how best to separate random error from inefficiency, since neither of them is observed. The different types of parametric methods (SFA, TFA, and DFA) differ in the distributional assumptions imposed to accomplish this disentanglement.

2.4.2.1 Stochastic Frontier Analysis

The SFA employs a composed error model in which the random errors are assumed to follow a symmetric distribution, usually standard normal, while the inefficiencies are assumed to follow an asymmetric distribution (either half-normal, exponential, truncated normal, or gamma) (Aigner et al., 1977; Broeck, 1977). A description of these distributions has been comprehensively covered in Kumbhakar and Lovell (2000).

An important question is whether the choice of distributional assumptions influences the outcome of the estimated efficiency parameters. Kumbharkar and Lovell (2000) observe that sample mean efficiencies are no doubt likely to be sensitive to the distribution assigned to the one-sided error component *v*. They point out that there is ample experiential evidence in support of existence of such sensitivity. What is not clear is whether a ranking of DMUs by their individual efficiency scores is sensitive to distributional assumptions. Green (1993) estimated a stochastic cost frontier for a cross section of 123 US utilities using all the four one-sided distributional assumptions. He reported sample mean efficiencies of 0.8766 (for half normal), 0.9011 (exponential), 0.8961 (truncated normal), and 0.8949 (gamma). Computations of rank correlation coefficients between pairs of efficiency estimates for all sample observation (later on by Kumbharka and Lovell (2000), but using the same data set) revealed that the lowest rank correlation coefficient was 0.7467 (between exponential and gamma). It was highest (0.9803) between half normal and truncated normal.

This evidence suggests that the choice between the two one-parameter densities is largely immaterial. In this regard, the property of the SFA, that ranking of DMUs by their individual efficiency scores is not sensitive to distributional assumptions taken, has intuitive appeal for measurement of performance of the AS&T policy system, and is likely to prove helpful in meeting the consistency conditions that are based on rank ordering.

2.4.2.2 Thick Frontier Approach

TFA uses the same functional form for the frontier as SFA, but is based on a regression estimated using only the ostensibly best performers in the data set – i.e., those in the highest production quartile. Parameter estimates from this estimation are then used to obtain estimates of best-practice production for all DMUs in the data set (Berger and Humphrey, 1991). DMUs in the highest average production quartile are assumed to have above-average efficiency and form a 'thick frontier'.

TFA assumes that deviations from predicted performance value within the highest and lowest performance quartiles of DMUs represent the random error, while deviations in predicted performance between the highest and lowest average-production quartiles represent the inefficiencies (a special case of error) plus exogenous differences in the regressors. Measured inefficiencies are thus embedded in the difference in predicted production between the lowest and highest production quartiles. This difference may occur in either the intercepts or in the slope of the parameters.

In most applications, TFA gives an estimate of efficiency differences between the best and worst quartile to indicate the general level of overall efficiency, but does not provide point estimates of efficiency for all individual DMUs. In this study, the objective is to obtain efficiency estimates for each DMU in each time period so that these can not only be compared to efficiency estimates derived from DEA but also in deciphering the determinants of performance of policy system. In this regard, application of TFA was found unsuitable.

Another shortcoming of the TFA is that it is based on average production quartiles such that the estimated production inefficiency would increase if arbitrary quintiles were used. This attribute would not only have made this study more complicated, but also put in

[9] It is because of the error term comprising of two components that the stochastic frontier model is often referred to as a 'composed' error model.

doubt any inferences made. In addition, TFA uses only half of the data (or 40% if quintiles are used), which would have led to problems of degrees of freedom due limited size of data available in this study (Kumbhakar and Lovell, 2000).

2.4.2.3 Distribution-Free Approach

DFA specifies a functional form for the production function as does SFA and TFA, but separates inefficiencies from random error in a different way. It does not impose a specific shape on the distribution of efficiency (as does SFA), nor does it impose that deviations within one group of DMUs are all random error and deviations between groups are all inefficiencies (as does TFA). Instead, DFA assumes that there is a 'core' efficiency or average efficiency for each DMU that is constant over time, while random error tends to average out (Schmidt and Sickles, 1984; Berger, 1993). Unlike the other approaches, a panel data set is required, and therefore only panel estimates of efficiency over the entire time interval are available. These estimates may be derived using three different techniques.

The first DFA technique, DFA-P WITHIN, is a fixed-effects model which estimates inefficiency from the value of a DMU-specific dummy variable (derived by estimating with all the production function variables measured as deviations from DMU-specific means). Efficiency is estimated using the deviation from the most efficient DMU's intercept term. A single set of parameters are obtained so inefficiency is fixed over time. However, since inefficiency is no longer a separately specified element in a composed error term, the assumption that inefficiency is uncorrelated with regressors (as in SFA) is not required.

The second DFA technique, DFA-P GLS, applies generalised least squares (GLS) to panel data, obtains a single set of parameters, assumes that DMU inefficiencies are fixed over time[10], and that inefficiency is uncorrelated with regressors. The third DFA technique, DFA-P TRUNCATED, estimates the production function separately for each year. The efficiency estimates are based on the average residuals for each DMU. Since some noise might also be persistent over time, the residuals may be truncated at a selected upper and lower percentage point (i.e., 1%) of the distribution, thus limiting the effects of extreme average residuals at both ends (Berger, 1993).

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[10] This assumption is not strictly necessary. Cornwell et al., (1990); Kumbhakar (1990), and Battese and Coelli (1992) generalized the approach to allow inefficiencies to vary over time, but in a structured manner.

The fact that DFA gives a ‘core’ or ‘average’ efficiency over time and it also assumes that production efficiency is time invariant (time invariant and variant models are discussed later in this review) made it unsuitable for use in this study. The time invariant requirement becomes less tenable as time increases.

2.4.2.4 Issues to consider in the choice of appropriate SFA model specification

The foregoing analysis has identified SFA as the most appropriate parametric approach for deriving AS&T policy system performance indicators for purposes of triangulating findings obtained from DEA. The subsequent section highlights the specific considerations that need to be taken into account in the selection of an appropriate SFA model specification. These include:

(i) whether the model will have time invariant or time variant technical efficiency;

(ii) whether the model will be estimated using random effects, fixed effects or by using the maximum likelihood estimation (MLE) approach; and,

(iii) the choice of the distribution of the technical inefficiency effects, i.e., whether they will be half-normal, exponential, truncated normal, or gamma.

The appropriateness to this study of either time variant or invariant measures of technical efficiency, and whether these should be estimated by random effects (RE), fixed effects (FE) or MLE are explained next.

(a) Time invariant stochastic frontier models

The original time invariant efficiency model can be presented as:

$$y_{it} = \alpha + \sum_{k} \beta_k x_{kit} + \varepsilon_{it} \ , \qquad (2.16)$$

where

$$\varepsilon_{it} = v_{it} - u_i \qquad (2.17)$$

$i = 1, 2, ..., N$

$t = 1, 2, ..., T$

$k = 1, 2, ..., K,$

where i indexes the DMUs, t indexes the time periods and k indexes the inputs. The endogenous variable y_{it} is output and the exogenous variables x_{kit} are K different inputs. The v_{it} random variables are assumed to be independent, uncorrelated with the regressors and often assumed to be normally distributed. Technical inefficiency is represented by u_i. The properties of u_i, other than being non-negative, are determined by the specific model that is selected: i.e., time invariant random effects model or time invariant fixed effects model.

In the random effects (RE) model, the u_i are assumed to be randomly distributed with a constant mean and variance. They are also assumed to be independent of both the random errors and the regressors. Being that inefficiency can only take non-negative values, the distribution of u_i is often assumed to be half-normal, truncated normal, gamma or exponential. Estimation of the RE model can be implemented using the standard two-step generalized least squares (GLS) method. However, such estimates are consistent as N and T tend towards infinity. It should be noted that GLS is most appropriate when N is large because consistent estimation of σ_u^2 requires N to go to infinity. Schmidt and Sickles (1984) have observed that when N is small, GLS is useless unless σ_u^2 is known a priori. This is not the case in this study as N=2, and T>35, where as σ_u^2 is unknown. This implied that the time invariant, RE model estimated using GLS was not suitable for this study.

In the fixed effects (FE) model, the model is similar to the RE model except now the u_i term is subtracted from the overall intercept. In this model, the u_i are again assumed to be non-negative, but no independence or distributional assumptions are made. The within estimator is obtained by applying the within transformation, in which each variable is expressed in terms of deviations from its mean.

One of the drawbacks of the FE model is that although the estimates of the β_n's are consistent as either N or T go to infinity, the estimates of the α_i's are only consistent as T tends towards infinity. This is often not the case in economic panel data sets, as envisaged in this study. In addition, even in the case that T does tend towards infinity; it makes little sense to assume that technical efficiency will remain time invariant. Further, not only does the FE model capture the variation across DMU's, but it also captures the effects of all phenomenon (regulatory environment, like changes in policy) that vary across DMU's, but are time invariant for each unit. This scenario is not envisaged in this study as the policy system has been changing from time to time.

Despite this shortcoming, there are advantages to utilising the FE model. Kumbhakar and Lovell (2000) show that besides its simplicity benefit, consistency does not depend on the distribution or independence of the variables. This could be potentially important since it seems quite possible that if a DMU knows its level of inefficiency, its input values may be affected by that knowledge. However, these advantages do not override the severe limitations posed by this modelling approach for application in this study.

It is important to point out that time invariant models can also be estimated through maximum likelihood estimation (MLE). The advantage of the RE and FE models is that they allow one to avoid strong distributional or independence assumptions. However, when these assumptions are reasonable within a particular panel, MLE is plausible (Kumbharkar, 1987; Battese and Coelli, 1988). It should be observed that MLE is generally more efficient than the FE and RE methods of estimation due to its exploitation of the distributional assumptions (Kumbhakar and Lovell, 2000).

(b) Time variant stochastic frontier model

Schmidt (1988) showed that time invariant technical efficiency though attractive, is a rather restrictive assumption. It seems quite doubtful to assume that technical efficiency would remain constant over an extended period of time, particularly when the environment is competitive. When the panels are short, it may make sense to assume time invariant technical efficiency. However, panels now have an increased time length leaving little reason to assume u_i to be time invariant. For this reason, it seems quite suitable to use the time variant models in this study. The next step illuminates on how the specification and estimation of the model should proceed.

Just like in time invariant models, time variant models can be estimated by FE, RE or MLE. However, the constraints identified in application of FE and RE under time invariant models still apply to time variant models, implying that the two approaches are not suitable for estimation of performance indicators in this study. This leaves the MLE as the only option, but still requires decision to be made on the distributional assumptions for the error terms. In this regard, it would be prudent to undertake statistical tests to determine the appropriate distributional assumptions for the error terms for the data being used.

(c) Constraints anticipated in application of time variant SFA model

The results of time variant SFA models estimated through MLE rely heavily on somewhat strict assumptions. These models assume that the variances of the error components are homoskedastic. Many times the errors are not homoskedastic and the variances change between observations. This problem of heteroskedasticity causes estimates to be inefficient, although unbiased and consistent. Heteroskedasticity can appear in either component (u or v) or in both, therefore affecting inferences dealing with technical efficiency.

Many difficulties arise when attempting to estimate the model under a heteroskedastic v_{it}. Under the usual assumptions of the error components, the ML approach may be impractical if either N or T are large. This is because there are N variance parameters and $T-1$ efficiency parameters to be estimated. Although possible, the ML approach is dominated by a method of moments (MM) estimator. Similarly, when u_i is heteroskedastic or when both v_{it} and u_i are heteroskedastic, the ML estimator is impractical and a method of moments (MM) estimator dominates. It is therefore important to test and correct for heteroskedasticity before application of MLE in time variant models.

The preceding review has identified the output-oriented DEA estimated under the CRS assumption as the suitable deterministic method of measuring technical efficiency as the performance indicator. In order to address the inherent deficiencies within indicators generated using this approach, a second set of performance indicators estimated using the time variant SFA would be suitable candidates for triangulation. The next step is to review approaches of linking the derived performance indicators to the potential structure of the AS&T policy system. These are discussed next.

2.5 Review of approaches for linking potential determinants of structure to performance indicators

It is apparent that literature in estimation of performance indicators is wealthy in both theoretical and empirical contributions. However, minimal attention, at least on the theoretical front, has been given to the natural second step: i.e. to model predicted performance indicators in terms of underlying factors. That is, which methods will be used to relate the selected performance indicators to the potential determinants of structure? Undoubtedly, there exists no well-grounded methodological framework to analyse the determinants of technical efficiency (and technical and efficiency change), possibly because of the difficulties involved.

Available literature provides two approaches that can be utilised to determine the relationship between performance (in this case technical efficiency) and the potential determinants of AS&T policy system structure (Bruton, 1995). The first approach, suggested by Ray (1988) and Kalirajan (1991) involves two-stage procedure to analyse the determinants of efficiency, in which the first stage involves estimation of a frontier production function and prediction of efficiency scores. As a second step, these scores are used as a dependent variable and regressed on a set of variables believed to determine efficiency. The shortcoming of this approach with respect to SFA is that efficiency scores are often regarded as independently distributed, in contradiction to it being modelled in a second step as a function of other variables (Battese and Coelli 1993). However, such an approach is empirically sound when DEA is used to estimate efficiency.

The second approach is applicable within the stochastic frontier approach and is designed to overcome the contradictions associated with the second step of modelling the determinants of technical efficiency. This is done through simultaneous estimation of two functions, i.e.: the stochastic frontier production function and the model of factors influencing efficiency (Battese and Coelli, 1993 and 1995, Reifscheider and Stevenson 1991, Huang and Liu 1994). However, this approach rests on a set of assumptions concerning the functional form of the production technology, and the distributions of the errors and efficiencies that are hard to explicitly test for. Furthermore, as it has been shown, stochastic frontier models are sensitive to heteroskedasticity (Caudill and Ford 1993). In addition to this, convergence to global maximums of the likelihood functions can also be hard to achieve. Given this scenario, it is prudent to employ an alternative methodology to examine the robustness of the stochastic frontier results.

The second step DEA approach is a natural candidate for such an alternative model. Compared to the simultaneous equation SFA, and due to its non-parametric nature, it avoids the risk of misspecification. However, it is deterministic, which implies that noise, should it exist, may feed directly into the efficiency estimates. In addition, two other concerns need to be addresses while applying the second-stage DEA approach. First inputs and determinants may be correlated and so cause biased and inconsistent estimates in either step. This is an apparent critique against a two-stage SFA, but whether the same argument applies to a two-step DEA is not as evident. One could perhaps argue that DEA-efficiency is a type of index and therefore remains unaffected by such correlation. Secondly, the distribution of efficiencies is restricted to the [0, 1]-interval with a mass point at one corresponding to the population of frontier DMUs. Thus, using efficiency as the dependent variable in a regression model may cause problems and needs careful consideration.

Available literature presents seven applications of the two-stage DEA model although none of them seriously addresses the first problem. However, evidence of attention being directed to the second is available and different regression models are proposed for the second-step analysis. These include:

i. the Ordinary Least Squares by Nyman and Bricker (1989), Ray (1991), Chirkos and Sears (1994), and Stanton (2002);
ii. the Tobit model by Bjurek, Kjulin and Gustafsson (1992), McCarthy and Yaisawarng (1993), Kooreman (1994), Chilingerian (1995), Zheng, Liu and Bigsten (1998), Rosenman and Friesner (2004);
iii. the logistic regression model by Ray (1988), Brännlund, Färe and Grosskopf (1996).
iv. Beta distribution Sengupta (1998); and,
v. Beta-Binomial distribution (Sohn and Choi, 2006)

Some of the important lessons from these studies that favour application of Tobit model include:

i. That the dependent variable is restricted to values between zero and one, and a considerable number of observations have zero value for the dependent variable, a Tobit model is therefore suitable for use for estimation (Bjurek, Kjulin and Gustafsson, 1992).
ii. Since efficiency scores computed from the DEA model are truncated from below at one, an OLS regression would produce biased and inconsistent estimates. Tobit model is appropriate when it is possible for the dependent variable to have values beyond the truncation point, yet those values are not observable. This is likely to be the case for the DEA efficiency scores. Given that the best observable DMUs receive scores of one, it can be argued that it is likely that some DMUs might perform better than the best DMUs. If these unobservable DMUs could be compared with a reference frontier constructed from the observable DMUs included in the sample, they would have efficiency scores less than one (McCarthy and Yaisawarng, 1993).
iii. Since by definition there is always a non-negligible proportion of observations reaching the maximum score of one, censored regression models can be employed. Based on this consideration, Nyman and Bricker (1989) applied a linear regression model to explain the score differences. However, it was later shown that OLS applied to a censored regression model yields estimates that are asymptotically biased toward zero (Kooreman, 1994).
iv. Due to a relatively large number of fully efficient DEA estimates, the distribution of efficiency is truncated from above at unity. Applying the OLS method would produce biased parameter estimates. One way to get around this problem is to employ a limited dependent-variable model; an example of which is a censored regression model. The

Tobit model gives the parameter estimates of the original normal distribution of technical efficiency while taking account of the censored distribution of the DEA efficiency scores. What is of interest under this scenario is the original normal distribution, because under this distribution the probability of being fully efficient will be the same as it is for its being extremely inefficient (Zheng, Liu and Bigsten, 1998).

Therefore, the choice of Tobit model is motivated by the idea that efficiency can be regarded as censored, implying that there exists a latent variable that can take values greater than one. Clearly, the existence of such a latent variable is inconsistent with the definition of the frontier. Nevertheless, from a purely statistical point of view, the Tobit model seems an appropriate stochastic specification for this particular purpose.

2.6 Conclusion

This review has established that empirical studies into the structure and performance of AS&T policy system has been constrained two factors. Firstly, there is lack of an understanding of what comprises this policy system, and secondly, there is absence of a suitable approach for its assessment.

This review has proposed a preliminary framework for evaluating the structure and performance of the policy system. The framework is called the 'systems components – shift effects' framework and comprises of a 3x4 matrix of potential determinants of the AS&T policy system structure. However, operationalisation of the framework requires fulfilling a set of key conditions. First, a suitable performance indicator needs to be identified. This review has presented an assessment of alternative approaches and selected those that are more appropriate. Second, there is need for a suitable approach to link the potential determinants of structure to the performance indicators. In this regard, available options have been evaluated and those deemed apposite for use recommended. With this review complete, it is important to turn to the empirical analysis.

CHAPTER 3: METHODOLOGY

This chapter starts with a brief description of the study countries. This is followed by a description of the empirical techniques used in deriving the policy system performance indicators. Subsequently, a presentation of the econometric models employed to delineate the influence of the potential determinants of AS&T policy system structure on the computed performance indicators is given. A full description of data used in the study is given in the final part of the chapter.

3.1 Countries of study

3.1.1 Kenya

Kenya has total area of 582,650 square kilometres that includes 13,400 square kilometres of water. Its economy is market-based, with some state-owned infrastructure enterprises, and maintains a liberalised external trade system. The economy's heavy dependence on rain-fed agriculture and tourism leaves it vulnerable to cycles of boom and bust. The agricultural sector employs nearly 75 percent of the country's 37 million people. Half of the sector's output remains subsistence production (Kenya, 2007).

In 2006 Kenya's GDP was about US$17.39 billion. Per capita GDP averaged about US$450. Adjusted in purchasing power parity (PPP) terms, per capita GDP in 2006 was about US$1,200. The country's real GDP growth picked up to 2.3 % in early 2004 and to nearly 6 percent in 2005 and 2006, compared with a sluggish 1.4 percent in 2003 and throughout 1997–2002. GDP composition by sector, according to 2004 estimates, was as follows: agriculture, 25.7%; manufacturing, 14.0%; trade, restaurants, and hotels, 13.8%; transport and communications, 6.9%; government services, 15.6%; and other, 24.0%. The agricultural sector continues to dominate Kenya's economy, although only 15% of Kenya's total land area has sufficient fertility and rainfall to be farmed, and only 7 or 8% can be classified as first-class agricultural land. In 2006 almost 75% of working Kenyans made their living on the land, compared with 80% in 1980 (Kenya, 2005).

The principal cash crops are tea, horticultural produce, and coffee. Horticultural produce and tea are the main growth sectors and the two most valuable of all of Kenya's exports. In 2005 horticulture accounted for 23% and tea for 22% of total export earnings. Coffee has declined in importance with depressed world prices, accounting for just 5% of export receipts in 2005. The production of major food staples such as maize is subject to sharp weather-related fluctuations. Production downturns periodically necessitate food aid (Kenya, 2007).

3.1.2 Uganda

Uganda has total land area of 241,040 square kilometres of which 18% is inland water and swamps, 12% national parks, forest, and game reserves; and 70% forest, woodland, grassland suitable for agricultural production. Uganda's economy has great potential, endowed with significant natural resources, including ample fertile land, regular rainfall, and mineral deposits. However, chronic political instability and erratic economic management produced a record of persistent economic decline that left it among the world's poorest and least-developed countries.

In the last 22 years, the government of Uganda has taken important steps toward economic development. Key policies implemented in the recent past include those aimed at restoring price stability and sustainable balance of payments, improvement of capacity utilisation, rehabilitation of infrastructure, restoration of producer incentives through proper price policies, and improvement of resource mobilisation and allocation in the public sector. At the moment, Uganda's macroeconomic policies are sound and have led to a 7% growth rate in fiscal year 2006-2007, compared to 5.1% in financial year 2005-2006 (Uganda, 2007).

Agricultural products supply nearly all of Uganda's foreign exchange earnings, with coffee (of which Uganda is Africa's second leading producer) accounting for about 19% and fish 15.5% of the country's exports in 2002. Exports of non-traditional products, including apparel, hides, skins, vanilla, vegetables, fruits, cut flowers, and fish are growing, while traditional exports such as cotton, tea, and tobacco continue to be mainstays (Uganda, 2007). The industrial base is also related to agriculture. The industrial sector has been rehabilitated to resume production of building and construction materials, such as cement, reinforcing rods, corrugated roofing sheets, and paint. Domestically produced consumer goods include plastics, soap, cork, beer, and soft drinks.

3.2. Deriving indicators of performance of agricultural science and technology policy system

Performance of AS&T policy system was tracked by measuring agricultural productivity that was computed as the level of technical efficiency, together with technical change and efficiency change.

3.2.1 The non-parametric approach

3.2.1.1 First step DEA

This entailed the estimation and decomposition of the Malmquist total factor productivity (TFP) index to obtain technical and efficiency change estimates based on the exposition of Färe et al (1989). Under this approach, S^t represents the production technology available at time period t =1,…….,T such that:

$$S^t = \{(x,y) : x \ \ can \ \ produce \ \ y \ \ at \ \ time \ \ t\} \tag{3.1}$$

where $x \in \Re^n_+$ is a vector of inputs used to produce vector of outputs $y \in \Re^m_+$.

Assuming that set S^t satisfies standard properties[11] as outlined in Shephard (1970), and following his arguments, the output distance function[12] D_o at time t is defined as:

$$\begin{aligned} D^t_o(x^t, y^t) &= \inf\{\theta : (x^t, y^t / \theta) \in S^t\} \\ &= (\sup\{\theta : (x^t, \theta y^t) \in S^t\})^{-1} \end{aligned} \tag{3.2}$$

This is essentially the inverse of the maximum proportional expansion of output vector y given input vector x under specified technology S^t. This function completely characterises the technology at time t (Fare et al., 1994). Specifically, $D^t_o(x^t, y^t)$ is less or equal to 1 if and only if (x^t, y^t) ∈ S^t. $D^t_o(x^t, y^t) = 1$ indicates that the net-put vector (x^t, y^t) lies on the technology frontier, and if $D^t_o(x^t, y^t) < 1$, then the unit is technically inefficient and lies

[11] These properties include: (1) Inaction is possible, i.e., given any input vector, it is always possible to produce no output; (2) There is a weak disposability of outputs; (3) Finite amounts of inputs can produce finite amounts of outputs; and (4) For all inputs, output sets are closed sets.

[12] It is important at this point to mention that the **Output Distance Function** is a reciprocal of the Farrel output-based measure of technical efficiency (Färe et al., 1989).

within the technology frontier. This implies that the proportional expansion of outputs is possible for this production unit given its input values.

Similarly, an output distance function D_o at time $t+1$ is defined as:

$$\begin{aligned} D_o^{t+1}(x^{t+1}, y^{t+1}) &= \inf\{\theta : (x^{t+1}, y^{t+1}/\theta) \in S^{t+1}\} \\ &= (\sup\{\theta : (x^{t+1}, \theta y^{t+1}) \in S^{t+1}\})^{-1} \end{aligned} . \tag{3.3}$$

The definition of the Malmquist TFP index requires deriving distance functions with respect to two different time periods, i.e.:

$$D_o^t(x^{t+1}, y^{t+1}) = \inf\{\theta : (x^{t+1}, y^{t+1}/\theta) \in S^t\} . \tag{3.4}$$

and

$$D_o^{t+1}(x^t, y^t) = \inf\{\theta : (x^t, y^t/\theta) \in S^{t+1}\} . \tag{3.5}$$

In the first mixed-period distance function, the input-output vector (x^{t+1}, y^{t+1}) belongs to the period $t+1$, while the technology S^t is from period t. Therefore, the function measures the maximum proportional change in outputs given the set of inputs relative to technology existing at the previous period t. Similarly, the second distance function measures the maximum proportional change in outputs given the set of inputs relative to the technology at time period $t+1$.

According to Caves et al (1982), an output-based Malmquist productivity index (MI) with reference to the technology in time t is presented as:

$$MI_o^t = \frac{D_o^t(x^{t+1}, y^{t+1})}{D_o^t(x^t, y^t)} \tag{3.6}$$

and subsequently, the output-based index with reference to the technology in time period $t+1$ is:

$$MI_o^{t+1} = \frac{D_o^{t+1}(x^{t+1}, y^{t+1})}{D_o^{t+1}(x^t, y^t)} \tag{3.7}$$

Färe et al. (1989) defined the output-based Malmquist productivity index as the geometric mean of the two indexes specified above as:

$$MI_o(x^{t+1}, y^{t+1}, x^t, y^t) = \left[\left(\frac{D_o^t(x^{t+1}, y^{t+1})}{D_o^t(x^t, y^t)}\right)\left(\frac{D_o^{t+1}(x^{t+1}, y^{t+1})}{D_o^{t+1}(x^t, y^t)}\right)\right]^{1/2}. \tag{3.8}$$

This avoids making arbitrary choice of selecting either one of the analysed time periods as the reference point. This index can be decomposed into two components, i.e.:

$$MI_o\left(x^{t+1}, y^{t+1}, x^t, y^t\right) = \frac{D_o^{t+1}(x^{t+1}, y^{t+1})}{D_o^t(x^t, y^t)}\left[\left(\frac{D_o^t(x^{t+1}, y^{t+1})}{D_o^{t+1}(x^{t+1}, y^{t+1})}\right)\left(\frac{D_o^t(x^t, y^t)}{D_o^{t+1}(x^t, y^t)}\right)\right]^{1/2}. \tag{3.9}$$

The first component (outside parenthesis) measures efficiency change, that is, how the position of the DMU has changed relative to the frontier between time *t* and *t+1*. The second component (within parenthesis) represents technical change, that is, how the frontier has shifted between time *t* and *t+1*.

Noting that the output distance function is the reciprocal of the Farrel output-based measure of technical efficiency, the output distance function is computed for each DMU (i.e., represented by k_i) at time *t* (i.e., for every year) under the assumption of constant return to scale (CRS), given the production possibility set S^t, as a solution to the following linear programming problems:

$$\begin{aligned} &(D_o^t(x^{k_i,t}, y^{k_i,t}))^{-1} = Maximise\,\theta^{k_i} \\ &Subject\ to: \theta^{k_i} y_m^{k_i,t} \le \sum_{k=1}^{K} \lambda^{k,t} y_m^{k,t} \\ &\qquad \sum_{k=1}^{K} \lambda^{k,t} x_n^{k,t} \le x_n^{k_i,t} \\ &\qquad \lambda^{k,t} \ge 0. \end{aligned} \tag{3.10}$$

where θ^{k_i} is the DEA measurement of $D_o^t(x^t, y^t)$. The computation of $D_o^{t+1}(x^{t+1}, y^{t+1})$ under the assumption of CRS follows the same procedure with the only difference being the substitution of *t* with *t+1*[13]. DMU *k* is construed to be technically efficient in a given time period only if its output distance function is equal to 1 in that period. The technically efficient DMUs define the production frontier in each of the time periods *t*, while those that were technically inefficient lie below the frontier.

The mixed-period distance functions, which are used in deriving technical change, are computed as follows. The output distance function for DMU *k* at time *t+1* under the assumption of CRS, given the production possibility set S^t, is computed as a solution of the following linear programming problem:

$$
\begin{aligned}
&(D_o^t(x^{k_i,t+1}, y^{k_i,t+1}))^{-1} = Maximise\,\theta^{k_i} \\
&Subject\ to: \theta^{k_i} y_m^{k_i,t+1} \le \sum_{k=1}^{K} \lambda^{k,t} y_m^{k,t} \\
&\qquad\qquad \sum_{k=1}^{K} \lambda^{k,t} x_n^{k,t} \le x_n^{k_i,t+1} \\
&\qquad\qquad \lambda^{k,t+1} \ge 0.
\end{aligned}
\tag{3.11}
$$

As noted earlier, since (x^{t+1}, y^{t+1}) may not be included in S^t, the output distance function $D_o^t(x^{t+1}, y^{t+1})$ may achieve values greater than one. $D_o^t(x^{t+1}, y^{t+1})$ will exceed unity when (x^{t+1}, y^{t+1}) is not feasible given the production possibility set S^t. Finally, the output distance function $D_o^{t+1}(x^t, y^t)$ is obtained by solving problem (3.11) with interchanged time periods *t* and *t+1*.

By using these equations measures for technical efficiency (*TE*), technical change (*TC*) and efficiency change (*EC*) were computed, for each country for each year. Interpretation of technical and efficiency change indexes was that technical/efficiency progress (regress) had occurred if *TC* and *EC* were greater (less) than one. The indicators were derived using DEAP Version 2.1 (Coelli, 1996). Twenty-one countries[14] from sub-Saharan Africa were purposively selected and used as peers in DEA application so as to avoid dimensionality problem[15].

3.2.1.2 Delineating the determinants of AS&T policy system structure - Second step DEA

The important determinants of structure of AS&T policy system were delineated through a second step limited dependent variable regression on the efficiency scores. Potential determinants of system structure exogenous to the production process and assumed to be the sources of the different efficiency levels were used as independent variables.

Although several estimation procedures have been suggested for this step (see literature review), the censored Tobit regression analysis was used. The DEA technical efficiency scores were conceptualised as presenting a censored normal distribution, i.e., the values of the dependent variable in the regression model above a threshold are measured by a concentration of observations at a single value. The equation (right-censored at unity) for the Tobit model was, (Tobin, 1958):

$$\begin{aligned} &Z_{k'}^{*} = \beta' X_{k'} + \varepsilon_{k'} \\ &\textit{where} \qquad Z_{k'} = 1, \quad \textit{if} \quad Z_{k'}^{*} \geq 1, \\ &\textit{or} \qquad Z_{k'} = Z_{k'}^{*}, \quad \textit{if} \quad Z_{k'}^{*} < 1. \end{aligned} \tag{3.12}$$

where β was a vector of estimated parameters, $Z_{k'}^{*}$ was the limited dependent variable (i.e., technical efficiency score), $X_{k'}$ was a vector of independent variables (i.e. potential determinants of AS&T policy system structure), and $\varepsilon_{k'}$ was assumed to be a normal, *i.i.d.* error term. Separate models were estimated for Kenya and Uganda.

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[13] This equation becomes

$$\begin{aligned} &(D_o^{t+1}(x^{k_i,t+1}, y^{k_i,t}))^{-1} = Maximise\,\theta^{k_i} \\ &Subject\ to: \theta^{k_i} y_m^{k_i,t+1} \leq \sum_{k=1}^{K} \lambda^{k+1,t+1} y_m^{k+1,t+1} \\ &\sum_{k=1}^{K} \lambda^{k+1,t+1} x_n^{k+1,t+1} \leq x_n^{k_i,t+1} \\ &\lambda^{k,t+1} \geq 0. \end{aligned}$$

[14] They include Angola, Botswana, Burundi, Cameroon, Central Africa Republic, Congo Brazzaville, DR-Congo, Gabon, Kenya, Malawi, Mauritius, Mozambique, Namibia, Nigeria, Rwanda, South Africa, Swaziland, Tanzania, Uganda, Zambia and Zimbabwe.

[15] Based on the arguments of Leibenstein and Maital (1992)

3.2.2 The parametric approach

3.2.2.1 Key reasons in application of the SFA

DEA has at least two key shortcomings that required application of other methods to triangulate DEA results. First, DEA estimates may over-predict efficiency in limited samples because the randomly collected samples may not contain sufficient truly efficient production units to accurately characterise the efficient production frontier. Therefore, the frontier calculated by DEA may be above (or below) the true efficient production frontier, because the most efficient production units in the sample, against which the estimated frontier is computed, may not lie on the true frontier. Several remedies to the small sample mis-measurement problem have been suggested. One remedy proposed in literature is to use DEA only in cases where the sample size is satisfactorily large, especially relative to the number of inputs and outputs included in the analysis. However, what constitutes a large sample is still controversial. In this study, 21 peer countries were used in derivation of DEA estimates to circumvent this constraint.

Secondly, and probably the most significant limitation of DEA, is that its statistical basis is complex (Schmidt 1985). Unfortunately, the two stage approach forces the researcher to make additional assumptions that may lead to detrimental statistical consequences. One possibility is to assume that DEA efficiency estimates follow a particular distribution, which allows the researcher to employ standard maximum likelihood regression techniques (censored Tobit model is used in this study). A shortcoming to this methodology is specification bias, that is, if one assumes an incorrect distribution, which is a likely probability in this complex statistical context, any coefficient estimates generated by this approach will be generally biased and inconsistent. Moreover, as Simar and Wilson (2007) note, because the efficient frontier is calculated relative to the production units in the data, DEA scores are serially correlated in an unknown and complicated manner. Thus, even if the distributional choice is correct, any coefficient estimates may be substantially inefficient unless the distributional choice accounts explicitly for this correlation.

Some studies (e.g., Simar and Wilson, 2007) have suggested the use of semi-parametric regression techniques as an alternative to the estimation of the second stage model. Such an approach would entail supplementing an MLE-based regression with a specific form of bootstrapping aimed at adjusting for any potential mis-measurement and serial correlation. However, even with this approach, one must still identify an appropriate distribution for the likelihood function, which still allows for the possibility of specification bias. Moreover, it has been observed that even with a census of all production units, the problem of mis-measurement is not curtailed implying that bootstrap methods cannot solve these problems completely.

One of the approaches that has been widely applied in literature to cross-check findings from second-stage DEA estimations is the stochastic frontier approach (SFA) as suggested by Battese and Coelli (1995). Given the advantages and disadvantages of both DEA and SFA methods, it may be helpful to use and compare them on the same data set. Therefore, this study applied the SFA approach as a basis of providing further evidence about the structure of the AS&T policy system in Kenya and Uganda, and evaluated the findings against those obtained from DEA.

3.2.2.2 Foundation for the theoretical model

The stochastic frontier model used in this study was of the form suggested by Battese and Coelli (1995) where two functions are estimated simultaneously. The first function is the production function (analogous to the first step DEA) that uses output-input data to estimate productivity coefficients for each input and also derives the technical efficiency estimates. The second function models the determinants of technical inefficiency using a set of environmental variables. This is analogous to the second stage DEA model. Regarding the distribution of the error term, u_{it}, there was no a priori justification for its distribution to enable making a definite choice at this stage. The suitable distributional form was statistically tested.

3.2.2.3 The empirical model

In the empirical estimation, the stochastic frontier production function was conceptualised as a general translog functional form incorporating the possibility of non-neutral technical change[16]:

[16] The utilization of fairly long panel data in this study necessitated the inclusion of technical change since it is less likely that technology would remain constant. One approach in which this is done is by inclusion of time among the regressors as a proxy for technical change, and doing so causes no unusual problems in the estimation process (Kumbhakar and Lovell, 2000).

$$\ln y_{it} = \alpha + \sum_k \beta_k \ln x_{kit} + 0.5\sum_k\sum_j \beta_{kj} \ln x_{kit} \ln x_{jit} + \sum_k \xi_k \ln x_{kit} t + \zeta_t t + \zeta_{tt} t^2 + u_{it} + v_{it} \quad (3.13)$$

where y_{it} represented output for country i in year t; x_{kit} represented the k-th input of country i in year t; t reflected the time technical change; α, β_k, β_{kj}, ξ_k, ζ_t, and ζ_{tt} were parameters to be estimated; u_{it} was the time variant technical efficiency; and, v_{it} was statistical noise.

This form of stochastic frontier was adopted with the knowledge that a number of other functional forms were nested within it. Specifically, by restricting $\xi_k = 0$, the model reduced to a translog frontier production function with neutral technical change. By setting $\beta_{kj} = 0$, the model condensed to a Cobb-Douglas frontier production function[17]. These specifications were tested formally in this study.

The rate of technical change is defined from Equation (3.13) as the percentage change in output due to a unit change in time, that is,

$$TC_{it} = \partial(\ln y_{it}) / \partial t = \zeta_t + \zeta_{tt} t + \sum_j^J \xi_{jt} x_{jit} \quad (3.14)$$

Neutral technical change is given by the first two terms of Equation (3.14) and non-neutral technical change is given by the third term (Hesmati, 1996; Nishimizu and Page, 1982). If ζ_t is positive/negative then there is technical progress/regress over the period. The sign on ζ_{tt} determines whether or not technical change is taking place at an increasing or decreasing rate. Technical change is said to be input-using in the j^{th} input if the sign on ξ_{jt} is greater than zero and input-saving in the j^{th} input if ξ_{jt} is less than zero.

The v_{it}s in Equation (3.13) were assumed to be independent and identically distributed normal random variables with mean zero and variance, σ_v^2; and, the u_{it}s were at the onset taken as non-negative random variables, which were assumed to be independently distributed, such that u_{it} was truncated (at zero) of the normal distribution with mean, μ_{it}, and variance σ^2, and μ_{it} was defined by:

$$\mu_{it} = \delta_0 + \delta_1 t + Z_{it}\delta_{it} \quad (3.15)$$

[17] Though not useful in this estimation, it can also be observed that by restricting $u_{it} = u_i$ for all t, the efficiency effects are time invariant.

where Z was a vector of specific variables defining the potential determinants of AS&T policy system structure, t was time and δ were the unknown parameters to be estimated. The appropriateness of the choice of the u_{it} as being truncated normal was statistically tested. By including a time trend in Equation (4.14) it was possible to capture the linear change in technical efficiency over time (Karagiannis et al., 1999; Battese and Coelli, 1995). (The likelihood function of the Battese and Coelli (1995) is given in Battese and Coelli (1993)).

In a bid to increase the precision in estimates, it was necessary to have sufficient degrees of freedom, which was attained by estimating a pooled model for Kenya and Uganda (unlike the second stage DEA where separate models were estimated, one for each country). Prior to this, a Chow test was done to determine whether the full set of regression parameters (the intercepts and slopes taken together) differed across the two countries (Chow, 1960). Two Chow tests were done, first for the main production model and second for the technical inefficiency effects model. The Chow test was important for two reasons. In the event that the quality of inputs is controlled for, a non-significant Chow test would imply that the linear regressions for factors of production did not vary between Kenya and Uganda. This would imply that Hypothesis 2 of this study is rejected). The same would apply for the technical inefficiency model (that is, the linear regression for potential determinants of AS&T policy system structure varies between Kenya and Uganda).[18]

In addition to the pooled SFA model, a pooled second stage DEA censored Tobit model (for Kenya and Uganda combined dataset) was also estimated for purposes of comparing with the pooled SFA model.

3.2.3 Performance of the AS&T policy system

Whereas the parametric SFA and the second stage DEA were used to delineate the structure of the AS&T policy system (with technical efficiency estimates as the dependent variable), performance of the policy systems was analysed using technical and efficiency change. Technical change encompassed the extent to which the production frontier, representing the state of technology in a particular time period, shifted upwards over time, reflecting application of new innovations and technologies. Therefore performance of the

[18] In the event that it is difficult to sufficiently control for the inherent quality differences between inputs, then care should be taken with regard to interpretation of the Chow test results. Validity of Hypothesis 2 would then be deduced from the effects of individual variables (i.e., the potential determinants of the policy system structure). Fulginiti and Perrin (1998) have noted that non-correction for quality does not necessarily render the outcome from such data invalid for policy inference.

AS&T policy system was measured by the extent to which it facilitated uptake of new technologies (shifts in frontier) and also by how much it contributed to rate of improvement in efficient use of inputs. As stated earlier, AS&T policy is assumed to contribute to these gains by increasing access to innovations through research and transboundary acquisition; and secondly, by creating an environment that foster learning by firms/farms in application of these innovations.

A logistic regression was used to capture the relationship between the direction of technical and efficiency change and the specific innovations within the agricultural science and technology policy system in Kenya and Uganda. The regression model was of the general form:

$$p^*_{it} = z'_{it}\beta + y'_{it}\alpha + e_{it} \quad i = 1,........, N.;\ and\ t = 1,........, T. \tag{3.16}$$

where p^* was the change in productivity index (either progress for p>1; or regress for p<1), z'_{it} represented a (1 × J) vector of explanatory agricultural science and technology policy systems' institutional variables posited to induce productivity change in the agricultural sector; y'_{it} was a (1 × k) vector of explanatory government programs that support functioning of AS&T institutions; β and α were vectors of parameters to be estimated, and $e_{it} \approx N(0,\sigma^2)$. A similar approach has been utilized by Worthington (2000) in evaluating efficiency and technical change determinants in Australian building societies.

3.2.4 Data

3.2.4.1 Input-output data

Technical efficiency was derived using FAOSTAT production data for the years 1969 to 2002 (FAO, 2006). The dependent variable was net production at 1999-2001 international dollar prices (combined for crops and livestock) derived using a Geary-Khamis formula as an agricultural production index[19] (PIN) (Rao and Coelli, 2004). This index represented the relative level of production for each year in comparison the base period 1999-2001. It was based on the sum of price-weighted quantities of different agricultural commodities produced after deductions of quantities used as seed and feed weighted in a similar manner. The resulting aggregate represented, therefore, disposable production for any use except as seed and feed. Production quantities of each commodity was weighted by 1999-2001 average international commodity prices and summed for each year. To obtain the index, the aggregate for a given year was divided by the average for the base period 1999-2001.

Inputs (the independent variables) were agricultural land, agricultural labour, capital, fertilizer and livestock. Agricultural land referred to the share of land area that is arable, under permanent crops, and under permanent pastures. Arable land included land under temporary crops (with double-cropped areas counted once), temporary land for pasture, land under market or kitchen gardens, and land temporarily fallow. Land abandoned as a result of shifting cultivation was excluded. Land under permanent crops referred to land cultivated with crops that occupy the land for long periods and need not be replanted after each harvest, such as cocoa, coffee, and rubber. This category includes land under flowering shrubs, fruit trees, nut trees, and vines, but excluded land under trees grown for wood or timber. Permanent pasture referred to land used for five or more years for forage, including natural and cultivated crops.

Labour entailed the number of people economically active in agriculture, forestry, hunting or fishing and also included those people actively searching for employment in agriculture, forestry, hunting or fishing. Although this variable by including people actively searching for employment in agriculture, forestry and fishing is a second best proxy for labour input in agriculture, according to Rao et al (2004) it is appropriate because what is being measured is the agricultural sector productivity of the study countries that are typically characterised by people seeking seasonal employment. Fertiliser comprised the total consumption in nutrient equivalent terms of nitrogen (N), potash (K_2O) and phosphates (P_2O_5) consumed by a country and expressed in tones. These nutrient equivalents were derived by a method suggested by Hayami and Ruttan (1970) and Fulgitini and Perrin (1997). Livestock comprised the aggregate total livestock units (TLU) that were derived as a weighted sum of different livestock species including camels, cattle, pigs sheep, and goats using the weights suggested by ILCA (1990) (1TLU=250kg camel=2, cattle=0.7, pig=0.2, shoat=0.1). Capital was a simple aggregate number of tractors in use at national level with no quality adjustment.

[19] More information regarding derivation of this index is available at http://faostat.fao.org/site/612/default.aspx#ancor

3.2.4.2 Agricultural S&T policy system structure indicators

This followed the framework given in Table 3. They included:

(i) Agricultural research capital (AG_RE_CAP) – This was computed as a ratio of the lagged total agricultural research expenditure to full time researcher equivalent. The science of constructing research capital from public expenditures remains in its infancy (Griliches, 1998). Many researchers have included many lags of agricultural research expenditures without much structure. For example, Rosegrant and Evenson, (1995) computed the research capital as a weighted distributed lag of research expenditures in currency units with a lag period of 27 reflecting accumulation in its timing weights. Furthermore, Griliches (1998) argued that research outputs most likely will have a short gestation period, then blossom, and eventually become obsolete. Huffman and Evenson (2004) employed a similar argument in their study on influence of funding source on agricultural productivity in US states. The gestation period was approximated at 2 years during which the impacts were negligible, then assumed to be positive over the next 7 years represented by increasing weights, followed by 6 years of maturity, during which weights were high and constant. This was followed by 20 years with declining weights where they eventually fade out to zero. This weighting pattern is known as 'trapezoid-shaped time weights'. A modified version was used in this study to translate the real agricultural research expenditures into real agricultural research capital. The country's stock of research was created by summing public research expenditure in agriculture by applying a weight of 0.50 to the current year and then 0.25, 0.125, 0.0625, and 0.031 for the following four years. A similar approach has been applied in lagging public extension capital in studying impact of funding composition in the US agriculture (Huffman and Evenson, 2004). To standardise the obtained value for all the study countries, this value was divided by the full time equivalent (FTE) for researchers in public research, higher education research, private and non-governmental oriented agricultural research, to obtain the research capital per FTE. Data on expenditures on research were obtained from ASTI (2006) and also from government expenditure estimate records and statistical abstracts of study countries (various). Expenditures included salaries, operating costs, and capital from all sources (government, donors, private, civil society) reported in *constant 1993 US dollars*. It covered key sectors including crops, livestock, forestry, fisheries, natural resources, use of agricultural inputs as well as the socioeconomic aspects of primary agricultural production. Also included was research concerning the on-farm storage and processing of agricultural products, commonly referred to as post-harvest or food-processing research. Excluded were data on research activities in support of agro-chemical, agricultural machinery, or food processing industries as well as the more basic and discipline-oriented research activities undertaken by departments such as microbiology and zoology at universities.

(ii) Human capital stock (HUM_CAP) - This variable was derived from expenditures on education by applying a lagging approach similar to research capital and then dividing by total enrolment in primary, secondary and higher education to obtain the human capital stock per student. Expenditures included salaries, operating costs, and capital from all sources (government and donors) for primary and secondary education, and agricultural related tertiary education. They were reported in *constant 1993 US dollars*. This data was derived from the World Bank online database (World Bank, 2006), individual country expenditure estimates and statistical abstracts. Primary education was taken to encompass the form of education that provides children with basic reading, writing, and mathematics skills along with an elementary understanding of such subjects as history, geography, natural science, social science, art, and music. Secondary education was taken as that aiding the completion of the provision of basic education that began at the primary level and aimed at laying the foundations for lifelong learning and human development by offering more subject- or skill-oriented instruction using more specialized teachers. Tertiary education entailed that leading to an advanced qualification (certificate, diploma or degree in agricultural fields). Data on total school and collages enrolment was obtained from the Ministry of Education offices in Kampala and Nairobi.

(iii) Degree of economic openness (ECO_OPEN). This was computed as the ratio of imports of goods and services plus export of goods and services to GDP. This ratio indicated the level at which the economy is 'open' to allow the flow of transboundary technologies (Rao et al., 2004). Imports of goods and services entailed the value of all goods and other market services received from the rest of the world, including the value of merchandise, freight, insurance, transport, travel, royalties, license fees, and other services. Labour and property income and transfer payments were excluded. Exports of goods and services were the value of all goods and other market services provided to the rest of the world, including the value of merchandise, freight, insurance, transport, travel, royalties, license fees, and other services. Compensation of employees and investment income (formerly called factor services) were excluded, as were transfer payments. GDP included the gross domestic product at purchaser prices. It included the sum of the gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. It was calculated without deductions for depreciation of fabricated assets or for depletion and degradation of natural resources. Data used in deriving this variable was obtained from the World Bank database (World Bank, 2006).

(iv) Annual scientific journal articles published (JOURNAL). This variable was taken as a proxy representing output from domestic research. It entailed the total number of scientific publications in all fields, with the assumption that this was a reflection the level of research output in agriculture. This was based on the realisation that agricultural studies dominate most publications in the study countries (Kenya, 2002; Uganda 2004). Data on journal publication was obtained from the World Bank (2006) database, the Kenya National Bibliography (Kenya, 2002) and the National Bibliography of Uganda (Uganda, 2004). These were supplemented by primary data collection on publications from Kenya Agricultural Research Institute (Nairobi), National Agricultural Research Organization (Kampala), Makerere University (Kampala), University of Nairobi (Kabete), Egerton University (Njoro), Jomo Kenya University of Agriculture and Technology (Nairobi), and Kenya Forestry Research Institute (Nairobi). It had been envisaged that the actual technologies developed would be a suitable indicator. However, application of this variable was constrained by: (a) absence of a complete catalogue of technologies developed in Uganda in plant and animal health and production, soil science and biotechnology; (b) lack of the corresponding years of inception for each of the identified technologies in Kenya.

(v) Literacy level (LITERACY)**.** The population over 15 years was used the micro-level indicator of investments in education. Adult literacy encompassed the ability to read and write a short, simple statement about their everyday life. The significance of the literacy level will depend on whether the technologies in use are complex and knowledge intensive. Literacy level data was obtained from the World Bank (2006) online database, supplemented by review of records from the Uganda Bureau of Statistics in Kampala and the Kenya Bureau of Statistics in Nairobi.

(vi) Road density (ROAD). This was measured as total length of paved road per square km of agricultural land and acted as a proxy for the transaction costs that may be incurred in obtaining technologies at farm level. Paved roads include roads surfaced with crushed stone (macadam) and hydrocarbon binder or bituminized agents, with concrete, or with cobblestones, as a percentage of all the country's roads, measured in length. Data on length of paved road was obtained from the records available at the Uganda Bureau of Statistics in Kampala, perusal of records at the Ministry of Works in Entebbe Uganda, records at the Kenya Bureau of Statistics in Nairobi, and also from the World Bank (2006) online database.

(viii) Telephone connection per 1000 economically active population (TELEPHONE). This comprised total fixed telephone and mobile lines per 1000 people of the population and was used as a proxy for transaction costs in accessing agricultural information. Household with access to telephone services have been shown to be more likely to access extension services than those without (Mugunieri and Omiti, 2007). Population was the estimate of all residents regardless of legal status or citizenship, except for refugees not permanently settled in the country of asylum. Data on telephone connections (mobile and land-line) was obtained from the Statistical abstracts (various) and the World Bank (2006) online database.

(ix) Policy regulatory systems: Four policy regulatory systems were identified as being relevant and therefore included in the model: (i) Agricultural Research Regulatory System (REG_AG_RES***)*** that was represented by the presence of legislation that consolidated research under the National Science and Technology Act; (ii) Agricultural Extension Delivery System (REG_AG_EXT) representing the switch from centralized to decentralized extension services; (iii) Intellectual Property Rights Regulatory System (patent protection) (REG_PAT) representing the presence of legislation that conferred intellectual property rights within the economy; and , (iv) Transboundary Trade Regulatory System (REG_ECO_OPEN) that was represented by economic liberalisation and level of restrictions placed on foreign exchange transactions and foreign trade. These were represented as dummy variables denoting changes in the relevant legislation (policies) as stated in the statute books or policy documents. Policies that enhanced access to education (universal education) were not included as they were implemented in 1997 in Uganda and 2002 in Kenya. Details regarding these policy regulatory systems are discussed later in this study.

3.2.4.3 Determinants outside agricultural S&T policy system

(i) Irrigation investment (IRRIGATE). Was computed as the ratio of net irrigated area to net-cropped area and captured the influence of irrigation on productivity above and beyond its value as an input, that is, its role in increasing the impact of AS&T policy system (Rosegrant and Evenson, 1995). Data used was obtained from FAO (Faostat, 2006).

(ii) Life expectancy (LIFE). The number of years a newborn infant would live if prevailing patterns of mortality at the time of its birth were to stay the same throughout its life was included as an indicator of the quality of the agricultural labour, as suggested by Fulginiti and Perrin (1998). Labour quality was envisaged to play a critical role in the proper functioning of the AS&R policy system. Data was obtained from the Uganda Bureau of Statistics, the Kenya Bureau of Statistics, and the World Bank online database (World Bank, 2006).

(iii) Rainfall (RAIN) – Rain is an important factor in determining the level of agricultural production realizable in a country in a given season. Rainfall data was obtained from the IFPRI database, where a single rainfall entry was derived to represent rainfall-level for the whole country.

CHAPTER 4: RESULTS AND DISCUSSION

4.1 Developing a framework to analyse the structure and performance of agricultural science and technology policy systems in Kenya and Uganda

4.1.1 Summary of data used

Two sets of data were used; (i) input-output data for estimation of performance indicators, and (ii) data on the potential determinants of AS&T policy system structure to delineate the important components of structure.

4.1.1.1 The input-output data

Table 5 gives a summary of the input-output variables in Kenya and Uganda. Except for labour, all other inputs were significantly higher in Kenya than Uganda (F-test, P< 000). On the other hand, output was higher in Uganda (though not significantly different). The trend in output is shown in Figure 5. It was markedly higher in Uganda than Kenya until around 1980, when it dropped to almost similar levels like Kenya, but recovered to show a sturdy and uninterrupted increase thereafter.

Table 5: Input and output levels in Kenya and Uganda (1970-2002)

Variable	Kenya	Uganda
Inputs (Means)		
Fertilizers (NPK-nutrient tones)	90,471.71 (6,457.80)	2,561.71 (478.35)
Labour (000' people)	8,025.24 (424.57)	6,686.76 (273.98)
Land (000' Ha)	25,787.65 (69.73)	11,329.15 (145.03)
Livestock (000' TLU)	105,006.62 (2,967.30)	45,667.26 (1,106.64)
Capital (Tractor numbers)	8913.9 (2390.82)	3441.70 (1281.79)
Output (Mean)		
Agricultural PIN (1999 international dollars)	69.61 (21.25)	75.4 (13.68)

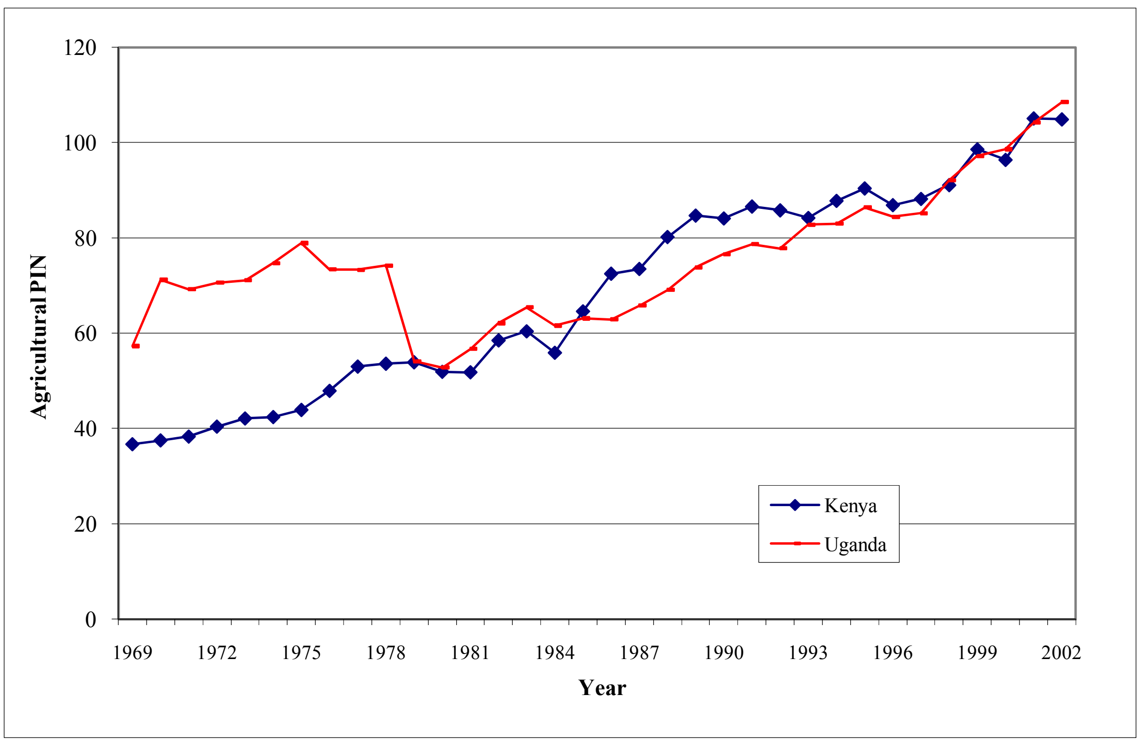
Values in parentheses are standard deviations of means.

Source: Own computations based on FAO data (2006).

A look at input use showed a lower fertiliser and capital to land ratios for Uganda, while that of labour to land was higher. With these combinations of inputs, both countries realised comparatively similar levels of output, perhaps a pointer towards the importance of labour and land as production drivers in the two east African countries.

The apparent low returns realised from fertiliser, and perhaps other capital inputs may be due to their minimal use. For example, since the decade of the 1980s to around 1996-2000, fertilizer use in Sub-Saharan Africa (excluding South Africa) has risen by only 17%, from 1.09 million tons in the 1980-89 period to 1.26 million tons. Over the same period, fertilizer use intensity, defined as kilograms of fertilizer consumed per hectare of cultivated land, rose by only 5% (Ariga et al., 2006). In a broader context, the reasons for the low application rates are often attributed to a political-economic environment that is not conducive to private investment and competition, under-provision of public investments on improved fertilizer-responsive technologies, limited supportive extension services, transport infrastructure that could reduce farmers' costs to improve profitability of using fertilizer, and financial constraints on the purchase of fertilizer where much of the population earn less than a dollar per day per capita (Crawford et al. 2006).

Figure 3: Trends in Agricultural PIN in Kenya and Uganda between 1969 and 2002



Source: FAO (2005)

The first stage DEA model and the first equation of the simultaneous SFA model used the data described above. Besides, the following variables were also included in the SFA model:

(i) time trend that was used to capture the neutral technical change;

(ii) for the Non-Hicksian technological change (i.e. biased technical change), both livestock and labour were envisaged as suitable entries in order to investigate the effect of genetic progress in livestock and the progressive improvement in labour quality consequent to enhanced investments in education.

However, only labour was found significant (5%) and retained in the model. All the second order terms (except fertiliser) and all interaction terms were dropped during estimation since most of them were not statistically different from zero at 5 per cent level and only contributed to decrease the precision of the estimates.

4.1.1.2 Data on the potential determinants of AS&T policy system

A summary of the indicators of potential structure of AS&T policy system are given in Table 6. These were used as independent variables in both the second stage DEA and SFA technical inefficiency models (Equations 4.12 and 4.15). Those used in the logistic regression (Equation 4.16) are summarised in Table 7.

4.1.2 Indicators of AS&T policy system performance – 1st stage DEA

The combined mean DEA technical efficiency for Kenya and Uganda was 0.714 (std. dev. = 0.154). The estimate for Uganda (0.766; std. dev. = 0.124) was significantly higher than that of Kenya (0.661; std. dev. = 0.164). Figure 6 shows the trend in efficiency estimates in Kenya and Uganda.

It was expected that Kenya, being a second generation policy system would be more efficient than Uganda (first generation). However, the results reveal the contrary. This is not surprising when one interrogates the data. With the exception of labour, Uganda has consistently used significantly lower levels of all the other inputs, yet it has realised higher output. This could be due to the inherent differences in the quality of some of the inputs used, in this case, land. Uganda has more fertile agricultural land than Kenya supported with higher rainfall levels. Whereas the proportion of land under arable farming in Kenya was 9% and 8% in 2002 and 1992 respectively, that for Uganda was 37% in 2002 and 35% in 1992. In contrast, the proportion under pasture (lower quality) was 37% for Kenya and 26% for

Uganda in 2002. In absolute figures, the total agricultural land in Kenya in 2002 was 5.1 million hectares compared to Uganda's 7.1 million. The size of land under irrigation was 89,700 Ha (1.7%) in Kenya compared to 5,600 Ha (0.1%) in Uganda in 2002 (SID, 2006; FAO, 2002).

Table 6: Potential determinants of AS&T policy system performance - Independent variables in the second stage DEA model and the SFA technical inefficiency model

Country	Kenya (n = 33)	Uganda (n = 33)	Pooled (n = 66)
Potential policy-level determinants (means*)			
Research capital (research expenditure per FTE- constant 1993 US$) – (AG_RE_CAP)	30513.97 (5067.76)	24896.82 (8430.82)	27705.39 (7459.59)
Education capital (education expenditure per enrolled student - constant 1993 US$) – (HUM_CAP)	398.98 (103.16)	290.94 (96.22)	345.79 (113.00)
Export and Imports to GDP ratio (%) – (ECO_OPEN)	34.12 (7.25)	26.82 (8.82)	30.47 (8.82)
Potential micro-level determinants (means*)			
Journal research articles (number/year) – (JOURNAL)	246.79(36.81)	28.83 (24.47)	144.84 (114.05)
Telephone connection per 1000 people – (TELEPHONE)	21.78 (22.17)	7.32 (9.65)	14.55 (18.46)
Paved road per 10,000 Ha of agric land – (ROAD)	2.57 (0.75)	1.89 (0.85)	2.23 (.86)
Literacy rate (%) – (LITERACY)	64.14 (13.53)	52.50 (11.00)	58.32 (13.57)
Potential non-policy determinants (means*)			
Annual rainfall (mm) (RAIN)	784.50 (146.9)	1228.9 (89.84)	1006.77 (254.53)
Investments in irrigation (ratio of irrigated over arable land - %) – (IRRIGATE)	0.21 (0.067)	0.06 (0.015)	0.13 (.09)
Life expectancy at birth (years) – (LIFE)	54.23 (3.29)	47.79 (3.27)	51.01 (4.60)
Potential institutional arrangement determinants (frequencies)			
Extension services (REG_AG_EXT)			
Centralized	72.7%	84.8%	78.8%
Decentralized	27.3%	15.2%	21.2%
Intellectual property rights regulation system (REG_PAT)			
Not well regulated	87.9%	72.7%	80.3%
Act enacted and operationalise	12.1%	27.3%	19.7%
Coordination of research (REG_AG_RES)			
S&T Act not available	30.3%	63.6%	47.0%
S&T Supportive Act available	69.7%	36.4%	53.0%

*All means are significantly higher in Kenya. Figures in parentheses are standard deviations.

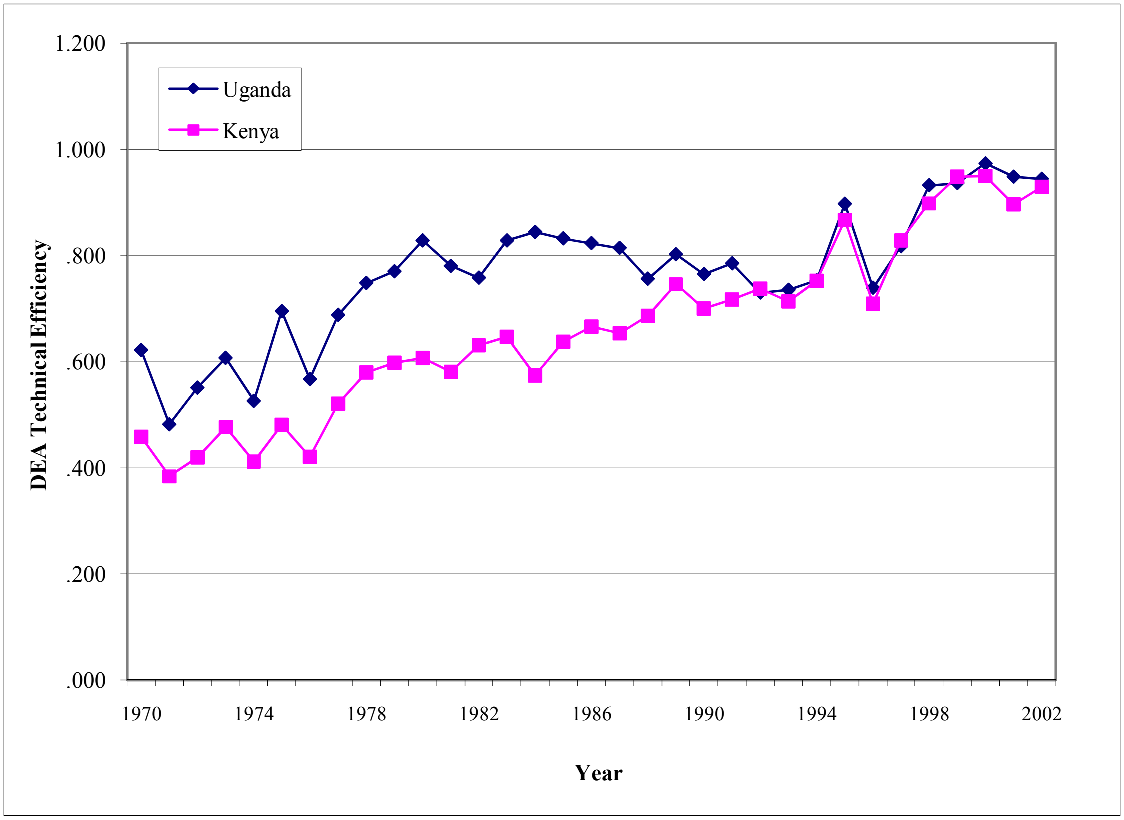
Table 7: Description of variables hypothesised to influence progress/regress in technical and efficiency change

Description of the institutional/policy/support determinants	Kenya (n = 33)	Uganda (n = 33)	Pooled (n = 66)
Frequencies			
REG_ECO_OPEN - Economic openness			
Liberalized trade regime	30%	30%	30%
Controlled/protected trade regime	70%	70%	70%
REG_AG_RES - Agricultural research coordination			
Research undertaken by agencies	70%	36%	53%
Research fragmented	30%	64%	47%
REG_PAT - Intellectual property rights regulatory system			
Intellectual property rights laws enacted	12%	27%	20%
No clear intellectual property rights laws	88%	73%	80%
REG_AG_EXT - Agricultural extension regulatory system			
Decentralized R&D	15%	15%	15%
Centralized R&D	85%	85%	85%
Means$^{\Psi}$			
RAIN - Mean annual rainfall in mm	784.58 (146.91)	1228.96 (89.87)	1006.77 (254.53)
LITERATE – Adult literacy level (%)	64.14 (13.53)	52.50 (11.00)	58.32 (13.57)
IRRIGATE – Irrigated land over total arable land (%)	0.21 (0.067)	0.064 (0.015)	0.135 (0.087)
ROAD - Paved road length in km per 10000 Ha agricultural land	2.57 (0.75)	1.89 (0.84)	2.23 (0.86)
LIFE – Quality of the agricultural labour force: Life expectance at birth (Years)	54.23 (3.29)	47.79 (3.27)	51.01 (4.60)
TELEPHONE - Telephone connections per 1000 head	21.78 (22.17)	7.32 (9.65)	14.55 (18.46)

Source: Author's estimates.

$^{\Psi}$Figures in parentheses are standard deviations.

Figure 4: Trends in DEA technical efficiency estimates in Kenya and Uganda between 1970 and 2002



Source: Authors computations

In addition, the labour intensity, the number of agricultural workers per agricultural land area in Kenya in 2002 was 2.34 workers per hectare compared to 1.29 for Uganda (World Resources Institute, 2007). This is because Uganda has more abundant agricultural land which is tilled by relatively fewer people. Nevertheless, agricultural production in both countries is significantly more labour intensive than elsewhere on the African continent (with an average of one person per hectare) and in the world (0.87 workers per hectare) (SID, 2006). This study did not make adjustments for these quality differences due to lack of adequate data.

Under such circumstances, some studies have argued that even though the absolute measures of technical efficiency may give a measure of DMU's level performance, they may be unsuitable for cross-DMU comparative analysis (without appropriate adjustments). In such circumstances, what would be more useful is the rate of change of the indicators (in response to the external environment) (see Rezetis, 2006). All other factors held constant, DMUs with higher rate of change would be those at lower level of development, and as such would grow faster. The phenomenon has variously been referred to convergence in productivity studies.

4.1.3 Delineating the structure of the AS&T policy system – 2nd step DEA analysis

Table 8 presents the second stage Tobit results of technical efficiency scores on the AS&T policy system indicators for Kenya and Uganda. Both models were statistically significant (with LR-χ^2 of 100.6 and 64.69; p>0.000; for Kenya and Uganda respectively) and most of the estimated coefficients were statistically significant. In the second generation policy system, performance was significantly influenced by research expenditures (AG_RE_CAP), expenditure on human capital development (HUM_CAP), degree of economic openness (ECO_OPEN), literacy level (LITERACY) and presence of a regulatory framework for intellectual property rights (REG_PAT). On the other hand, within the first generation policy system, performance was influenced by research expenditure (AG_RE_CAP), expenditure on human capital development (HUM_CAP), domestic research output (JOURNAL), extension regulatory framework (REG_AG_EXT) and road network (ROAD)[20]. The squared correlation between the observed and predicted technical efficiency values for the models were 0.953 and 0.904 indicating that the matrix of 10 predictors of AS&T policy system structure (together with the other support variables) accounted for about 95% and 90% of the variability in technical efficiency for Kenya and Uganda respectively.

It is important to note that the LR-χ^2 [21] estimate was in actual fact the results of testing for Hypothesis 1 of this study based on the 2nd stage DEA model. Hypothesis 1 stated: ***The potential determinants of AS&T policy system structure (individually and collectively) significantly influence the performance of the policy system***. i.e., $\mathbf{H_0: \beta_0 = \beta_1 = \ldots\ldots\ldots = \beta_i \neq 0}$. Acceptance of the null hypothesis (a significant χ^2 means that the variables jointly influence technical efficiency and are therefore not equivalent to zero). This implied that the potential determinants of AS&T policy system as conceptualized in this study influences performance.

[20] It is worth mentioning that these coefficients are interpreted as in OLS regression: the expected efficiency score changes by magnitude of coefficient for each unit increase in the corresponding predictor

[21] The Likelihood Ratio (LR) Chi-Square estimate tests that at least one of the predictors' regression coefficients is not equal to zero. The number in the parentheses indicates the degrees of freedom of the Chi-Square distribution used to test the LR Chi-Square statistic and is defined by the number of predictors in the model.

Table 8: Potential determinants of AS&T policy system structure in Kenya and Uganda – Censored Tobit regression results (Depended variable – DEA technical efficiency estimates)

Variables	Estimated coefficients	
	Kenya	**Uganda**
PU_AG_RE	4e-6* (0.000)	1e-5* (0.000)
HUM_CAP	2.4e-4** (0.0001)	0.001*** (0.000)
ECO_OPEN	0.0025** (0.001)	-0.0011 (0.002)
JOURNAL	3.7e-4 (0.00035)	3.7e-3* (0.002)
LITERACY	0.0107*** (0.0027)	0.0041 (0.005)
ROAD	0.0685 (0.1047)	0.2302* (0.146)
TELEPHONE	5e-4 (0.000)	4e-4 (0.003)
REG_AG_RES	0.0231 (0.0465)	0.1521 (0.1071)
REG_AG_EXT	0.0294 (0.0435)	-0.1368* (0.093)
REG_PAT	0.1162*** (0.0353)	0.0860 (0.097)
REG_ECO_OPEN	0.0361 (0.0459)	-
IRRIGATE	0.5411 (0.416)	0.0800 (2.064)
RAIN	0.0001 (0.000)	0.0001 (0.000)
CONSTANT	0.0912 (0.171)	1.0209*** (0.241)
Other statistics		
Observations	33	26
Standard error of estimate	0.035 (0.004)	0.040 (0.005)
Log-likelihood	63.62	44.36
LR-χ^2	100.6 (df=12) (P>000)	64.69(df=11) (P>000)
R^2	0.953	0.904

Key: Coefficients ***p<0.01; **p<0.05; *p<0.10 (figures in parentheses are standard errors)

These results reveal some salient comparative findings. At policy level, economic openness had positive and significant effect in the second generation policy system, but negative (and insignificant) in first. Similarly, literacy and intellectual property regulations were significant in the second, but not first generation policy system. Local research had impact in first and not second generation systems. It is important to mention that all key macroeconomic indicators like public expenditures (in education, research and extension) and level of economic openness are expected to be positively related to agricultural productivity, provided there are no substantial urban biases in these expenditures (Rao et al, 2004). This aphorism was valid only for education and research but not economic openness in the two policy systems.

Since transboundary trade leads to importation of goods, and in the process allows a country to access foreign technology, it is expected to contribute to improved technical efficiency. This phenomenon was valid only in the second generation policy system. The opening up of the economies was associated with increased importation of agricultural products, heralding additional competition against local produce, probably against a background of an under-developed private sector in first generation policy systems[22]. It is apparent that such a private sector was yet to be stimulated to establish trading networks and institutions needed for proper functioning of a liberalised economy. Furthermore, the risks associated with adopting a more exposed position in a highly competitive global agricultural market presented countries with smaller economies with some serious difficulties (Badiane and Mukherjee, 1998). Therefore, it can be argued that a combination of the impact of liberalisation policies and partial reform of the rules governing international trade that led to reduction in the prices of primary commodities exported by developing countries and an increase in imports of agricultural products from more competitive (and perhaps subsidised) producers had a more profound negative effect on first generation policy systems than on second. However, it is anticipated that as these economies develop and the role of the private sector becomes more prominent, the effect of open trade is bound to be positive in the long term. This is based on the argument that agricultural reforms, reductions in trade barriers and entrenchment of intellectual property rights (IPR) regulations are envisaged to help farmers both in the industrialised and developing worlds get a better deal in a more cost-effective way (Monika, 2005). The fact that enactment of IPR regulations becomes important in second generation policy systems while not in first attests to this line of argument.

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[22] This line of argument is in line with posits of North (2005). North argues that economic change depends largely on "adaptive efficiency," a society's effectiveness in creating institutions that are productive, stable, fair, and broadly accepted--and, importantly, flexible enough to be changed or replaced in response to political and economic feedback. While adhering to his earlier definition of institutions as the formal and informal rules that constrain human economic behavior, North extends his analysis to explore the deeper determinants of how these rules evolve and how economies change. Drawing on recent work by psychologists, North identifies intentionality as the crucial variable and proceeds to demonstrate how intentionality emerges as the product of social learning and how it then shapes the economy's institutional foundations and thus its capacity to adapt to changing circumstances.

The observation that indicators of reduction in transaction costs (i.e., improved road network, perhaps with enhanced conditions for efficient market performance) had positive and significant impact on technical efficiency (in first generation system) gives credence to the argument that in the long-run, liberalisation is likely to have an overall positive effect on efficiency. Increased road network not only exposes producers to efficiency enhancing circumstances like ease of access to better technologies and information, but also to efficiency reducing environments like higher competition as consumers are likely to access favourably priced imports. One may thus intuitively conclude that in the first generation policy systems, the immediate negative relationship between technical efficiency and economic openness may also be due to the upwards shifts of the frontier, without commensurate shift in technical efficiency. Further evidence to this assertion is provided later in this thesis.

Another important finding of this study is that increased literacy levels had significant impact in second generation system and not in first. The significance of literacy level is depended upon whether the technologies in use are complex and knowledge intensive (Rosegrant and Evenson, 1995). Economic openness exposes developing countries to such types of technologies (i.e., biotechnologies), but the first generation policy systems may not have deepened their infrastructural capacity to derive optimal benefits from such efficiency augmenting transboundary technologies. The first generation systems may thus have derived more benefits from domestically developed technologies, a pointer to why productivity in this first generation policy system was significantly influenced by domestic research.

The finding that domestic research diminishes in importance as policy systems evolve is a cause for alarm. This can intuitively be attributed to two factors: first the weaknesses in the research-extension continuum, and secondly, the relevance or appropriateness of such domestic research in sustaining rapid growth in productivity in developing African economies. Linkages between research and extension are crucial in driving the benefits realisable from research (Sharma, 2003). Although a suitable proxy for extension capital was not available in this study, the fact that changes in extension regulatory system had no effect in second generation systems and negative effect in first generation system may be evidence towards weaknesses in extension services. There is evidence that extension decentralisation in Kenya and Uganda was undertaken without developing facilitating infrastructure leading to the alienation of larger segments of smallholder producers and the dominant livestock production within pastoral and agro-pastoral settings (Mugunieri and Omiti, 2007). Similarly, further evidence from this study shows that the institutional reforms within research organisations have had insignificant impact implying that fewer benefits have been obtained from investments in domestic research.

4.1.4 Indicators of AS&T policy system performance indicators - the SFA approach

The 2nd stage DEA has been used to estimate individual models for policy systems in Kenya and Uganda. The results indicate existence of differences in the structure of the policy systems between the two generations. However, lack of sufficient degrees of freedom did not permit estimation of individual generation models under SFA. A pooled model (for combined data set) was therefore estimated. A similar pooled 2nd stage DEA model was also estimated for comparative purposes. The estimation of these models was made feasible following results of the Chow tests that revealed that the set of linear regression for factors of production and also for the potential determinants of the AS&T policy system structure did not vary significantly between Kenya and Uganda[23]. This does not however invalidate the AS&T policy system generations thesis since the production levels of Uganda were not adjusted downwards (or inputs adjusted upwards) to reflect the inherent higher quality of inputs.

The purpose of applying the SFA model was to triangulate the results obtained from second stage DEA model. The validity of the stochastic analysis results was dependent upon the statistical soundness of the estimated model which was undertaken through a series of tests.

SFA model specification tests

The first test revolved on the validity of the translog over the Cobb-Douglas specification within the ML specifications using a log likelihood test. The test statistic was computed as: $LRI = 1 - \ln L_o/\ln L$, where $\ln L_o$ was the log-likelihood value for the model computed with only the constant term and $\ln L$ was the log-likelihood function value for the model having all the regressors (Greene, 2003). The null hypothesis that $\beta_{ij}=0$, $i \leq j=1, 4$ was rejected ($\chi^2 = 1.023$; df=5; $p<0.05$). Therefore, the translog production technology was considered to be a better representation of Meta-production function technology than the Cobb-Douglas specification[24].

The second stage of testing used log likelihood tests to examine the alternative specifications of technical change within the family of ML translog models. The null

[23] See **Appendix 1** for details.
[24] See **Appendix 2** for details.

hypothesis that there was neutral technical change was rejected against the alternative hypothesis of non-neutral technical change[25]. The third stage of testing was used to test the null hypothesis that there were no technical inefficiency effects in the model. The null hypothesis that there were no in-efficiency effects, that is, the one sided error $\gamma=0$[26] was rejected (z = -1.633, p< 0.051).

The final stage of testing concerned the distribution of the efficiency effects. The null hypothesis that the technical efficiency effects have a half-normal distribution, that is, $\mu=0$, was rejected against the null that the technical efficiency effects have a truncated normal distribution (μ = 0.12; p<0.002). Given these results, the translog with non-neutral technical change was the best representation of Kenyan and Ugandan agricultural technology given the alternative specifications considered. The maximum likelihood estimates of this stochastic frontier production function model were obtained using STATA 8.2 after correcting for heteroskedasticity[27] by transforming the data into natural logarithms. The results for the estimation of this model (step 1) are shown in Table 9.

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[25] See **Appendix 3** for details.

[26] Where
$$\sigma = (\sigma_u^2 + \sigma_v^2)^{1/2}$$
$$\lambda = \sigma_u / \sigma_v \qquad ,$$
$$\gamma = \sigma_u^2 / [\sigma_u^2 + \sigma_v^2]$$
where σ_u and σ_v are the standard deviations of the technical inefficiency effects (u) and the measurement errors (u) respectively. It is important to note here that this was the testing for Hypothesis 1 of this study based on the SFA model, i.e.: H_0: $\delta_0 = \delta_1 = \ldots\ldots\ldots = \delta_i = 0$. This implied that the potential determinants of the AS&T policy systems as conceptualised in this study significantly influenced levels of technical efficiency.

[27] The Breusch-Pagan heteroskedasticity test was used to detect for the presence of heteroskedasticity. This was performed by squaring the error term, e_i^2 and dividing each error term squared by the mean error term to obtain v_i^2. Subsequently, v_i^2 was then regressed against all the dependent variables. Specific steps followed for the test were:

(i) Run an OLS for regression, and obtain e_i^2

(ii) Calculate $\tilde{\sigma}^2 = \sum e_i^2 / N$

(iii) Construct $\hat{v}_i^2 = e_i^2 / \sigma^2$

(iv) Regress $\hat{v}_i^2$ on the dependent variables

(v) Obtain R^2.

Since this was a considerably large sample, the product of the R^2 and the sample size was assumed to follow a Chi-square distribution. (N-P)* $R^2 \sim \chi^2_P$, where P was the number of dependent variables in the regression. The computed chi-square was 14.09 (1% confidence), against a critical value of 1.15, and the null hypothesis of homoscedasticity rejected. Details of this procedure are given in **Appendix 4**.

Table 9: The first equation stochastic production frontier estimation for the pooled Kenya and Uganda data – Dependent variable Agricultural PIN

Variables	Coefficient	Standard Error
LN LIVESTOCK	0.2991***	0.0995
LN LABOUR	5.3255***	0.1641
LN LAND	0.3581302***	0.0527
LN CAPITAL	0.5273744***	0.0557
LN FERTILISER	0.0135*	0.0099
LN LABOUR*TIME	-0.0785067***	0.00517
LN FERTILISER*FERTILISER	0.0009**	0.0001
TIME	0.0369702***	0.0017
TIME*TIME	0.0033***	0.0000
CONSTANT	43.3049***	0.0009
Other statistics		
μ (mu)	0.1208882***	0.0392
lnsigma2	3.846632	0.0322
Ilgtgamma	15.15223	5.81264
σ^2_v	5.61e-09	3.26e-08
σ^2_u	0.02135	0.000686
σ^2	0.02136	0.000687
γ	0.9999997	1.53e-06
Log likelihood = 99.272264; N = 59		
H_0: No inefficiency component: z = -1.633 Prob<=z = 0.051		

Key: Coefficients ***p<0.01; **p<0.05; *p<0.10

The time trend coefficient showed that there was positive neutral technological progress. The stochastic frontier meta-production function, evaluated at the first observation, was moving upward at an annual rate of about 3.697 per cent per annum. The coefficient on *γ* implied that 99.99 per cent of the two components disturbance term was represented by technical inefficiency. Labour had the highest production elasticity followed by land, machinery, livestock and fertilisers in that order. Although a perfect comparison with other studies is not possible because of the different number of countries and the different reference period considered, the production elasticities estimated in this study were quite similar to those found in Hayami and Ruttan (1970) and Kawagoe, Hayami et al. (1985) who estimated respectively a meta-production function for 38 and 43 developed and underdeveloped countries. Progress in technical change was found to be labour saving.

4.1.5 A comparative analysis of the SFA and DEA generated performance indicators

Table 10 gives a comparative descriptive summary of the SFA and DEA derived technical efficiency estimates for Kenya and Uganda. Unlike DEA scores that were significantly different between the first and second generation policy system, SFA scores were not, even though the scores from first generation were higher[28]. Both approaches identified Uganda as having higher efficiency estimates. Within the same generation, there were significant differences between DEA and SFA efficiency estimates. This is because the deterministic DEA and SFA approaches differ in structure and implementation and therefore are likely to yield different efficiency estimates (Kasman and Turgutlu, 2007). The level and trends of DEA and SFA estimates are shown is shown in Figure 7. The DEA estimates, unlike the SFA showed a steady upward trend with time.

Results indicate that parametric methods yielded relatively higher mean efficiency estimates (between 80% and 99%), which did not vary much over time (i.e., had lower standard deviation). DEA efficiencies on the other hand were much lower with wider dispersion. Similar findings are numerous in literature (e.g. see. Bauer et al, 1998). It is, however, useful to observe that the determination of which method (DEA or SFA) was more useful for regulatory analysis needed an evaluation of other consistency conditions, particularly with regard to which approach yielded more realistic or believable efficiency estimates.

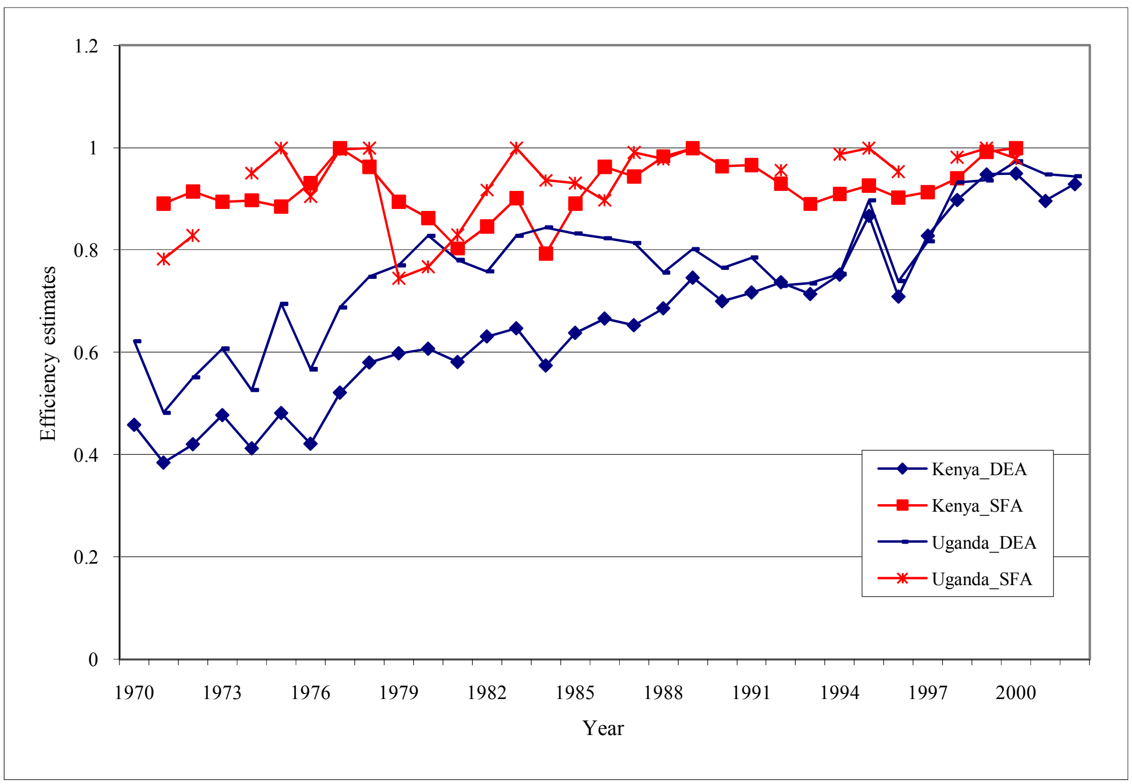
[28] These differences between first and second generation DEA, between first and second generation SFA, and finally between DEA and SFA for first and second generation were implemented using the Mann-Whitney tests (Mann and Whitney, 1947). Details of the tests are given in **Appendix 5**.

Table 10: Comparative summary of the SFA and DEA generated technical efficiency estimates for Kenya and Uganda, 1970-2002

Item	Country	N	Mean	Std. Error
DEA generated technical efficiency estimates	Kenya	33	0.6614	0.0286
	Uganda	33	0.7659	0.0216
	Total	***66***	***0.7137***	***0.0189***
SFA generated technical efficiency estimates	Kenya	26	0.9219	0.0097
	Uganda	26	0.9321	0.0160
	Total	***52***	***0.9265***	***0.0089***

Source: Author's calculation

Figure 5: Trends in the SFA and DEA generated technical efficiency estimates in Kenya and Uganda, 1970-2002



Source: Author's calculation

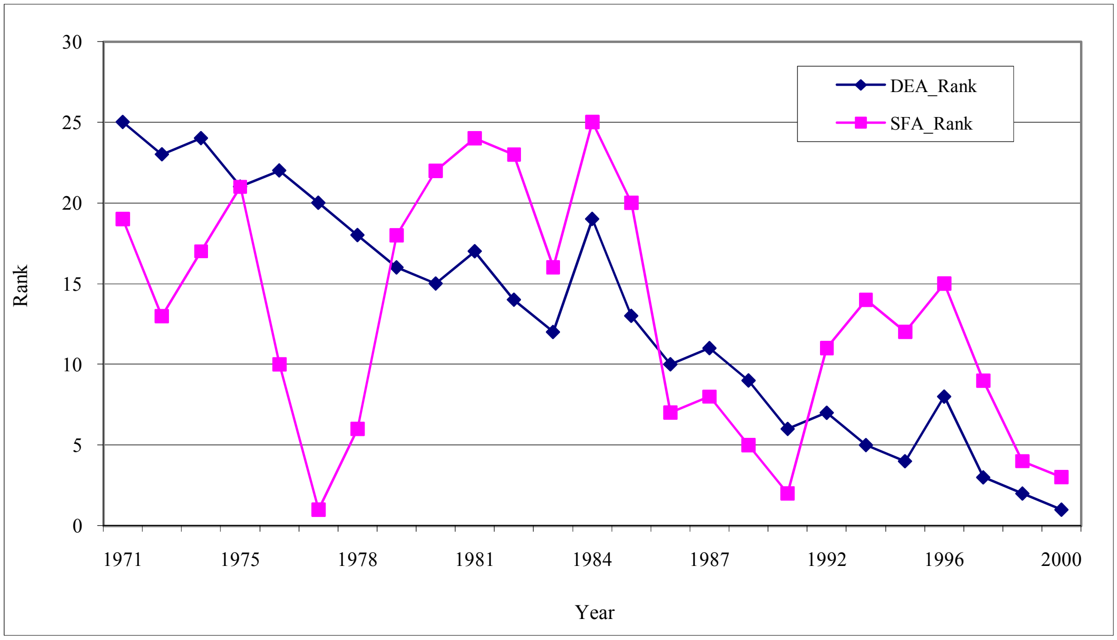
Both the SFA and DEA TE estimates revealed that when TE is used as a performance indicator, Ugandan agriculture performed better than that of Kenya. Higher technical efficiency estimates imply that one DMU performs better than the other, *ceteris paribus*. That is to say, correcting for all other factors, a DMU with higher technical efficiency estimates utilises less of the inputs to produce the same level of output. In this study, since there was limited capacity to make adjustments for the apparent inherent inputs quality differences (i.e. land); care should be taken in the interpretation of these productivity estimates.

Although the efficiency estimates from SFA and DEA were different across years for each country, it was still possible that these methods generated similar annual rankings in each country. Identifying the ***rough ordering*** of which years were more efficient than other is bound to be of more importance for regulatory policy decisions than is the measuring of the level of efficiency *per see*. In this regard, policy regulators can determine whether regulatory-influenced events like 'decentralisation' resulted in improved or worsened performance of the agricultural sectors. If the methods do not rank annual performances in roughly the same order, then policy conclusions may be 'fragile' and dependent on which frontier efficiency approach is employed (Bauer, 1998).

Figures 8 and 9 give the trends in the ranking of the annual performances based on the DEA and SFA generated technical efficiency estimates. The Spearman rank-order correlation test was used to test whether the two frontier approaches ranked the annual performances in each country in approximately the same order. The pair-wise Spearman rank-order correlation coefficients of the average technical efficiencies were computed. These statistics provided estimates of the correlation between the rankings of annual performances in each of the two frontier specifications. In implementing this test, two other economic indicators – namely per-capita agricultural GDP and the productivity index (PIN) were also rank-correlated with the technical efficiency estimates to establish if the estimates were believable. All the rank order correlation coefficient estimates were statistically significant (Table 11).

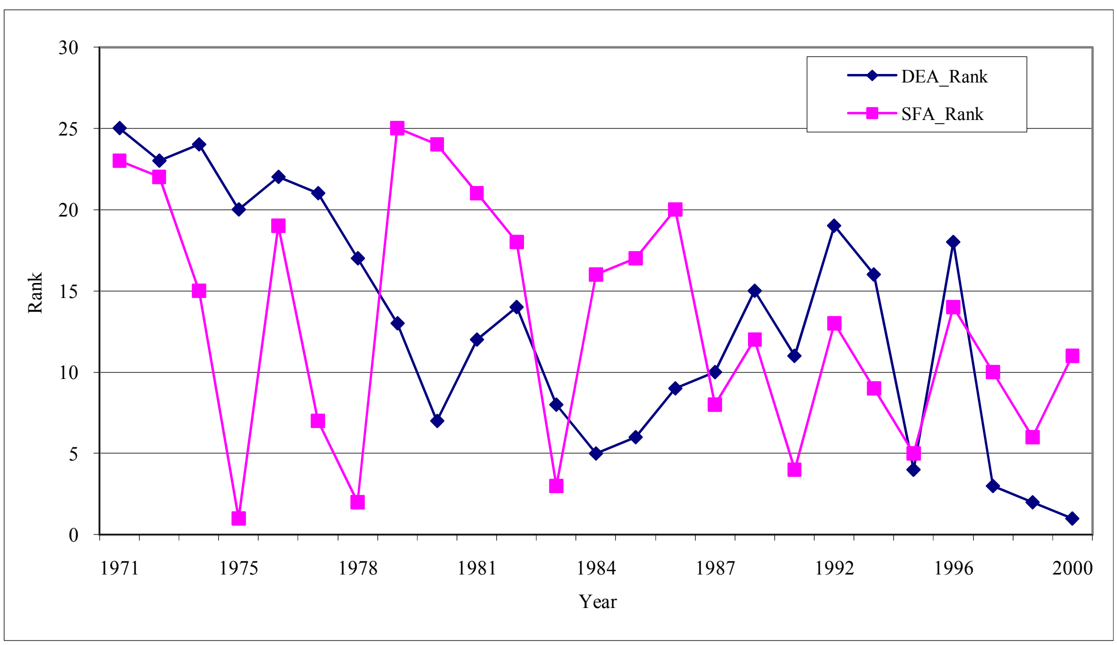
These findings reveal that DEA and SFA approaches are largely consistent in the identification of best and worst performing time periods, and that when applied, both approaches are likely to give the same answers to regulatory policy questions. In addition, the significance of the Spearman's rank correlation coefficients between the frontier estimates and the economic indicators shows that both the SFA and DEA estimates are reasonably consistent with standard economic performance measures. This means that both measures of efficiency are in tandem with economic reality and are therefore credible.

Figure 6: Trends in ranking of years based on technical efficiency derived by DEA and SFA in Kenya



Source: Author's calculation

Figure 7: Trends in ranking of years based on technical efficiency derived by DEA and SFA in Uganda



Source: Author's calculation

Table 11: Spearman rank-order correlation matrix between the SFA and DEA generated technical efficiency estimates and other economic indicators for Kenya and Uganda, 1970-2002

Country	Item	DEA generated technical efficiency	SFA generated technical efficiency	Agricultural GDP (2000 constant US $)	Agricultural output index (FAO PIN)
Kenya (N=33)	DEA generated technical efficiency	1.000	0.401 (0.014)	0.957 (0.000)	0.950 (0.000)
	SFA generated technical efficiency	0.401 (0.014)	1.000	0.373 (0.021)	0.493 (0.003)
	GDP (2000 cont $)	0.957 (0.000)	0.373 (0.021)	1.000	0.986 (0.000)
	agricultural output index	0.950 (0.000)	0.493 (.003)	0.986 (0.000)	1.000
Uganda (N=25)	DEA generated technical efficiency	1.000	0.355 (0.041)	0.591 (0.000)	0.622 (0.000)
	SFA generated technical efficiency	0.355 (0.041)	1.000	0.414 (0.020)	0.423(0.007)
	Agricultural GDP (2000 constant US $)	0.591 (0.000)	0.414 (0.020)	1.000	0.935(0.000)
	Agricultural output index (FAO PIN)	0.622 (0.000)	0.423 (0.007)	0.935 (0.000)	1.000

Note: Values in parentheses are *p*-values

Source: Author's calculation.

4.1.6 Delineating the structure of the AS&T policy system –the simultaneous SFA model

Table 12 gives the results of part 2 of the SFA technical inefficiency model. A pooled (Kenya and Uganda data) second stage DEA technical efficiency Tobit model was also estimated for purposes of comparison (Table 13).

Table 12: Structure of AS&T policy system - Estimates from the SFA technical inefficiency model (pooled)

Variable	Coefficient
LN PU_AG_RE	-0.6026*** (0.1631)
LN HUM_CAP	-0.0820** (0.0106)
LN ECO_OPEN	-0.0630 (0.0607)
LN JOURNAL	-0.1603 (0.910)
LN LITERACY	2.2796*** (0.7874)
LN LIFE_EXP	-1.5318** (0.7794)
LN ROAD	-0.0359 (0.1752)
LN TELEPHONE	-0.5049*** (0.1590)
REG_AG_RES	-0.0394 (0.0721)
REG_AG_EXT	-0.0175 (0.2578)
REG_PAT	-0.6404** (0.3179)
REG_ECO_OPEN	0.4412*** (0.1267)
LN IRRIGATE	-0.0737 (0.1276)
LN RAIN	-0.098** (0.0497)
GENERATION (country dummy)	0.1961 (0.300)
TIME	-0.1003*** (0.0217)
Constant	5.0467** (2.8209)
μ (mu)	0.1209*** (0.0392)
lnsigma2	3.8466 (0.0322)
Ilgtgamma	15.1522 (5.81264)
σ^2_v	5.61e-09 (3.26e-08)
σ^2_u	0.02135 (0.00068)
σ^2	0.02136 (0.00069)
γ	0.9999 (1.53e-06)
Log likelihood = 99.272264; Wald chi2(9) = 1399574.89; Prob > chi2 = 0.0000; N = 59	

Key: Coefficients ***p<0.01; **p<0.05; *p<0.10 (figures in parentheses are standard errors).

Table 13: Structure of AS&T policy system - Estimates from the second stage DEA censored Tobit model (pooled)

Variables	Coefficient
PU_AG_RE	0.00001^{***} (0.000)
HUM_CAP	0.0004^{***} (0.000)
ECO_OPEN	-0.0007 (0.001)
JOURNAL	0.0010 (0.010)
LITERACY	0.0088^{***} (0.003)
LIFE_EXP	0.0088^{*} (0.006)
ROAD	0.1097^{**} (0.056)
TELEPHONE	0.0112^{***} (0.004)
REG_AG_RES	0.0361 (0.053)
REG_AG_EXT	-0.0697^{**} (0.041)
REG_PAT	0.0921^{**} (0.041)
REG_ECO_OPEN	-0.0266 (0.047)
IRRIGATE	0.7109 (0.521)
RAIN	0.0001 (0.000)
GENERATION	-0.1786^{**} (0.092)
TIME	0.0831 (0.0868)
CONSTANT	0.9942^{***} (0.343)
Log-likelihood	95.24
LR-χ^2 (df=14)	137.85 (P>000)
R^2	0.918
N	59
Standard error of estimate	0.043 (0.004).

Key: Coefficients ***p<0.01; **p<0.05; *p<0.10 (figures in parentheses are standard errors).

Both the SFA and second stage DEA identified similar determinants as comprising the structure of AS&T policy system in Kenya and Uganda, except for: (i) extension decentralisation regulatory framework that was significant under second stage DEA and not SFA; and (ii) economic openness regulatory system that was significant under SFA and not

DEA. Other non policy features that were only significant under SFA were level of precipitation (rain) and time trend. From the SFA model, the results indicated that time contributed to reduction of inefficiency levels, implying that with time there may be a tendency towards capturing learning by doing. Alternatively there could have been limited negative lagged reactions to changes in the policy environment. The sign of the time parameter in the second stage DEA model was of the expected sign, but did not attain the desirable level of significance.

The second stage DEA model was statistically significant (χ^2 = 137.85, df = 14), where most of the estimated coefficients were significant. The squared correlation between the observed and predicted technical efficiency values for this model was 0.918 indicating that the matrix of 15 predictors accounted for about 92% of the variability in the technical efficiency. At policy level, both models revealed intuitive positive responsiveness of technical efficiency to policies that support investments in human capital development and deepening of agricultural research, while policies that lead to opening up of economies contributed to losses in efficiency (based on DEA). At micro-level, interventions that reduced transactions costs in accessing technologies and information (road network and telephone density) contributed most to enhanced technical efficiency, followed by investments in human capital development (literacy and health) and research (technology output). Regarding institutional arrangements, enactment of intellectual property rights laws led to enhanced technical efficiency as opposed to decentralisation of extension services. Reorganization of research agencies did not have a significant effect on efficiency.

It is however important to point out that even though economic openness had an overall negative effect (based on DEA model, but positive and insignificant effect based on SFA), earlier results (based on individual country models) had shown that the specific country effects were positive and significant in the second generation policy system, but negative in first. It then implies that the negative (generation 1) effects could be outweighing positive (generation 2) impact in the joint DEA model. Similarly, these results had indicated that literacy levels and intellectual property laws were significant in the second, but not in first generation policy system. However, both determinants turned out to be significant in the joint models. The significance of literacy levels is in tandem with arguments indicating that education is associated with better agricultural practices with the incessant increase in agricultural productivity and reduced poverty (Fan, et al., 2005). Both models reveal the insignificant impact of local research output on technical efficiency, a factor that was observed in second and not first generation systems.

A trend that can be discerned in the preceding analysis indicates that variables that were significant in the second generation individual country 2nd stage DEA models but insignificant in first generation appeared to be significant in the pooled model. However, those variables that were significant in first generation model but not significant in second generation remained non-significant in the joint models.

Results from both the SFA and DEA models indicated the significance of generational stage of the AS&T policy system on technical efficiency, but in favour of the first generation. There was expected to be a positive shift in technical efficiency as one moved from first to second generation, however, such a shift appears to have been countervailed by limitations in data due to absence of adjustment for quality differences.

4.2 Policy reforms and institutional innovations that have improved performance of AS&T policy systems in Kenya and Uganda

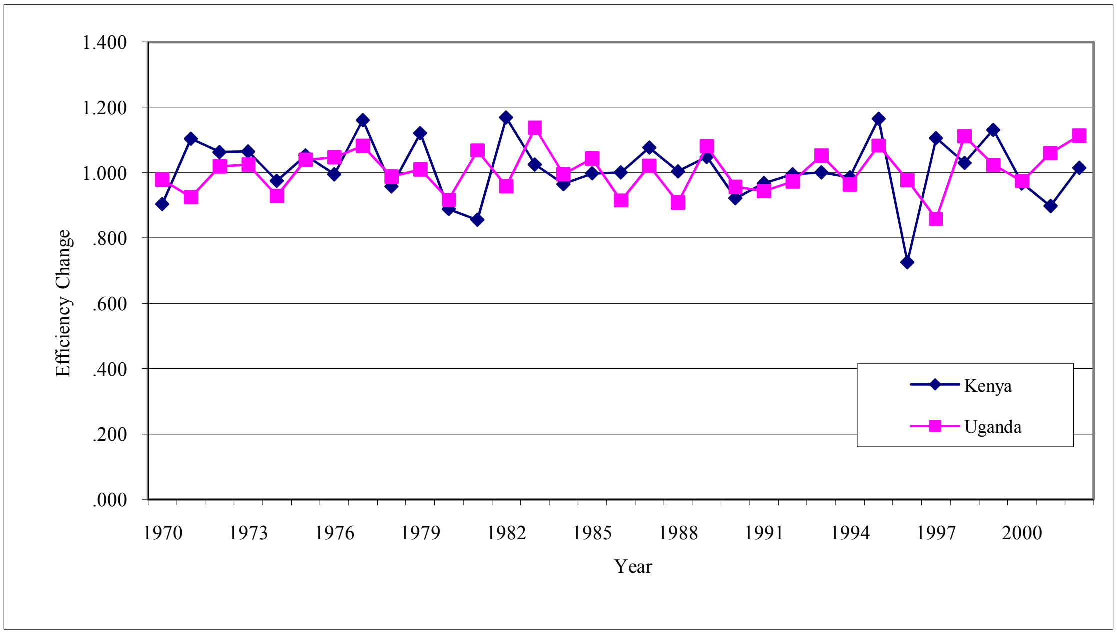
4.2.1 Indicators of performance of AS&T policy system institutions: - Efficiency and technical change

The performance of AS&T policy system was tracked through the analysis of technical and efficiency progress/regress estimated using DEA. Overall, technical efficiency progress was recorded in 53% of the years under investigation, being lower in Uganda (52%) than Kenya (55%). This difference was not statistically significant ($\chi^2 = 0.06$; $p>0.800$). On the other hand technical change progress was experienced in 56% of the years, being higher in Kenya (61%) than Uganda (52%). The differences were also not significantly different ($\chi^2 = 0.224$; $p>0.600$). The mean technical efficiency change index was higher for Uganda (1.0103; std. dev. 0.096) than Kenya (1.0054; std. dev. 0.0676). The same applied to the technical change estimates, being higher for Uganda (1.0082; std dev. 0.0417) than Kenya (1.0024; std dev. 0.0482). These scores were however not significantly different.

These figures provide some form of evidence towards the theory of convergence, where countries at lower of development (first generation) grow faster than countries at higher level of development (second generation). The non-significance of the difference between first and second generation estimates could also be due to the non-correction for quality of inputs used in deriving the estimates, which was in favour of first generation. The trends in technical and efficiency changes are summarised in Figures 8 and 9.

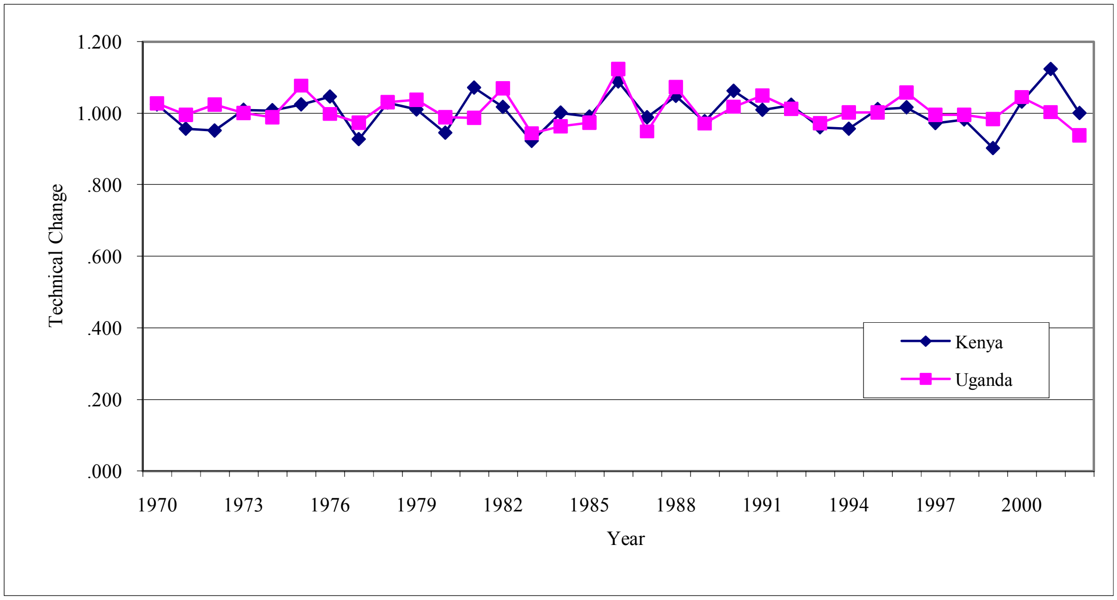
A more incisive analysis of the proportion of years recording either progress or regress in both efficiency and technical change for periods under alternative policy regimes was undertaken, i.e., under closed *vs*. open trade regime; fragmented *vs*. regulated agricultural research regimes; presence *vs*. absence of intellectual property rights regulations; and centralised *vs*. decentralised extension systems. Specifically, there were no significant differences in the proportion of years under which progress in efficiency and technical change were realised for the periods under different regimes of economic openness in Kenya and Uganda. The same applied to the different policy regimes under agricultural research institutionalization and intellectual property rights enforcement. However, the proportion of years for which technical progress was realised was significantly higher during the period of decentralised agricultural extension services than under the centralised system.

Figure 8: Trends in efficiency change estimates in Kenya and Uganda between 1970 and 2002



Source Author's calculations

Figure 9: Trends in technical change estimates in Kenya and Uganda between 1970 and 2002



Source Author's calculations

In order to identify the effect of each of these institutional changes on technical and efficiency change, two logistic models were estimated (using pooled data). The first model used the efficiency change (progress or regress) as the dependent variable whereas the second used technical change (progress or regress). Estimation of the pooled model relied on the Chow test done under the SFA analysis ($\chi^2 = 0.0441$; $p>0.646$). This provided a basis for estimating a pooled model for the two countries.

4.2.2 Impact of AS&T policy systems' institutional arrangements on efficiency and technical change

Table 14 provides the results of the specific institutional settings that enhanced the probability of experiencing efficiency change progress in Kenyan and Ugandan Agriculture. The results demonstrate the intuitive responsiveness of success of the agricultural sectors of the study countries to realising progress in technical progress to six factors: economic liberalisation (REG_ECO_OPEN), decentralisation of research and extension (REG_AG_EXT), introduction of an institutionalised agricultural research framework (REG_AG_RES), improved literacy (LITERATE), enhanced road network (ROAD) and investments in irrigation system (IRRIGATE). Factors that had negative influence included introduction of a regulatory system for intellectual property rights (REG_PAT) and improvement in life expectancy (LIFE). The Hosmer and Lemeshow Goodness-of-fit test statistic[29] was 7.140 ($P<0.522$) implying that the model's estimates fitted the data well, and that it explained much of the variance in the dependent variable.

[29] The Hosmer and Lemeshow Goodness-of-fit test divides subjects into two deciles based on predicted probabilities, then computes a chi-square from observed and expected frequencies. If the test statistic is 0.05 or less, we reject the null hypothesis that there is no difference between the observed and predicted values of the dependent; if it is greater, we fail to reject the null hypothesis that there is no difference, implying that the model's estimate fit the data at an acceptable level.

Table 14: Logit estimates of probability of having technical change progress in Kenyan and Ugandan agriculture (Dependent variable: Technical change progress)

Variable	Coefficient (β)	Standard Error	Exp(β)
REG_ECO_OPEN (1)	6.383***	2.491	591.555
STAGE (1)	-2.882	2.609	0.1786
REG_AG_RES (1)	3.012*	2.131	20.331
REG_PAT (1)	-3.040*	2.063	0.048
REG_AG_EXT (1)	4.840***	2.026	126.520
RAIN	-0.002	0.003	0.998
LITERATE	1.196**	0.108	8.822
IRRIGATE	34.099**	19.344	7.54e+14
ROAD	5.602***	2.449	270.998
LIFE	-0.383*	0.235	0.682
TELEPHONE	0.074	0.205	1.077
CONSTANT	7.001	10.703	1097.576
N	66		
-2Loglikelihood	69.646		
Model χ^2	13.815; df (10), P<0.182		
Hosmer and Lemeshow χ^2	7.140; df (8); P<0.522		

Key: Coefficients ***p<0.01; **p<0.05; *p<0.10

On the other hand, technical efficiency change was positively influenced by the reorganisation of the regulatory framework of the intellectual property rights system (REG_PAT), investments in irrigation (IRRIGATE), enhanced road network (ROAD) and higher level of precipitation (RAIN) (Table 15). However, economic liberalisation process (REG_ECO_OPEN) and decentralisation of research and extension services (REG_AG_EXT) had the immediate effect of causing negative efficiency change. The same applied to country specific variables like quality of production resources. The estimated parameters for improved literacy levels (LITERATE) and enhanced life expectancy at birth (LIFE) had positive sign but their impact on the probability of effecting technical efficiency change was insignificant. The state of these set of institutions, i.e. economic openness, decentralisation, IPR and education and how they relate to the findings in Tables 14 and 15 is discussed in detail in the subsequent sections below.

Table 15: Logit estimates of probability of having positive technical efficiency change in Kenyan and Ugandan agriculture (Dependent variable: Efficiency change progress)

Variable	Coefficient (β)	Standard Error	Exp(β)
REG_ECO_OPEN (1)	-4.551**	2.154	0.011
STAGE (1)	-5.175**	2.777	0.006
REG_AG_RES (1)	-1.244	2.002	0.288
REG_PAT (1)	2.255*	1.852	9.531
REG_AG_EXT (1)	-4.002**	1.885	0.018
RAIN	0.005*	0.003	1.005
LITERATE	0.105	0.104	1.110
IRRIGATE	28.845*	18.502	152.009
ROAD	3.441*	2.254	14.263
LIFE	0.244	0.228	1.276
TELEPHONE	0.018	0.202	1.002
CONSTANT	3.499	10.513	20.030
N	66		
Model χ^2	12.426; df (10), P<0.258		
-2Loglikelihood	70.485		
Hosmer and Lemeshow χ^2	5.522; df (8); P<0.701		

Key: Coefficients ***p<0.01; **p<0.05; *p<0.10

4.2.2.1 Economic openness – transboundary technology transfer

Economic liberalisation in Kenya and Uganda involved changes in trade and foreign exchange regimes by shifting from a protectionist (closed) regime through a short transitional reform phase that still remained largely protectionist, towards a more liberalised (open) regime. This shift was accompanied with significant changes in some selected key economic indicators under the two economic management regimes (closed *vs*. open) (Table 16).

Table 16: AS&T policy system indicators in Kenya and Uganda under closed and open trade and foreign exchange regimes

AS&T policy indicator (*Means*)	Kenya		Uganda	
	Closed (n=23)	Open (n=10)	Closed (n=23)	Open (n=10)
Agricultural output index (PIN)	59.28* (16.51)	93.36* (7.49)	68.57# (7.65)	92.24# (9.38)
Imports (current prices – US$)	1,442,137,044.9* (553654742)	2,865,483,996.8* (516806749)	321,557,042.8 (191,904,701)	1,180,906,673.1 (347,308,826)
Exports (current prices– US$)	902,247,129.0* (308,708,542)	1,850,825,011.2* (238,880,305)	315,964,738.8# (99,350,616)	464,247,094.8# (101,913,982)
GDP (2000 const $)	7,219,916,198.9* (2217967615)	12,113,706,905.6* (910,587,891)	2,656,707,515.4 # (287,533,339)	5,096,655,044.0# (1,012,143,131)
Telephone lines/1000 people	13.54* (4.61)	40.72* (33.51)	3.912# (0.25)	15.164# (15.25)
Paved road (km)/10,000 Ha agricultural land	2.237* (0.67)	3.330* (0.04)	1.39# (0.25)	3.05# (0.44)

Note: Values with the same superscript within a row are significantly different

Source: world Bank Online (2006); Faostat (2006)

This study has shown that accompanying these changes and holding the other factors constant, the agricultural sector under the open/liberalised economic regime was more likely to realise positive technical change, but not efficiency change in the short term. The odds[30] that these economies would realise technical progress in an open economic policy regime was 592 times the odds that they would in a protected economy (see Table 14). This implies that by opening up their economies, Kenya and Uganda created an environment that enabled more

[30] Odds is the ratio of probability something is true divided by the probability that it is not; i.e. odds=probability/(1-probability). Similarly, probability=odds/(1+odds). Subsequently an odds ratio is the ratio between of two odds.

robust technology transfer from foreign countries. However, this transformation had a negative effect on efficiency change.

There exists consensus among researchers that the form of trade policies influences productivity growth within the agricultural sector through their impact on technology transfer (Odhiambo et al, 2004). Considerable amount of work has been done to try and determine the direction of the effect of trade policies on productivity (Ram Rati, 1985; Tybout, 1992; Edwards, 1992; Mwega, 1995, Onjala, 2002: Odhiambo et al, 2004). There are two main theoretical perspectives that inform the productivity-trade policy nexus. The first supposition is that increased outward trade contributes to growth through specialisation and intensification effects, greater economies of scale associated with ability to access larger markets, greater capacity utilisation and rapid technological change emanating from transboundary technology exchange (Ram Rati, 1985; Havrylyshyn, 1990). Trade encourages learning by doing and supports innovation adaptation, leading to productivity growth.

The second postulation is that trade policy can also influence productivity through the foreign exchange market. There are two hypotheses that explore the relationship between the exchange rate and productivity (Odhiambo et al, 2004). First is the 'exchange-rate-sheltering' hypothesis which presupposes that a depreciating real exchange rate reduces growth in domestic productivity since it shelters domestic producers from foreign competition. This reduces their incentives to make productivity enhancing investments. The second hypothesis, the 'factor-cost' hypothesis, states that movements in the real exchange rate affects the absolute and relative cost of new capital and labour, therefore impinging on the productivity levels. Exchange rate depreciation does reduce growth, and an overvalued exchange rate can sometimes contribute to productivity growth by forcing productivity gains in the tradable sector (Porter, 1998). The foregoing analysis thus provides two fronts on which trade policies can influence productivity: first through levels of economic openness, and secondly through the effect of the exchange rate regimes.

It is apparent that in the case of Kenya and Uganda, the opening up of economies led to positive technical change perhaps due to transboundary inflows of technologies and increased opportunities for learning. However, there was no commensurate gain in efficiency that would have been expected to emanate from increased trade outflows, specialisation and intensification thus keeping efficiency change in tandem with the improved technology frontier. One reason for lack of commensurate increase in efficiency gain could be that opening up of economies was accompanied with depreciating of local currencies, reducing the effective demand of new technologies. In addition, with the opening up of economies, many farmers have continued to engage in subsistence agriculture, thus unable to benefit from liberalised markets. The reasons are varied, ranging from structural problems of poor infrastructure (Dorward et al., 2005) to lack of supportive market institutions (World Bank, 2002). Together these factors have led to high transaction costs, coordination failure, and pervasive market imperfections.

In addition, the apparent slow down in efficiency gains can also partly be explained by producer's loss of benefits that accrued from policies that distorted the agricultural sector's factor and product markets in Kenya and Uganda (Collier and Reinikka, 2001; WTO, 2000). Under the controlled trade regime, there were three categories of such policies that protected producers. The first group included policies that restricted market access of imports into the domestic markets. This was achieved through use of instruments like tariffs, non-tariff barriers and quotas. Second, there existed domestic support policies, that included various forms of assistance to domestic producers such as production subsidies and price support which raised the prices of agricultural products while reducing those of inputs. Third, there were direct export subsidies (export compensation). By removing these support schemes, producers might have been exposed to shocks that affected their capacity to use the available newer technologies. Results from the earlier analysis of individual country DEA models intimated that such effect might have been more profound in Uganda than Kenya.

4.2.2.2 Decentralisation of extension services

In Kenya and Uganda like most developing countries, where the majority of the population live in rural areas and agriculture is the main source of livelihood, agricultural research and extension has been considered as one of the key drivers and vital catalyst for rural development (Wanga, 1999). Research and extension has however not performed to expectation. Chambers (1993, p. 67), listed several propositions advanced to explain this failure. In the 1950s and 1960s, the problem was stated to be farmers' ignorance, apathy, inadequate social arrangements and lack of local leadership. In the 1970s, the problem was assumed to be farm level constraints such as lack of credit and poor infrastructure. In the late 1980s, lack of participatory processes was identified as one of the primary causes of ineffective extension services. In the 1990s, the failure was attributed to lack of technologies that fit the needs of the potential adopters. In its more recent guise, it has been attributed to poor governance and lack of suitable policies and institutional innovations to ensure greater efficiency and accountability in the mobilisation, organisation, control and utilisation of resources.

In developing countries, various strategies have been advanced to redress this apparent failure within agricultural research and extension continuum with varying degrees of success (Rivera, 1996; Rivera at al, 1997; Rivera et al, 2002). The main strategy has been through decentralisation of delivery of research and extension services that has been undertaken through three different approaches. The first approach has entailed redesigning the fiscal system, which has enhanced participation of non-state, private and local authorities in financing and managing these services. The second approach has involved the shifting of government responsibility for research and extension through structural reform from central government to sub-government institutions with the notion of improving institutional responsiveness and accountability (Antholt, 1994). The third strategy has been the decentralisation of management of programs through farmer participatory involvement in decision-making and, ultimately taking the responsibility for extension programs.

In Kenya and Uganda, decentralisation has been undertaken through the National Agricultural and Livestock extension Program[31] (NALEP) and Plan for modernisation of Agriculture[32] (PMA) policy initiatives respectively. In both countries, decentralisation was based on partnership concept that entailed deliberate investments and participation of various stakeholders in the agricultural research and extension (i.e., increasing role of non-state service providers). This has led to: (i) making research and extension more "demand driven"

[31] NALEP as a policy framework was designed to bring on board both public and private service providers, as a way of finding means of addressing the complex, systematic issues that faced rural communities. This shift had been agitated by an increasing recognition of the socio-economic and agroecological conditions of resource poor farmers as being complex, diverse and risk prone (Farrington, 1998). There was also the general realisation that the centralised research and extension agencies may not have had the capacity to generate a mix of technologies to the level required by farmers (Thrupp and Altieri, 2001). The Government of Kenya, through the NALEP initiative, has recognised the need to diversify and decentralise the provision of agricultural research and extension services to respond to such challenges. Among other issues, NALEP was built on a partnership concept that entailed deliberate investments and participation of various stakeholders in the agricultural sector. It was designed to offer a move towards participatory approaches that involved farmers directly in setting and fulfilling their own development goals. NALEP also endeavoured to make extension demand driven, offered to increase efficiency in research and extension service provision, putting in place alternative funding apart from the exchequer, promoting gender issues in extension and curbing environmental degradation.

[32] This was implemented under the National Agricultural Advisory Services (NAADS), a component of PMA. The NAADS had five sub-components:

i. Advisory and information services to farmers;
ii. Technology development and linkage with markets;
iii. Quality assurance—regulations and technical auditing;
iv. Private sector institutional development; and,
v. Programme management and monitoring.

The NAADS aimed to develop a demand-driven, client oriented and farmer led agricultural service delivery system particularly targeting the poor and the women (Ministry of Agriculture, Animal Industry and Fisheries 2000.

though increased role of the private sector and to some extent non-governmental and community based organisations; (ii) increased efficiency in service provision leading to general increase in agricultural production; (iii) putting into place alternative funding procedures that have led to increased expenditure on research and extension (increasing role of non-public players); and, (iv) promoting gender issues in research and extension and supporting efforts to curb environmental degradation (Mugunieri and Omiti, 2007). All these changes were exemplified through shifts in resource (human and financial) allocated by various actors (public, private and non-profit) to R&D under the two forms of research and extension services delivery systems (centralised vs decentralised) in Kenya and Uganda as shown in Table 17.

From Table 17, it can be observed that there was a significantly higher level of resources expended on research under a decentralised regime than centralised system, except for non-profit research in Uganda that experienced a decline. For output indicators, significant increase was observed in overall agricultural output (PIN) in both countries. However, for medium research outputs like (journal articles) there was a positive and significant increase in Uganda but not Kenya, perhaps an indication of greater emphasis put in domestic research in Uganda. Information on total registered patents under the decentralised system was not accessible in Uganda for purposes of comparison. It can therefore be concluded that the decentralisation system entailed not only a change in the way of undertaking research and extension activities but also in level of resources expended to achieve this.

It could be because of these changes that this study has shown that the odds that the agricultural sectors in Kenya and Uganda would experience technical progress in a decentralised agricultural extension regime were 127 times more than in a centralised extension regime. These findings confirm the widely accepted notion that decentralisation of extension services predisposes the agricultural sectors of developing nations to increased technology acquisition (Wanga, 1999). Embracing of decentralisation by most developing countries emanated from the realisation that centralised systems had been associated with poor governance and a lack of institutional innovations that would spur greater efficiency and accountability in the mobilisation, organisation and control of resources (Irungu et al., 2006; Amudavi, 2003).

Table 17: Agricultural Science and Technology policy system indicators in Kenya and Uganda under centralised and decentralised research and extension system

AS&T policy indicator (*Means*)	Kenya		Uganda	
	Centralised (n=28)	**Decentralised (n=5)**	**Centralised (n=28)**	**Decentralised (n=5)**
Government agencies research expenditure (million 1993 US$)	13.904* (4.81)	19.10* (2.00)	3.786# (1.20)	7.520# (1.04)
Higher education research expenditure (million 1993 US$)	1.375* (1.26)	4.040* (0.57)	0.461# (0.40)	1.96# (0.40)
Non Profit expenditure (million 1993 US$)	1.661* (0.55)	2.44* (0.11)	0.036# (0.05)	0.00# (0.0)
Business research expenditure (million 1993 US$)	0.379* (0.19)	0.780* (0.04)	0.018# (0.05)	0.133# (0.06)
Government research scientists – full time equivalent (FTE)	524.130 (192.61)	659.170 (34.24)	175.46 (42.19)	194.47 (3.83)
Higher Education research (FTE)	52.893* (44.65)	141.584* (4.28)	17.586# (11.39)	52.131# (3.93)
Non Profit research (FTE) – mostly non-governmental organisations	26.360* (5.32)	38.83* (1.44)	0.38# (0.76)	2.55# (0.07)
Ratio of research expenditure (million 1993 US$) to total FTE	30,333.735 (5,245.95)	31,523.293 (4,265.80)	22,173.71# (4,992.26)	40, 146.26# (7,603.43)
Total registered patents (not restricted to agriculture)$^{\psi}$	61.60 (34.91)	33.50 (0.71)	17.67 (5.85)	-
Total journal research articles	246.07 (39.15)	250.80 (21.63)	19.0# (11.01)	76.0# (11.57)
Agricultural output index (PIN)	64.321* (18.55)	99.220* (5.94)	71.389# (9.27)	100.12# (6.36)

Source ASTI (2006); Faostat (2006).

Notes: Figures in parenthesis are standard deviations.

[*, #]Values with the same superscript are significantly different between groups for individual countries (F-test). [Ψ]N=12 for centralised and 3 for decentralised (for Kenya); N=6 for centralised and missing for decentralised (for Uganda).

Just like economic liberalisation, decentralisation of agricultural extension services appears to have had the immediate effect of slowing down the progress in technical efficiency growth. A critical look at the decentralisation process in Kenya and Uganda reveals some salient underlying features. This process appears to have been relatively successful for major crops where the responsibility of farmer education and dissemination of agricultural information was transferred to various development authorities, boards, cooperatives and factories. This transfer of responsibilities contributed to farmer participation in the running and management of extension programmes and in meeting the cost of the extension services, implying that these services were successfully decentralised and privatised (Mugunieri and Omiti, 2007). By contrast, the low-value or traditional food crops sector, which form a significant part of the agricultural sectors in both countries benefited much less, if at all, from decentralisation (Bekele et al, 2008)[33]. Livestock production within the pastoral and agropastoral areas was another relatively neglected, but significant sector. There appears to have been an apparent lack of inertia to harness the potential of this sub-sector through proper management and education. Last but not least, there is the smallholder dairy sub-sector that contributes 60–80% of Kenya's milk output and owns about 83% of its dairy cattle. Previously reliant on the public sector for extension support, the extension infrastructure these farmers face following the collapse of government support is not well understood. These three important sub-sectors seem not to have benefited from decentralisation, and probably led to decline in overall efficiency gain.

4.2.2.3 Intellectual property rights (IPR)

Intellectual property rights (IPRs) are rights designed to protect innovations and reward innovative activity (US-CIB, 1985). They comprise of a bundle of rights focusing on the physical manifestations of intellectual activity in any field of human endeavour. IPRs are concerned with the expression of an idea for an invention, the details of which have been

[33] Bekele et al (2008) observed the predominance of formal extension system on major staples rather than for marginal dry-land legumes in their study on "Rural market imperfections and the role of institutions in collective action to improve markets for the poor" in a case study of Mbeere and Makueni districts of semi-arid Eastern Kenya. Moreover it is also evident that extension services focuses more on major staples by encouraging crops such as maize to be cultivated in such areas when it is comparatively advantageous to promote drought resistant crops that are well adapted to such harsh environments.

worked out and which takes the form of a product or process that can be applied in a production process. Development process over the past century has given rise to various IPRs that include patents, trade and service marks, copyright, rights in performances, designs, plant breeders' rights, utility models, appellations of origins, layout designs and topography (Sikoyo et al., 2006). In recent times debate on IPRs has given rise to controversy, particularly because of the interface of IPRs with sustainable agriculture or trade or economic development. The intellectual property laws such as those on patents were designed to protect the product of the inventive genius. Intellectual property can therefore be seen to be intricately related to trade, competition, industrial growth and economic development.

This study has shown that the enactment of the intellectual property rights regulation system had a significant but negative influence on technical change but positive impact on efficiency change in the agricultural sectors of Kenya and Uganda. The impact on technical change is contrary to the argument put forward while instituting intellectual property rights in a country that they are likely to spur technological growth, encourage innovation, promote trade and contribute to overall development in a country (Sikoyo et al., 2006). The intellectual property rights regulatory system in Kenya and Uganda comprise of copyright laws, trademarks, patent, and seed and plant varieties protection laws. With the exception of the copyright laws, all the others laws are expected to affect agricultural productivity through their influence on product and factor markets (Davis, 2004). This system of regulations is expected to create incentives to invent and to apply knowledge in production. However, the important policy question particularly for developing countries, is whether this system of laws may work as a tool for enhancing technological innovation, in the same way they do in developed countries due to lack of supportive infrastructure (Sikoyo et al., 2006).

In both countries, the staffing of intellectual property management and implementing organisations has been a major challenge. These countries experience resource constraints in terms of trained personnel to manage the volume and complexity of work envisaged under the new IPR regulatory regime. It is a major hurdle for the organisations to attract and maintain a multi-disciplinary work force with a good grasp of intellectual property issues and how they relate to developmental goals. Another shortcoming is that, historically scientists who have limited understanding of the law have continued to man these organisations. Personnel within these organisations require training to bring them up to date with the latest concepts, issues and technologies in intellectual property regulation and administration, current practices and interpretation of intellectual property laws in line with evolving international regimes and ensuing national obligations. In addition, the training of enforcement officers such as police inspectors, customs and revenue officers is critical for the effective implementation of the IPR laws (Siyoko et al., 2006). These constraints may have impeded realisation of the desired benefits from IPR regulatory system and by extension the movement of the frontier.

One way in which Kenya and Uganda can fast-track benefits from IPR is by taking a pro-active role in fostering close working relationships with regional and international organisations. As a starting point, the East African region boasts of regional and international organisations whose mandates vary but do have IPR implications. Examples include the Consultative Group on International Agricultural Research (CGIAR) comprising of the International Plant Genetic Resources Institute (IPGRI), International Livestock Research Institute (ILRI), and, the World Agroforestry Centre (ICRAF). These organisations have individually and also collectively under the CGIAR formulated intellectual property policies to guide their investment in research. The main thrust of these policies is developing public goods and putting all intellectual properties generated in the public domain, building the capacity of partners e.g., the Genetic Resources Policy Initiative (GRPI) established by IPGRI to strengthen the capacity of national policy makers in southern countries to develop comprehensive genetic resources policy frameworks. Other fora from which intellectual property capacity can be sourced include the United Nations Food and Agriculture Organization (FAO) that is supporting some initiatives in the region with regard to reviewing local phytosanitary laws in order to bring them to conformity with the International Plant Protection Convention (IPPC) and the revision of the seeds and Plant Varieties Acts.

It is generally accepted that a comprehensive system of law, which protects intellectual property rights by providing creators of ideas a safe and conducive atmosphere in which to develop those ideas, is a prerequisite for technological growth. While it is essential to adopt legal and policy measures in regard to IPRs in order to effectively address the existing challenges and emergent problems, Kenya and Uganda need to budget for adequate resources for implementing and training institutions to carry out the relevant administrative and capacity enhancing activities.

4.2.2.4 Agricultural education policies

Competent and well-resourced farmers are key to improved agricultural productivity. Farmers competences are improved by appropriate agricultural education policies that include: (i) policies geared towards enhancing access to basic/primary education as a way of improving literacy levels among farmers; (ii) policies supportive of continuous farmer education programs leading to improved access to information and knowledge; and, (iii) policies aimed at improving human capacity development in agricultural research and extension services. Such policies were envisaged to play a pivotal role in improving technical and efficiency change in the agricultural sectors of Kenya and Uganda.

However, agricultural education policies in Kenya and Uganda have not functioned to the desired expectation due to a number of factors. First, both countries have had no clear and consistent agricultural education policy, particularly with regard to continuous farmer education and human capacity development in research and extension. This has led to scenarios where much time and resources have been committed to poorly focused and ad hoc agricultural training that has more often than not been supply driven. In actual fact, Uganda drafted its first 'National Agricultural Education Strategy' in 2003 targeting the years 2004-2015, whereas Kenya has had none. More often than not, formal and non-formal agricultural education and training has been delivered by many different institutions at various levels of the education system and to different target groups. There has been apparent lack of vertical and horizontal linkages between these providers and an absence of a national institutional framework to facilitate the whole process. The overall picture, therefore, has always been one of a wide range of institutions providing an inconsistent pattern of agricultural education and training, of which it has been difficult to evaluate its impact (Ngugi et al., 2002).

Second, the quality of output from the different levels of agricultural education has been reported to have declined. The main factors contributing to this have been lack of necessary teaching resources (particularly in technical institutes and universities) and insufficient refresher courses for teaching staff (to allow training in new fields that are introduced in the curricula from time to time) (Ngugi et al, 2002). This issue has been explicitly captured in Uganda's National Agricultural Education Strategy by observing that the agricultural education curricula in the country, like in many other developing countries has been of deficient quality and lacked relevance to the needs of contemporary society. There has been lack of emphasis on the commercial aspects of farming and the curricula have failed to develop the skills demanded by the labour market. In addition, the process of curriculum development has not been viewed as a dynamic process with regular reviews; it has failed to address the issue of inappropriate agricultural practices deeply embedded in the local communities; it has failed to involve all stakeholders and there has been inadequate consultation with and orientation of teachers (Uganda, 2003). These issues will need to be addressed in order to enhance effectiveness of agricultural education in the two countries.

Only the universal free basic education that was effected in Uganda in 1997 and in Kenya in 2002 was identified as having achieved the goal of increasing access to education. However, due to the expected lag effect of this policy in enhancing literacy level of the adult population, it was not included in the logistic model. Instead, the literacy level of the adult population was used as an indicator of the outcome of policies that were aimed at improving the education access within the agricultural labour force. The significance of the literacy level depends on whether the technologies in use are complex and knowledge intensive. If the technologies are complex, they may be demanding on farmers since they require more information and skills for successful adoption (Craig et al, 1997). These arguments are in tandem with findings of this study where increased literacy significantly influenced technical progress. Similarly, enhanced literacy had a positive influence on efficiency change but without reaching desirable levels of significance. This implies that improved literacy increases the propensity to acquire new production practices, but does not significantly contribute to the improved efficiency in utilisation of the acquired resources over time.

4.2.2.5 Impact of other policies

The consolidation of agricultural research into distinct research organisations led to progress in technical change but had insignificant effect on efficiency change. Following independence from the British in 1962 and 1963 for Kenya and Uganda respectively, regional research agencies were transferred with minimum disruption to newly established governments. Research continued to be implemented under these regional research organisations until 1977 when the East African community collapsed. Respective governments reorganised all agricultural R&D into a number of semi-autonomous organisations through reforms implemented under the National Council for Science and Technology that was effected in Kenya in 1977 and Uganda in 1992. Following inception of these institutes, they have continued to undergo continuous transformations to enhance efficiency and improve their research results and outreach capabilities, which have partly contributed to their contribution to improvements in technical change. However, the linkages between these organisations and farmers has been minimal (Mugunieri and Omiti, 2007), leading to limited farmer application of their outputs and consequent insignificant relationship to efficiency change.

Interventions outside the AS&T policy system framework that were envisaged to support system's functioning included irrigation, communication (road and telephone) and quality of agricultural labour force (i.e., in terms of health). Increased investment in irrigation and road network significantly contributed to positive changes in both technical and efficiency change, with the effect on technological change being more pronounced. The fact that irrigation provides assurance for water accessibility increases producer's proclivity for investments in new technologies. These results indicate that performance of the AS&T policy system would be enhanced with commensurate policies to shore up development of these supportive sectors.

CHAPTER 5: SUMMARY, CONCLUSIONS AND IMPLICATIONS

Kenya and Uganda are characterised by increasing human population and decreasing agricultural productivity. The decline in productivity has been occasioned by among others, inefficient use of resources, low technology development and use, and limited access to other supportive services. Agricultural intensification has long been regarded as the primary means by which governments could induce agricultural productivity. However, some policy advocates have argued that contrary to Boserup's hypothesis that suggests population pressure is a sufficient condition for inducing productivity growth; governments need to play a pro-active role by implementing suitable productivity enhancing policies (Lele and Stone, 1989).

This study was based on the premise that agricultural science and technology policy is one such tool that governments can utilise to stimulate agricultural productivity growth. This has been exemplified in various international policy proposals (see NEPAD, 2004; UN, 2004), but action has been constrained by limited knowledge on where the scarce resources need to be invested. Specifically, little is known about the structure and performance of this policy system in developing countries. At the onset, a clear-cut definition of AS&T policy is difficult to locate in literature making it hard to make incisive assessments regarding the policy system. To address this gap in knowledge, this study adopted and developed upon a definition of AS&T policy system suggested by Omamo et al (2005) as comprising the structures and processes for setting priorities, specifying agendas, financing, organising, delivering, monitoring, evaluating, and assessing impacts of agricultural research, extension, education, and transboundary technology acquisition and exchange.

An apparent feature of this definition was that AS&T policy system could be divided into four separate functional areas, namely, agricultural research; agricultural extension; agricultural education; and agricultural transboundary technology acquisition and exchange. These were named the policy 'system components'. Within each component were identified three levels of the policy system 'shift effects', namely: the policy environment; the institutional arrangements; and, the ensuing micro-level conditions. This gave a 3x4 matrix of potential determinants of the policy system structure, denoted in this study as the 'system components – shifts effects' framework. This framework was envisaged to exist as either first, second or third generation denoting the level of development of the policy system. This framework was preliminary and this study was aimed at providing empirical evidence to deepen its application in literature. Kenya was taken as a second generation system whereas Uganda was first.

Operationalisation of the framework first required identification of a suitable performance indicator, and secondly, linking the indicator to the framework in order to delineate important determinants of structure. It was realised that there are several indicators and methodological options that can be used to achieve these two steps. At the onset, technical efficiency, technical and efficiency change were identified as suitable indicators of performance. Subsequently, data envelopment analysis was used to derive technical efficiency estimates and a second stage censored Tobit model used to relate technical efficiency to the 'system components – shifts effects' framework. The results of this approach were tested against those obtained from the simultaneous two-step technical inefficiency effects translog stochastic frontier analysis model.

The results indicated that **the three-level 'systems components – shifts effects' framework can be used to delineate the structure of AS&T policy system in developing countries. In addition, the structure of the policy system differed between the first and second generation policy systems**. At policy level and based on DEA results, the level of economic openness was significant and positive in second generation, but negative (though insignificant) in first, a condition that was intuitively attributed to limited private sector implementation capacity to optimise benefits from transboundary technology infusions in first generation policy systems. However, education and research investment expenditures were important structural elements in both generations.

At institutional level, intellectual property rights regulatory systems contributed more to improved performance in second generation systems but was not significant in first. On the other hand, agricultural extension decentralisation was noted to have significant but negative effect in first generation systems, but had no effect in second. Coordination of research had no effect in both policy systems. At micro-level, literacy level was significant in second generation but not in first. Alternatively, domestic research was significant in first generation systems but not second. The same applied to indicators for policies that targeted to reduce transaction costs in accessing technologies (i.e., increased road network). The fact that improved road network had positive effect on performance may be a pointer towards realizing positive effects from economic openness in the long term within the first generation systems.

This study has offered empirical evidence that the three-level 'system components – shifts effects' analytical framework can be used to delineate the structure of AS&T policy system in developing countries. By applying this three-level scheme, the structure of the policy system can be categorised into different generations, depending on the level of development of different elements within the framework. This study therefore makes a significant contribution to the body of knowledge by offering a pioneering and novel approach of evaluating AS&T policy systems in developing countries.

By applying this framework for Kenya and Uganda, the following implications can be drawn

1. The realisation that the AS&T policy systems of developing countries can be categorised as 1st, 2nd and 3rd policy systems implies that generation specific productivity AS&T policies should be formulated and not generic policies for all developing countries.
2. At policy level, for first and second generation policy systems, investments in education and research should be enhanced. However, in order to benefit from economic liberalisation, incentives need to be given to private sector (particularly in 1st generation systems) for them to deepen their capacity to be able to capture benefits derivable from opening up of their economies. Examples of such incentives include grants, subsidies, tax rebates, tax holidays etc for actors (farmers, traders, processors, educationists, etc) to encourage investments in innovation generation and use.
3. Going by the evidence from Kenya and Uganda, institutional arrangement is perhaps the weakest link in AS&T policy systems in developing countries. Changes in institutional arrangements define (and sometimes shift) the comparative costs of actors within the policy system, which in turn influence micro-level performance. However, with the exception of IPR regulatory system in 2nd generation systems, a paradigm shift is needed to re-orient institutions within the 'system components – shifts effects' analytical framework. It is envisaged that such an undertaking would enhance the impact of the policy system at micro-level, a scenario that is currently lacking.

It is acknowledged that lack of data precluded effective application of the three-level scheme in this study, an option that offers further opportunities for research into this area. However, it is anticipated that the findings in this study will inspire debate and perhaps lead to implementation of further studies that will lead to execution of targeted productivity enhancing policies and investments, for increased agricultural output, incomes and food security, and in essence contribute to attainment of MDG 1 of eradicating extreme poverty and hunger.

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APPENDICES

Appendix 1: Chow Test Results

The Chow test is an econometric test of whether the coefficients in two linear regressions on different data are equal. The Chow test is most commonly used in time series analysis to test for the presence of a structural break. The Chow test provides a test of whether the set of linear regression parameters (i.e., the intercepts and slopes) is equal across groups. In this study, the test was undertaken to test for structural break in data sets for Kenya (first generation AS&T policy system) and Uganda (second generation). Two Chow tests were implemented. The first test investigated for existence of a structural break in input data-sets used in deriving performance estimates (technical efficiency, efficiency change and technical change) for Kenya and Uganda. The second test involved examining for existence of a break in data-set for potential determinants of structure of the AS&T policy system between Kenya and Uganda.

This test was undertaken using the SPSS statistical package and was operationalised by: first, building a simple model from the dialog boxes; secondly by pasting the syntax into an SPSS Syntax Editor window; third by making a slight modification to the DESIGN subcommand; and lastly by running the commands from the editor window.

For the first test, the dependent variable was AGRICULTURAL OUTPUT (PIN), a vector of continuous predictor variables (TLU for total livestock units, CAPITAL for tractors in use, FERTILISER for total nutrients used, LAND for total agricultural land and LABOUR for agricultural labour), and a categorical variable named STAGE (for the generation stage of the AS&T policy system 1=second and 0=first). Below are the steps used in conducting the Chow test.

- From the menus, go to Analyze->General Linear Model->Univariate
- In the Univariate dialog box, move PIN into the box labelled Dependent Variable.
- Move the grouping variable STAGE into the box labelled Fixed Factor(s).
- Move the continuous predictors TLU, CAPITAL, FERTILISER, LAND, and LABOUR into the box labelled Covariate(s).
- Now, instead of clicking OK, click PASTE. The contents of the syntax window should appear as follows.

```
UNIANOVA
pin BY stage  WITH tlu capital fertiliser land labour
```

```
/METHOD = SSTYPE(3)
/INTERCEPT = INCLUDE
/CRITERIA = ALPHA(.05)
/DESIGN = tlu capital fertiliser land labour stage  .
```

- In the SPSS Syntax Editor Window, modify the DESIGN subcommand to read as shown below.

```
UNIANOVA
  pin  BY group  WITH tlu capital fertiliser land labour
  /METHOD = SSTYPE(3)
  /INTERCEPT = INCLUDE
  /CRITERIA = ALPHA(.05)
  /DESIGN = tlu stage* tlu. (repeat this for all inputs)
```

- Finally, run the commands by going to the menu in the SPSS Syntax Editor Window and selecting Run->All.

Including the **stage*tlu** interaction--in the absence of a main effect for Group--causes SPSS GLM to pool the Sums of Squares and degrees of freedom from the sources stage and **stage*tlu** when it reports the F-test for **stage*tlu**. Given a model that included stage and **stage*tlu**, the **stage** term would test differences in intercepts and the **stage*tlu** term would test differences in slopes. Pooling these terms into a single **stage*tlu** term means that the F-test and the associated p-value for the **stage*tlu** test is the overall test of whether the full set of regression parameters (i.e., the slopes and intercepts taken together) differ among groups. Hence, the **stage*tlu** effect in this model is the Chow test we are looking for as far as the tlu input is concerned. All other inputs are interpreted in the same manner.

Table A1.1: Chow-test – Does the set of linear regressions for factors of production vary from one generation to another? - Dependent Variable: agricultural output index

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	19687.264(a)	8	2460.908	92.651	0.000
Intercept	0.000	0	.	.	.
FERTILISER	377.274	1	377.274	14.204	0.000
LABOUR	381.786	1	381.786	14.374	0.000
LAND	36.231	1	36.231	1.364	0.248
TLU	159.587	1	159.587	6.008	0.017
CAPITAL	68.158	1	68.158	3.158	0.081
STAGE * FERTILISER	36.204	1	36.204	1.378	0.246
STAGE * LABOUR	0.009	1	.009	0.000	0.986
STAGE * LAND	14.193	1	14.193	0.534	0.468
STAGE * TLU	20.395	1	20.395	0.768	0.385
STAGE * CAPITAL	63.420	1	63.420	1.788	0.166
Error	1513.977	57	26.561		
Total	369797.780	66			
Corrected Total	21201.241	65			

a - $R^2 = 0.929$ (Adjusted $R^2 = 0.919$)

Table A1.2: Chow-test – Does the set of linear regressions for potential determinants of the AS&T policy system structure vary from one generation to another? - Dependent Variable: DEA technical efficiency

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	1.086(a)	12	0.091	24.444	0.000
Intercept	0.000	1	0.000	0.045	0.832
RAIN_MEAN	0.001	1	0.001	0.314	0.578
JOURNAL_ARTCLE	0.001	1	0.001	0.207	0.652
ROAD	0.005	1	0.005	1.239	0.272
TELEPHONE	0.040	1	0.040	10.835	0.002
LITERACY	0.022	1	0.022	5.883	0.020
ECONOMY_OPEN	0.004	1	0.004	1.131	0.294
STAGE * RAINMEAN	5.002E-06	1	5.002E-06	0.001	0.971
STAGE * JOURNAL_ARTCLE	0.001	1	0.001	0.172	0.680
STAGE * ROAD	0.006	1	0.006	1.627	0.209
STAGE * TELEPHONE	0.002	1	0.002	0.634	0.430
STAGE * LITERACY	0.009	1	0.009	2.549	0.118
STAGE * ECONOMY_OPEN	0.000	1	0.000	0.132	0.718
Error	0.159	43	0.004		
Total	28.688	56			
Corrected Total	1.246	55			

a - $R^2 = 0.872$ (Adjusted $R^2 = 0.836$)

Appendix 2: Log likelihood ratio (LLR) tests for determination suitable model for estimation of the metaproduction function

The likelihood ratio, denoted as Λ (the Greek letter lambda), is the ratio of the maximum probability of a result under two different hypotheses. A **likelihood-ratio test** is a statistical test for making a decision between two hypotheses based on the value of this ratio.

Definition

A statistical model is often a parameterised family of probability density functions or probability mass functions $f_\theta(x)$. A null hypothesis is often stated by saying the parameter θ is in a specified subset Θ_0 of the parameter space Θ. The likelihood function is $L(\theta) = L(\theta \mid x) = p(x \mid \theta) = f_\theta(x)$ is a function of the parameter θ with x held fixed at the value that was actually observed, *i.e.*, the data. The **likelihood ratio** is:

$$\Lambda(x) = \frac{\sup\{L(\theta|x) : \theta \in \Theta_0\}}{\sup\{L(\theta|x) : \theta \in \Theta\}}$$

Many common test statistics such as the Z-test, the F-test, Pearson's chi-square test and the G-test can be phrased as log-likelihood ratios or approximations thereof.

Interpretation

Being a function of the data x, the LR is therefore a statistic. The **likelihood-ratio test** rejects the null hypothesis if the value of this statistic is too small, and is justified by the Neyman-Pearson lemma. How small is too small depends on the significance level of the test, *i.e.*, on what probability of Type I error is considered tolerable ("Type I" errors consist of the rejection of a null hypothesis that is true).

The numerator corresponds to the maximum probability of an observed result under the null hypothesis. The denominator corresponds to the maximum probability of an observed result under the alternative hypothesis. Under certain regularity conditions, the numerator of this ratio is less than the denominator. The likelihood ratio under those conditions is between 0 and 1. Lower values of the likelihood ratio mean that the observed result was less likely to occur under the null hypothesis. Higher values mean that the observed result was more likely to occur under the null hypothesis.

Approximation

If the distribution of the likelihood ratio corresponding to a particular null and alternative hypothesis can be explicitly determined then it can directly be used to form decision regions (to accept/reject the null hypothesis). In most cases, however, the exact distribution of the likelihood ratio corresponding to specific hypotheses is very difficult to determine. A convenient result, though, says that as the sample size *n* approaches ∞, the test statistic $-2\log(\Lambda)$ will be asymptotically χ^2 distributed with degrees of freedom equal to the difference in dimensionality of Θ and Θ_0. This means that for a great variety of hypothesis, a practitioner can take the likelihood ratio Λ, algebraically manipulate Λ into $-2\log(\Lambda)$, compare the value of $-2\log(\Lambda)$ given a particular result to the chi squared value corresponding to a desired statistical significance, and create a reasonable decision based on that comparison.

In this study, for the empirical model stated in Equation 3, i.e.:

$$\ln y_{it} = \alpha + \sum_k \beta_k \ln x_{kit} + 0.5 \sum_k \sum_j \beta_{kj} \ln x_{kit} \ln x_{jit} + \sum_k \xi_k \ln x_{kit} t + \zeta_t t + \zeta_{tt} t^2 + u_{it} + v_{it}$$

By stating the null hypothesis that $\beta_{kj_{ij}}=0$, this reduced the model to Cobb Douglas model. This hypothesis was tested using the LLR test, and was rejected in favour of Translog function.

Table A2.1: Likelihood-ratio test of the null hypothesis of the validity of the translog over the Cobb-Douglas model specification

Model	***Null hypothesis***	***Log-likelihood***	χ^2 ***statistic***	***Critical*** $\chi^2_{(df=5),}$ $_{(\alpha=0.99)}$	***Decision***
Translog	H_0: $\beta_{ij}=0$, $i \leq j=1,6$	90.22106 (-2.1518)	1.023	0.554	Reject H_0

Appendix 3: Log likelihood ratio test for determination of the alternative specifications of technical change (neutral technical change vs. non-neutral technical change)

For the empirical model stated in Equation 3:

$$\ln y_{it} = \alpha + \sum_k \beta_k \ln x_{kit} + 0.5 \sum_k \sum_j \beta_{kj} \ln x_{kit} \ln x_{jit} + \sum_k \xi_k \ln x_{kit} t + \zeta_t t + \zeta_{tt} t^2 + u_{it} + v_{it}$$

This log likelihood ratio test was used to test the hypothesis: $\xi_k = 0$, and in essence the model being reduced to a translog frontier production function with neutral technical change.

Table A3.1: Likelihood-ratio test of the null hypothesis of the validity neutral technical change

Model	*Null hypothesis*	*Log-likelihood*	*χ^2 statistic*	*Critical $\chi^2_{(df=6), (\alpha=0.99)}$*	*Decision*
Translog	$\xi_k = 0$	96.6218 (-2.1518)	1.022	0.872	Reject H_0

The null hypothesis that there was neutral technical change was rejected against the alternative hypothesis of non-neutral technical change.

Appendix 4: Testing for Heteroskedasticity in the data

The **Breusch-Pagan test** was used to test for heteroskedasticity. It tests whether the estimated variance of the residuals from a regression are dependent on the values of the independent variables.

Suppose that we estimate the equation:

$$y = x_0 + x_1\beta + u\ .$$

We can then estimate $\hat{u}$, the residual. Ordinary least squares constrains these so that their mean is 0, so we can calculate the variance as the average squared values. Even simpler is to simply regress the squared residuals on the independent variables, which is the Breusch-Pagan test:

$$\hat{u}^2 = x_0 + x_1\beta + v\ .$$

If an F-test confirms that the independent variables are jointly significant then we can reject the hypothesis of no heteroskedasticity.

The Breusch-Pagan test tests for conditional heteroskedasticity. It is a chi-squared test: the test statistic is $n\chi^2$ with k degrees of freedom. If the Breush-Pagan test shows that there is conditional heteroskedasticity, it can be corrected by using the Hansen method, using robust standard errors, log-linearising the variables or re-thinking the regression equation.

The test was undertaken using STATA 8.2 and the results are given in Table A4.1.

Table A4.1: The Breusch-Pagan test tests for conditional heteroskedasticity – Dependent variable Agricultural output index (PIN)

Source	**SS**	**Df**	**MS**	Number of observations = 66 F(5, 60) = 114.66 Prob > F = 0.0000 R-squared = 0.9053 Adj R-squared = 0.8974 Root MSE = 5.786	
Model	19192.5671	5	3838.51342		
Residual	2008.67335	60	33.4778892		
Total	21201.2404	65	326.17293		
Input Variable	**β**	**Std. Error**	**t**	**P>t**	**95% Confidence Interval**	
Capital	0.0063101	0.0015816	3.99	0.000	0.0031464	0.0094739
Fertiliser	0.0001346	0.0000464	2.90	0.005	0.0000419	0.0002273
Labour	0.0108722	0.0012059	9.02	0.000	0.0084601	0.0132842
Land	0.0015973	0.000468	3.41	0.001	0.0006612	0.0025333
TLU	4.07e-07	9.05e-08	4.50	0.000	2.26e-07	5.88e-07
Constant	23.14605	8.153723	2.84	0.006	6.836179	39.45593

Breusch-Pagan / Cook-Weisberg test for Heteroskedasticity

Ho: Constant variance

Variables: Capital Fertiliser Labour Land TLU

χ^2 (5) = 14.09 (Critical χ^2 (5) = 1.15)

Prob > chi2 = 0.0150

Appendix 5: Mann-Whitney U test to decide whether the DEA and SFA estimates differ between first and second generation

The **Mann-Whitney *U*** test (also called the **Mann-Whitney-Wilcoxon** (**MWW**), **Wilcoxon rank-sum test**, or **Wilcoxon-Mann-Whitney** test) is a non-parametric test for assessing whether two samples of observations come from the same distribution. The null hypothesis is that the two samples are drawn from a single population, and therefore that their probability distributions are equal. It requires the two samples to be independent, and the observations to be ordinal or continuous measurements, i.e. one can at least say, of any two observations, which is the greater. In a less general formulation, the Wilcoxon-Mann-Whitney two-sample test may be thought of as testing the null hypothesis that the probability of an observation from one population exceeding an observation from the second population is 0.5. This formulation requires the additional assumption that the distributions of the two populations are identical except for possibly a shift (i.e. $f_1(x) = f_2(x + \delta)$). Another alternative interpretation is that the test assesses whether the Hodges-Lehmann estimate of the difference in central tendency between the two populations is zero. The Hodges-Lehmann estimate for this two-sample problem is the median of all possible differences between an observation in the first sample and an observation in the second sample. It is commonly thought that the MWW test tests for differences in medians but this is not strictly true.

It is one of the best-known non-parametric significance tests. It was proposed initially by Wilcoxon (1945), for equal sample sizes, and extended to arbitrary sample sizes and in other ways by Mann and Whitney (1947). MWW is virtually identical to performing an ordinary parametric two-sample *t* test on the data after ranking over the combined samples

The test involves the calculation of a statistic, usually called *U*, whose distribution under the null hypothesis is known. In the case of small samples, the distribution is tabulated, but for samples above about 20 there is a good approximation using the normal distribution. Some books tabulate statistics equivalent to *U*, such as the sum of ranks in one of the samples.

The *U* test is included in most modern statistical packages. It is also easily calculated by hand, especially for small samples. There are two ways of doing this.

For small samples a direct method is recommended. It is very quick, and gives an insight into the meaning of the *U* statistic.

1. Choose the sample for which the ranks seem to be smaller (The only reason to do this is to make computation easier). Call this "sample 1," and call the other sample "sample 2."
2. Taking each observation in sample 2, count the number of observations in sample 1 that are smaller than it (count a half for any that are equal to it).
3. The total of these counts is *U*.

For larger samples, a formula can be used:

1. Arrange all the observations into a single ranked series. That is, rank all the observations without regard to which sample they are in.
2. Add up the ranks in sample 1. The sum of ranks in sample 2 follows by calculation, since the sum of all the ranks equals $N(N+1)/2$ where N is the total number of observations.
3. "U" is then given by:

$$U_1 = R_1 - \frac{n_1(n_1+1)}{2}$$

where n_1 is the two sample size for sample 1, and R_1 is the sum of the ranks in sample 1.

Note that there is no specification as to which sample is considered sample 1. An equally valid formula for U is:

$$U_2 = R_2 - \frac{n_2(n_2+1)}{2}.$$

The sum of the two values is then given by:

$$U_1 + U_2 = R_1 - \frac{n_1(n_1+1)}{2} + R_2 - \frac{n_2(n_2+1)}{2}$$

Knowing that $R_1+R_2 = N(N+1)/2$ and $N = n_1+n_2$, and doing some algebra, we find that the sum is

$$U_1 + U_2 = n_1 n_2$$

The maximum value of U is the product of the sample sizes for the two samples. In such a case, the "other" U would be 0

For large samples, the normal approximation:

$$z = (U - m_U) / \sigma_U$$

can be used, where z is a standard normal deviate whose significance can be checked in tables of the normal distribution. m_U and σ_U are the mean and standard deviation of U if the null hypothesis is true, and are given by

$$m_U = n_1.n_2 / 2$$

$$\sigma_U = \sqrt{\frac{n_1 n_2 (n_1 + n_2 + 1)}{12}}$$

All the formulae here are made more complicated in the presence of tied ranks, but if the number of these is small (and especially if there are no large tie bands) these can be ignored when doing calculations by hand. The computer statistical packages will use them as a matter of routine.

Note that since $U_1 + U_2 = n_1 n_2$, the mean $n_1 n_2/2$ used in the normal approximation is the mean of the two values of U. Therefore, you can use U and get the same result, the only difference being between a left-tailed test and a right-tailed test.

This test was undertaken between the following set of technical efficiency scores:

(i) DEA_Kenya vs DEA_Uganda

(ii) SFA_Kenya vs SFA Uganda

(iii) DEA_Kenya vs SFA_Kenya

(iv) DEA_Uganda vs SFA_Uganda

Table A5.1: Two-sample Wilcoxon rank-sum (Mann-Whitney) test for DEA technical efficiency estimates for Kenya and Uganda

Country	*Observation*	*Rank sum*	*Expected*
Kenya	33	881	1105.5
Uganda	33	1330	1105.5
Combined	66	2211	2211

Unadjusted variance 6080.25

Adjustment for ties -0.76

Adjusted variance 6079.49

H_o: DEA _Technical Efficiency (Kenya) = DEA _Technical Efficiency (Uganda)

z = -2.879

Prob > z = 0.0040

Table A5.2: Two-sample Wilcoxon rank-sum (Mann-Whitney) test for SFA technical efficiency estimates for Kenya and Uganda

Country	*Observation*	*Rank sum*	*Expected*
Kenya	30	746	840
Uganda	25	794	700
Combined	55	1540	1540

Unadjusted variance 3500.00

Adjustment for ties -15.78

Adjusted variance 3484.22

H_o: SFA _Technical Efficiency (Kenya) = SFA _Technical Efficiency (Uganda)

z = -1.592

Prob > z = 0.1113

Table A5.3: Two-sample Wilcoxon rank-sum (Mann-Whitney) test for SFA and DEA technical efficiency estimates for Kenya

Country	*Observation*	*Rank sum*	*Expected*
Kenya	33	647.5	1056
Uganda	30	1368.5	960
Combined	63	2016	2016

Unadjusted variance 5280.00

Adjustment for ties -1.01

Adjusted variance 5278.99

H_o: SFA _Technical Efficiency (Kenya) = DEA _Technical Efficiency (Kenya)

z = -5.622

Prob > z = 0.0000

Table A5.4: Two-sample Wilcoxon rank-sum (Mann-Whitney) test for SFA and DEA technical efficiency estimates for Uganda

Country	*Observation*	*Rank sum*	*Expected*
Kenya	33	659	973.5
Uganda	25	1052	737.5
Combined	58	1711	1711

Unadjusted variance 4056.25

Adjustment for ties -5.12

Adjusted variance 4051.13

H_o: SFA _Technical Efficiency (Uganda) = DEA _Technical Efficiency (Uganda)

z = -4.941

Prob > z = 0.0000