PHD DISSERTATION

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MICROECONOMETRIC MODELS OF THE LIVESTOCK SECTOR: A FARM-LEVEL ANALYSIS OF SOUTHERN RANGELANDS OF KENYA

PhD Dissertation

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DECLARATION

Candidate's declaration

I hereby declare that the content of this PhD thesis is my original research work and have not been presented elsewhere for any other award. There is no collaborative or jointly owned work in this thesis, whether published or not. The other books, articles and websites appendices, which I have made use of are acknowledged at the respective place in the text.

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Supervisors' declaration

This is to certify that the work incorporated in the thesis was carried out by the candidate under my guidance. Such materials as has been obtained from other sources have been duly acknowledged in the thesis.

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LIST OF PUBLICATIONS

The thesis is based on the following articles:

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ABSTRACT

Even though the livestock sector plays a crucial role in the Kenyan agricultural economy, livestock production and productivity has been declining over the last decades. Production and productivity can be boosted through the increase in efficiency of producer or improvement of technology, or by improving the marketing strategies and/or institutions, given the differentiation by production or farming system in the livestock sector. This thesis concerns on livestock farm-level production efficiency and marketing analysis (especially on products supply and factor input demand responsiveness and market participation behaviour) since they are an essential issue in the evaluation of economic viability and policy implication. The assessment of livestock farm-level performance requires the use of an adequate methodological approach to determine sound efficiency estimates, output products supply and factor input demand elasticities and market participation parameters. By targeting the pastoral and agro-pastoral smallholder livestock communities not previously investigated and using a new methodological approach, this thesis contributes to the literature both from a methodological and empirical point of view.

Three specific objectives have been pursued and constitute the main body of the present thesis. The first objective focus on the investigation of production efficiency of smallholder farm households leaving in the southern rangelands of Kenya while considering farm uses different technological scope. Its novelty is to address unobserved farm-heterogeneity in farm-level datasets and the necessity to take this heterogeneity into account to obtain unbiased measures of technical efficiency in a parametric stochastic frontier framework. The results are compared with a model which assumes that the technology is common to all farmers. Test statistics confirm that unless livestock farmers' heterogeneity is adequately considered, estimating a homogeneous stochastic frontier will lead to misleading implication about inefficiency policy recommendations.

The second objective concern investigation of livestock products supply and factor demand responsiveness for the smallholder pastoral livestock farmer leaving in the southern rangelands of Kenya. A system of livestock products supplies and factor input demand equations were derived from the normalized flexible-Translog profit function that permits the application of dual theory using farm-level household data. The results indicate that own-price elasticities were indifferent (elastic for cattle, while goat and

sheep were inelastic). Cross-price and scale elasticities were found to be within inelastic range in all cases. All factor inputs demand elasticities were inelastic.

The last objective focuses on the investigation of market participation and intensity of participation for the smallholder pastoral livestock farmer leaving in the southern rangelands of Kenya. Specifically, we used a sequential double-hurdle approach that was developed by Cragg (1971) and extend it to a consideration of transaction cost environment under which livestock production takes place, as applied by Alene et al. (2008) using farm-level household data. Results support the hypothesis that transactions costs rank among the main determinants of livestock market participation.

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LIST OF ABBREVIATIONS

ABA	Asset-Based Approach
AC	Average Cost
ACZ	Agro-climatic Zones
ADA	Agricultural Development Approach
AI	Artificial Insemination
AIC	Akaike's Information criterion
AR	Average Revenue
ASALs	Arid and Semi-Arid Lands
ASDSP	Agricultural Sector Development Support Program
CDF	Cumulative Distribution Function
DEA	Data Environment Approach
DFA	Distribution-Free Approach
DH	Double Hurdle
DMU	Decision Making Units
DSF	Percentage Distribution of Selected Farmers
EU	European Union
FDH	Free Disposal Hull
GDP	Gross Domestic Product
GIS	Global Position System
IGAD	Inter-Governmental Authority on Development
IID	Independent and Identically Distributed
KALRO	Kenya Agricultural and Livestock research Organization
KES	Kenya Shillings
KNBS	Kenya National Bureau of Statistic
LCM	Latent Class Models
LCSF	Latent Class Stochastic Frontier

LCSFA	Latent Class Stochastic Frontier Approach
LF	Likelihood Function
MC	Marginal Cost
MLE	Maximum Likelihood Estimation
MR	Marginal Revenue
MT	Metric Tonnes
NHSA	Number of Household Selected for Analysis
NIE	New-Institutional Economics
OLS	Ordinary Least Square
PPS	Probability proportional of Size
RTS	Return to Scale
SFA	Stochastic Frontier Approach
SSA	Sub-Saharan Africa
Std Dev.	Standard Deviation
TCA	Transaction Cost Approach
TE	Technical Efficiency
TFA	Thick Frontier Approach
TLU	Tropical Livestock Units
USA	United State of America

CHAPTER ONE

BACKGROUND OF THE STUDY

In this section, the context of the study is set by discussing the motive behind this study that includes the actuality and justification of the research topic - in short, the research problem. Furthermore, the specification of the research topic, objectives, conceptual framework and hypothesis of the study are presented, and the section concludes with a summary of the thesis structure.

1.1. Actuality and Justification of the Research Topic (Research Problem)

The livestock sector globally is highly dynamic. While many livestock production systems in developed countries are increasing their efficiency and environmental sustainability, demand for livestock products is growing only slowly or stagnating, although at high levels (Thornton 2010). In contrast, in developing countries, livestock production is evolving in response to rapidly increasing demand for livestock products. However, the production and consumption gap for the significant livestock products has been widening across the of sub-Saharan Africa – SSA (Otte–Chilonda 2002). This global mismatch between production and consumption of livestock products presents a significant opportunity for the expansion of livestock production, particularly in any of SSA country where the most demand is met by local production while moderating its impact on the environment.

Sub-Saharan Africa countries present the fastest growing human populations growth rate of 2.6% per annum in the world, yet they also have the world's lowest per capita consumption levels for livestock products[1] (Otte–Chilonda 2002). This situation is aggravated in that growth in the production of livestock products in SSA countries is not keeping pace with the growth in human population, resulting in declining per capita production in the case of beef (-2.2%), milk (-1.5%), sheep meat (-0.9%) and goat meat (-0.4%) per annum (Appendix 1). In Kenya, as is elsewhere in SSA countries, one of the significant challenges over the last few decades has been to maintain the increase in livestock production needed to satisfy rapidly increasing demand for meat requirements and the export needs of the country (Vivien 2004, Behnke–Muthami 2011) while attempting to make land available to more farmers through subdivision of the old settler

[1] Per capita consumption was estimated at 11.0 kg of meat and 27.2 kg of milk (compared with the developing world average of 26.4 kg for meat and 48.6 kg for milk), which are approximately one seventh and one quarter of those in the developed world (Otte–Chilonda 2002).

farms (GoK 2009). In the context of effective demand, the country is currently not self-sufficient in most of the animal products. The insufficient demand is verified by the tremendous increase in the annual deficit of the major livestock products, beef and mutton, of about 38,323 MT and 12,879 MT, respectively, in 2005 to 49,835 MT and 18,885 MT, respectively, in 2014 (GoK 2011)[2]. In the same spirit, Kenya has also not been able to supply its quota of 142 MT annually of beef awarded by European Union under the Lome and Cotonou Agreements and the European Beef and Veal Protocol since the year 2000. Thus, there is an urgent need to find ways to increase livestock productivity and output, so that it not only keeps pace with the rising population[3] but also creates surpluses for market disposal.

While the expansion of the livestock population can contribute to the necessary increase in output, increases in animal productivity are also necessary. Opportunities for substantial livestock production progress exist: in the efficiency in the use of resources at farmers' disposal, livestock marketing strategies, better animal management practices, institutional infrastructure, and focusing on smallholder pastoral farmers since livestock is estimated to be present on more than 75% of the smallholdings in Kenya (Edwards–Jones 2006, Salami et al. 2010) – pastoralists dominate with 80%, accounting for over 67% of meat supplies (KEPZA 2005). This study concerns on production efficiency and marketing since they are an essential issue in economics. For these reasons, first, it is paramount to measure and understand the causes underlying efficiency in the use of resources at pastoral farm level because a measure of producer's performance is often useful for policy purposes (Kolawole et al. 2006, Delgado et al. 2008, Nganga et al. 2010, Otieno et al. 2014). In productive efficiency measurements, we are familiar with three types of efficiency: technical, allocative and economic efficiency.[4] In this study, we consider technical efficiency (TE) because it is one of the crucial interventions proposed by modern economic theorists that could enhance producer productivity by ensuring TE

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[2] This demand was expected to grow at the same rate with the human population, which is 3.2 percent (GoK 2010).

[3] Recent statistics shows the population of the country will reach about 96 million by 2050, an increase from 46 million todays; 41 million people will live in urban areas compared with 12 million todays, and they are expected to consume more high-value food products, particularly animal-sourced foods, such as meat, milk and eggs (UN-DESA 2017). The consumption is approximated as 15-16 kg of red meat (meat and offal from cattle, sheep, goats and camels) per capita annually (Behnke et al. 2011) and based on the current population, red-meat demand is approximated to be 600,000 MT (GoK 2010).

[4] TE reflects the effectiveness with which a given set of inputs are used to produce output, while allocative efficiency reflects how different resource inputs are combined to produce a mix of different outputs, given their respective prices. Economic efficiency comprises both and refers to producing the 'right' amount of allocative efficiency in the 'right' way of TE.

of the factors of production that are at the producers' disposal (Farrell 1957). Additionally, data limitation necessitated this thesis focuses on estimating technical efficiency other than the other two.

So, what is farms' TE, and how can it be measured? Various options are suggested in the literature, but of particular importance is Lovell's (1993) definition of efficiency of a production unit in terms of *a comparison between observed and optimal values of its output and input*[5]. The comparison can take the form of the ratio of observed to optimal potential output obtainable from the given input or the ratio of minimum potential to observed input required to produce the given output. In these two comparisons, the optimum can be defined in terms of production possibilities. Much of the empirical evidence suggests that although producers may indeed attempt to optimize, from the theoretical point of view, they do not always succeed to maximize their production functions and fall short of the optimal level boundary (Simon 1957). In light of the evident failure of at least some producers to maximize, it is desirable to recast the analysis of production away from the traditional production function approach toward a frontier-based approach.

Beyond the TE measurement, the other aspect of ensuring livestock productivity is enhancing markets and improved market access. Despite the well-known potential benefits of engaging in markets, very low levels of market participation are observed among household farmers throughout most of SSA (Coulter–Onumah 2002, Poulton et al. 2006, Barrett 2008). However, despite a low level of markets participation, there is overwhelming evidence that practically all rural farmers depend on trading for some household needs and hence seek income-generating activities (Siziba et al. 2013). This increased dependence on markets puts a premium on understanding household market participation behaviour as the foundation for development strategies. The increased market dependency also justifies the need for livestock product and factor markets and marketing analyses as it represents an essential guide for the formulation of sectoral and microeconomic policies that aim to improve the welfare of agricultural households. This is because market-based development strategies may fail to facilitate wealth creation and

[5] TE is also defined by Galanopoulos et al. (2006) as *a measure of the ability of a firm or a decision making unit to produce maximum output from a given level of inputs and technology (output-oriented) or achieve a certain output threshold using a minimum quantity of inputs under a given technology (input-oriented).*

poverty reduction if many households do not participate actively in markets or do not respond to market signals.

So, what would motivate smallholder agricultural pastoral households to produce and participate in the livestock markets efficiently? Indeed, this provides an empirical basis for identifying farm-level factors that influence production and market participation. Such analysis would offer information for policy alternatives that could promote and enhance better commercial-orientation, and thus lead to improved rural household incomes. Most of the available literature on agricultural household production and marketing behaviour is on crop industry for high potential agricultural areas (e.g. Obare 2003, Omamo 2007, Nyagaka et al. 2010), while those addressing livestock industry are limited (e.g. Kavoi et al. 2010 in dairy, Otieno et al. 2014 in beef cattle). Additionally, a shared limitation among the researches mentioned above is that they assumed homogeneous production technologies overlooking the possible presence of heterogeneous, particularly in the production decision process. In Kenya, as is elsewhere in SSA, livestock is reared in different production systems, which face varying constraints, possess different potentials for growth and have different resource endowments. In other part of the world, many case studies have shown resource and production conditions in livestock producing societies to be highly heterogeneous (e.g. Alvarez et al. 2012, Sauer–Morrison 2013) and the use of a single characteristic to cluster sample, as was the case with study by Otieno et al. (2014), might be challenging when heterogeneity is likely to arise from more than one factor, leading to incomplete division of the sample. Therefore, differentiation by production or farming system is a powerful tool for communicating conclusions to policymakers in SSA livestock studies.

Under the maintained hypothesis that production and marketing behaviour is driven by a household's objective of maximizing profit it enjoys, one can usefully focus attention on the choice problem that relates optimal levels to household attributes and other environmental factors that condition production and market behaviour while accounting for unobserved farms heterogeneity. The recognition that agricultural pastoral farm households typically face natural, market and social uncertainties that influence their decision behaviour, then optimal (rational) level became unattainable, and therefore they are forced to 'satisfice' (Simon 1957). For this reason, structural micro-econometric models are applied, since they explicitly model the behaviour of individual farmers and are capable of accounting for deviation from the optimal outcome. Thus, the contribution of this study is threefold: first, to develop micro-econometric models of the critical structural relationships, which will provide insight into the key factors that influences the following endogenous variables: production, product supply and factor demand and market participation for cattle, sheep and goat component for the smallholder pastoral farmer leaving in the southern rangelands of Kenya; second, to estimate the parameters and obtain impact multiplier, technical inefficiency and elasticities; and three, deduce their policy implication. The results of this study provide some guidance for livestock sectoral policy development not only in the Kenyan economy but also in other SSA countries considering that the study takes the premise that livestock is kept in a different livestock production system with different potential for expansion.

1.2. Purpose of the Research

The study focuses on two main research topics namely 1) the livestock production behaviour, and 2) the livestock marketing behaviour in products supply and factors demand and market participation specifically for the smallholder pastoral farm household. The two topics are assumed to be independent but sequential, and this assists in developing a more comprehensive model conforming to current multivariate economic behaviour in the context of ongoing drastic change in the social-cultural, religion, economic, political and environment condition under which livestock sector in Kenya is being undertaken. The overall goal is to determine the key factors that contribute to decision making of smallholder pastoral farmer in production, supply and factor input demand and market participation behaviour for the beef cattle, sheep and goat meat component of the livestock sector. The specific objectives are:

1. To develop micro-econometric models of the critical structural relationships, which will provide insight into the factors that influences the following endogenous variables:
   1.1. Production efficiency of smallholder farm households leaving in the southern rangelands of Kenya while considering farm uses different technological scope.
   1.2. Supply and factor demand responsiveness of livestock products for the smallholder pastoral livestock farmer leaving in the southern rangelands of Kenya; and
   1.3. Market participation and intensity of participation for the smallholder pastoral livestock farmer leaving in the southern rangelands of Kenya.
2. To use the model in making recommendations to support policy formation associated with estimated parameters.

To address the above objectives, key research questions considered for this study fall along with categories of exploring the livestock production, output supply and input demand, and market participation in southern rangeland of Kenya. Aligned with this context, the research questions posed for this assessment are the following:

1. Can livestock farmers in southern rangelands of Kenya increase livestock production substantially by an efficient allocation of agricultural factors of production presently at their disposal?

Here, we not only intend to identify whether the factors of production currently at the farm-household level are efficiently utilized in livestock production, but also how far from the optimal levels are the smallholder pastoral farmers' operation, and what causes the deviation.

2. How does the law of supply and demand affect the output and factor input market?

In this research question, we intend to determine the factors substantially influences smallholder pastoral and agro-pastoral farms' household livestock products supply and input factor demand responsiveness.

3. What is the extent of participation in livestock markets by the smallholder's pastoral livestock farmers? For ones that do, what are the key factors that would greatly promote the decision of the farmers to participate in livestock marketing, and are the factors the same?

In this research question, our aim is to investigate the degree of smallholder livestock market participation and the key factors that would greatly influence the two decisions – probability and the level of participating in livestock marketing by the pastoral farmers.

1.3. Justification of the Study

The rationale for selecting the micro-econometric models as a tool for analysing the farm-specific smallholder pastoral farming behaviours is because they explicitly model the behaviour of individual smallholders' farmers. Micro-econometric models are the set of behavioural relationships that are based on microeconomic theory and estimated on farm-level data using econometric techniques (Cameron–Trivedi 2005). In the economics literature, micro-econometric models have been developed for explaining input demand and output supply behaviour (profit functions) in combination with explaining household decisions (household models), income risk (risk models) and investments in fixed assets (investment models. For this study, in order to understand the underlying causes of the production and marketing fluctuation and uncertainty, a micro-econometric analysis comprising of three hurdles that includes, first, the household production decision model, second, the product supply and factor demand decision model, and third market participation decision model was adopted and fitted to cross-sectional data analysis (objective 1).

The perceptions of the behaviour of smallholders have implications in the development of interventions and policy prescriptions as they are based on their predicted responses or lack thereof. A thorough understanding of smallholder farmers' production and marketing behaviour is, therefore, a prerequisite. Micro-econometric models are often used in such analysis of economic issues that affect the agricultural industries because of their rigour in modelling the behavioural nature of the relationships between the significant economic variables in the industries of interest. And since smallholders' pastoral farmers are also interested in the impact of changes in explanatory variables such as on their production, marketing and market participation, the coefficients of elasticity need to be estimated in order to determine the effect of changes in the explanatory variable on the quantity produced and marketed (objective 1).

Lastly, the study also seeks to provide participants and policymakers with the tools which will enable them to deal with variations in exogenous variables and the quantity produced and marketed. With adequate information, producers may be able to revise their expectations, and this could enhance the economic benefits that accrue to both producers and society in general. Since fluctuations quantities produced and marketed are also caused by exogenous variables, such as the supply of livestock inputs, it is essential to determine the policy implication of the significant exogenous variables on livestock production and market participation. Estimated elasticities and production, inefficiency and market participation parameters could provide policy insights; thus, enabling policymakers to better evaluate the effects of proposed policies (objective 2) and their implications on the livestock production and markets. Such insights are essential in formulating policies directed toward stabilizing producer incomes.

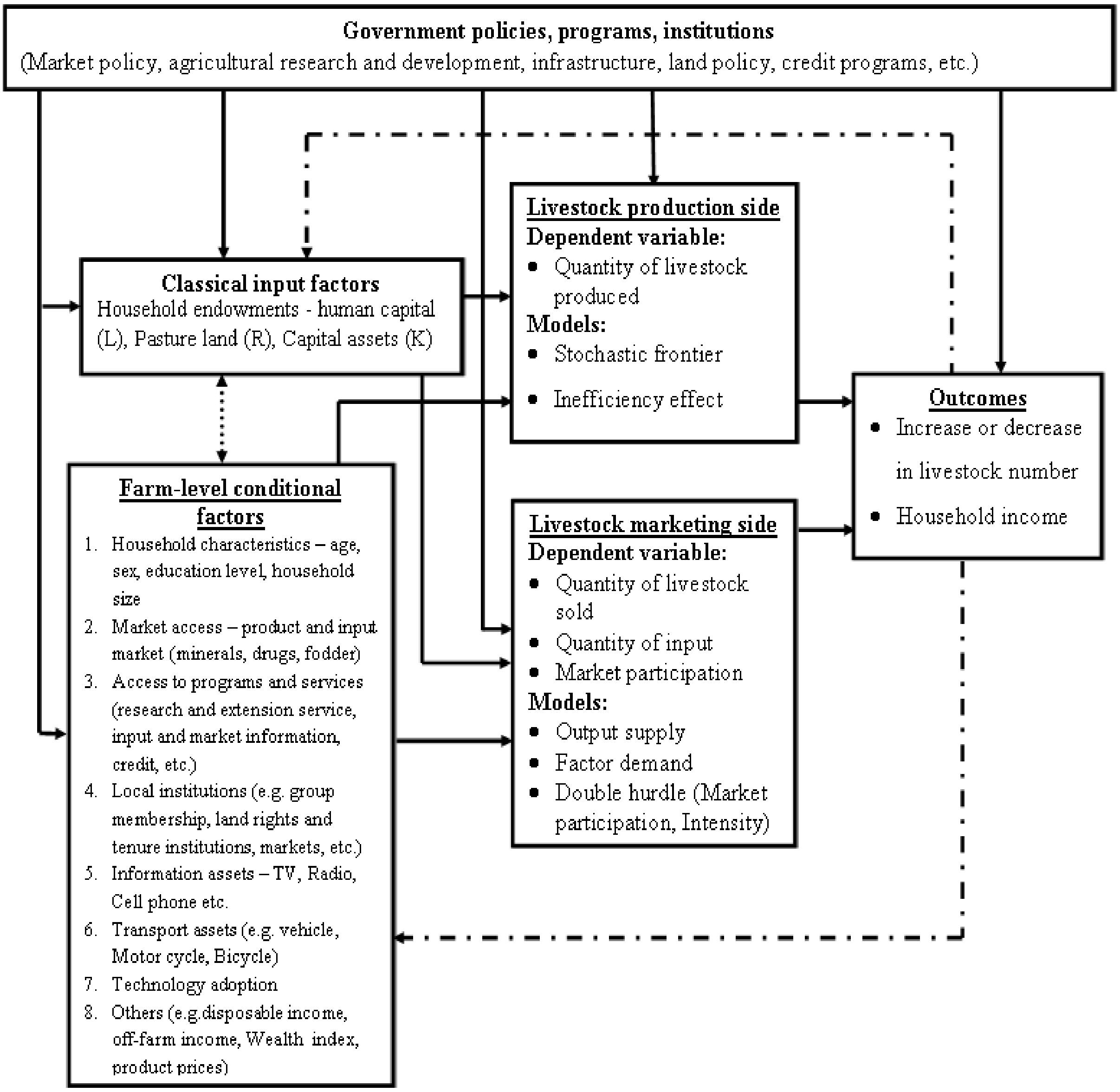
1.3. Conceptual Framework and Hypotheses

To address the above objectives and the research issues identified, a conceptual framework was developed (Figure 1) that served as a guide for developing hypotheses for testing during the various research activities undertaken. The arrows show the direction of the influence, while the bold and dotted lines show the strength[6] of the relationship. The conceptual framework considers the effects of farm-level conditional and classical factors. The conditional factors can be thought to include two types of factors: dynamic driving forces of change, such as changes in access to technology, markets, infrastructure, prices and information assets and more slowly changing conditioning factors such as local institutions and household characteristics. These farm-level conditional and dynamic factors are thought to contribute to production inefficiency and on the market side, influence smallholder pastoral farms market participation behaviour and through the accessibility to products and input market. The classical factors include physical human capital (mostly presented as labour), capital assets and pastureland sizes; these factors are thought to influence the outcome through the various production technologies available at the farm levels.

The conceptual framework also consider the influence of government policies, programs and institutions, which may influence livestock production and marketing (product supply and market participation) and outcomes (livestock numbers and household income) in many ways at different levels which are, (1)by affecting the driving forces (or classical factors) in livestock production and conditioning factors at the farm-level, or (2) by directly promoting or inhibiting different livestock production and marketing (supply and market participation) or (3) by directly affecting outcomes (e.g., through credits). The outcomes not only are essential for people at present (either for cultural purpose such as payment of dowry, gifts etc. or store of value) but also affect households' endowments (accumulation or improvement of classical factors) and enhanced opportunities in the future (indicated by the arrow from outcomes to the factors affecting production and marketing). For example, increases in livestock number and income can facilitate increase in investment in different types of capital, whether physical (e.g., purchase of livestock or equipment), financial (e.g., monetary savings) or human capital (e.g., investments in education) or improvements in land quality that represent an investment in natural capital through pasture improvement.

[6] Bold indicate strong relationship and dotted represent weak relationship

Figure 1:Conceptual Framework - Factors Affecting Livestock Production, Product Supply and Market Participation, and their Implications



Source: Author's own construction.

This study is a logical deductive process in which the conclusions are based on the concordance of multiple hypotheses that are generally assumed to be true. The conceptual frameworks for this research on the micro-econometric analysis of livestock sector presented in the previous section draw from theories of farm household and marketing behaviour in agriculture and try to explain the decisions making processes in terms of changing microeconomic incentives facing farmers as a result of changing relative factor endowments. Based on this conceptual framework, the classical theory that can be deduced from the neoclassical point of view is that the smallholder pastoral farmers are rational and therefore aims at maximizing profits. However, while using ‘bounded rationality’ (to be discussed in details in the next chapter), it can be theorized that smallholder pastoral farmers try to make decisions that are good enough and that represent reasonable or acceptable outcomes – referred to as ‘satisfice’ behaviour, which may be influenced by external shock or economic adversaries, such as changes in government policies. The general null hypotheses that are addressed by this study can be grouped into three as follows:

Group 1: On the Production model

The livestock production sector in Kenya is very heterogeneous with a diverse range of production systems operated on farms. Therefore, livestock production analysis should consider that households operate in different production systems, which cannot necessarily be assessed under the same production technology. Given that past studies in Kenya concentrates on the analysis of agricultural products using the common practice of estimating production functions under the assumption that the underlying technology is homogenous for all farms, estimating a single technology for all farms is not appropriate, because it may yield biased estimates of technological characteristics such as efficiency, and the effects might inappropriately be branded as inefficiency. In these regards, we hypothesize that:

H_1: The size and access to agricultural factors of production (land, labour and livestock production supplies) positively influence livestock production of the smallholder pastoral farming, and their impact is not homogenous in the farmer population.

H_2: Human related attributes (e.g. gender, age, education level), access to socioeconomics factors (e.g. land ownership, off-farm income etc.), service providers (extension, agricultural institution etc.), market factors (e.g. input markets, market information etc.) and financial institutions (e.g. credit facilities etc.) influence efficiency in the livestock production for smallholder pastoral farmers.

Group 2: On the supply and factor demand model

The issue of supply and factor demands response is ultimately an empirical question. In most cases, the use of some assumptions about the way in which expectations and the relationship between actual responses and intentions are formed. In some cases, it is necessary to use actual outcomes rather than intentions to represent supply or factor input demand response because intentions data are collected for relatively few agricultural products. Another primary concern with the past research was that the concept of supply response concentrates on the output-price relationship. However, the effect of input prices on output and demand for inputs has not been taken into account by these previous studies. It is also worth noting that many previous studies estimate agricultural supply response by aggregating many agricultural variables and, although these studies have provided insights into the degree of responsiveness, aggregation studies have been criticized for obscuring the behaviour of individual input variables. In this study, we hypothesize that:

H_3: The supply of livestock products is not affected by price and non-price input incentives (e.g. such as the size of pastureland, income and labour inventory).

H_4: Factor demand for livestock production is not affected by price factors and non-price input incentives (e.g. such as the size of pastureland, income and labour inventory).

Group 3: For Market participation model

What motivates some households to produce and participate in the livestock markets while others not? The answer to this question provides an empirical basis for identifying farm-level factors that influence or enhance market participation; this may offer information for policy alternatives that could promote and enhance better market orientation, and thus lead to improved rural household incomes. To do so and using the underlying theoretical background of transaction cost approach (TCA) in new-institution economics (NIE), our general theory was that household pastoral farmers always tend to avoid participation in the market if transaction costs are high. In order to enhance productivity, a mechanism to reduce market participation costs is prerequisites, and our hypotheses were:

H_5: Socioeconomic (e.g. household characteristics such as age, gender, education level, ownership of the mobile phone, radio, television, vehicle etc.; endowments factors such as farm size and livestock numbers etc.) factors have promoted market participation of the smallholder pastoral farmers.

H_6: Institutions (such as financial, markets, farmer groups, extension service providers) have promoted market participation of the smallholder pastoral farmers.

H_7: Factors affecting livestock farmers' decision to participate in the market are not different from those affecting the extent of participation.

1.4. Thesis structure

This thesis is organized into six chapters. The introduction chapter has laid out the research issues and rationale for the study. Chapter two discuss the status of the livestock industry that includes the economic importance of the livestock industry in Kenyan, the geographical distribution, and the livestock production system spotlight. Chapter three, four and five are organized in topical form and discuss the relevant theoretical framework and econometric models for (1) analysing smallholder pastoral farm households livestock production and marketing behaviour as well as (2) parts of the enormous literature in the field of productivity and efficiency analysis, product supply and factor input demand responsiveness, and market participation, (3) the specific research methodologies applied in the study and (4) conclude with the presentation and discussion of the results on the key factors that influence livestock production, product and factor market and market participation behaviours. Finally, some important conclusions, policy implication and suggestions for future research are offered in chapter six.

CHAPTER TWO

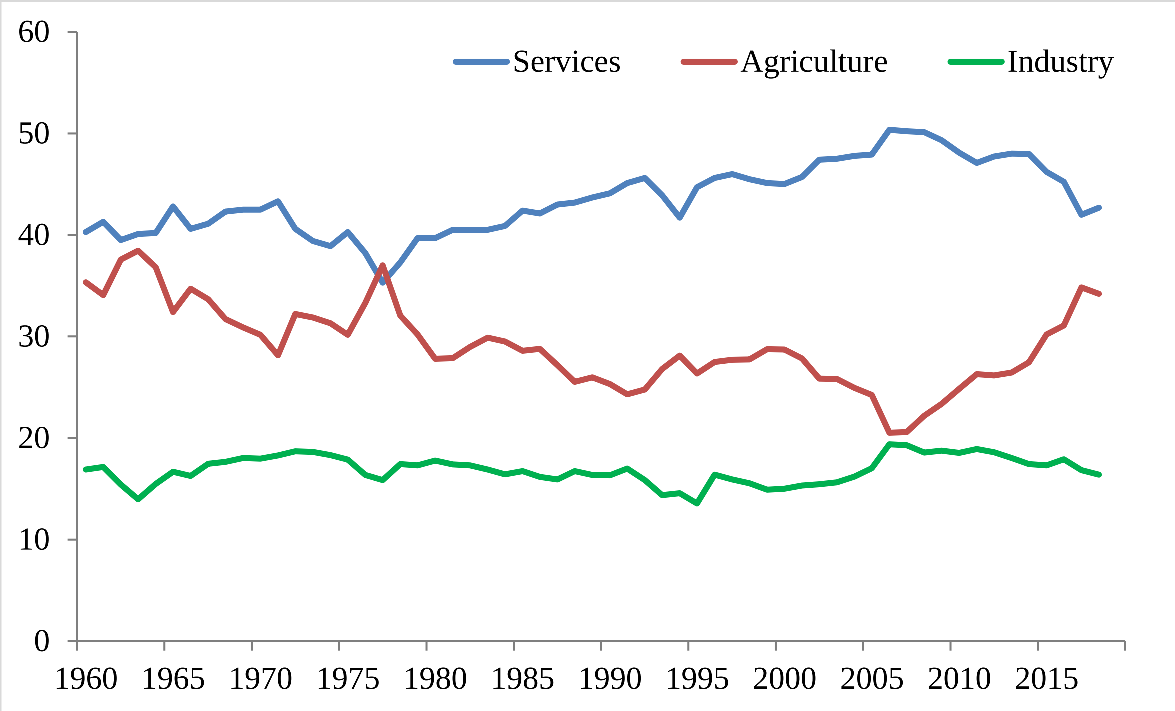
THE KENYAN LIVESTOCK INDUSTRY

The following chapter outlines the major characteristics of the livestock sector within the Kenyan agricultural economy. First, the economic importance of the livestock sector is outlined. The second sections include a description of the geographic distribution of livestock which is followed by its livestock production systems. A summary section is presented at the end of the chapter.

2.1. Economic Importance of the Livestock Industry in Kenya

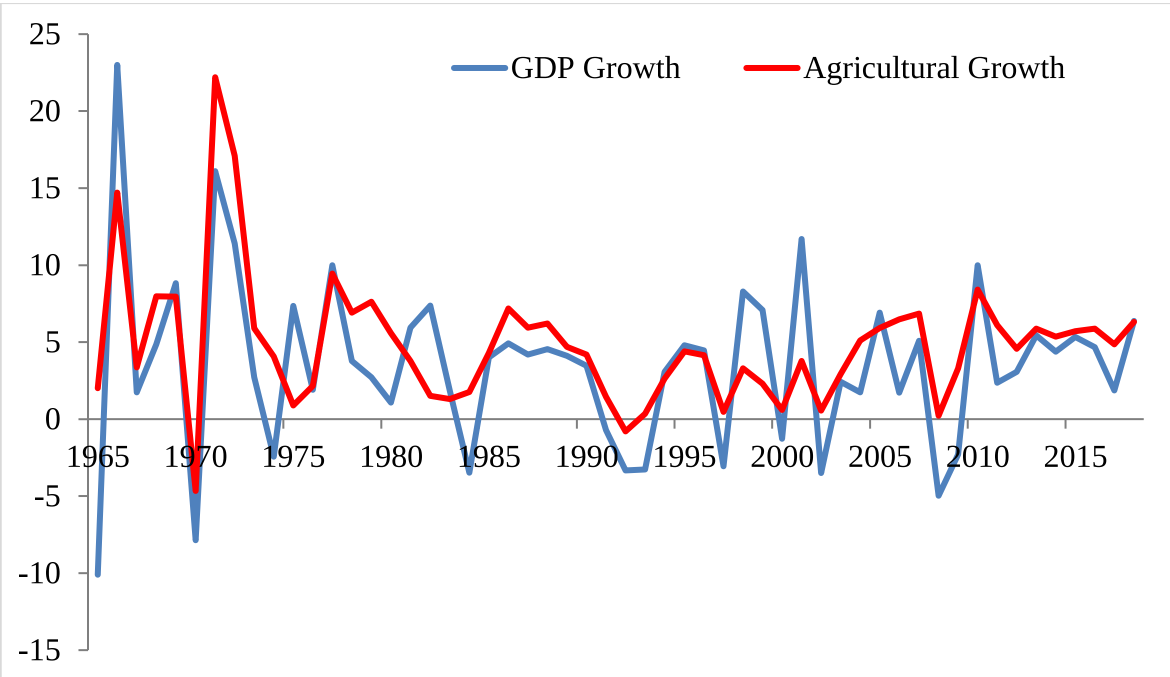
The importance of the livestock sector in the Kenyan economy is reflected in the relationship between its performance and that of the critical indicators like gross domestic products (GDP) and employment. Since livestock sector forms part of the vital activity of the Kenyan economy, the sector interacts with other sectors of the economy such as crop agriculture, service, manufacturer etc. There is, therefore, needs to situate livestock in the context of the overall economy and in particular to agriculture. Based on the relative contribution of different sectors to Kenya's national GDP (Figure 2), services sector (that cover government activities, communications, transportation, finance, and all other private economic activities that do not produce material goods) is the largest and has been growing by 19.98% annually since independence. Agriculture (crops, livestock and fisheries) is the second-largest sector but has been declining steadily at -21.41% per annum while industry sector is the least, growing sluggishly at 1.43% per annum (GoK 2010). Regarding the growth trend in the share of agricultural contribution to Kenya's GDP, the statistics show the two are highly correlated (Figure 3). This means that agriculture remains vital to Kenya's economic growth. However, over the years, there has been cyclical up- and down-swing in the GDP and agricultural GDP growth trend up to 2017, but the GDP seems to be rebounding, which can partially be supported by a strong rebound in agricultural output (Figure 3).

Figure 2: Percentage Share of Economic Sectors to National GDP (1960-2018)



Source: Author's own construction from the world bank (2016) dataset

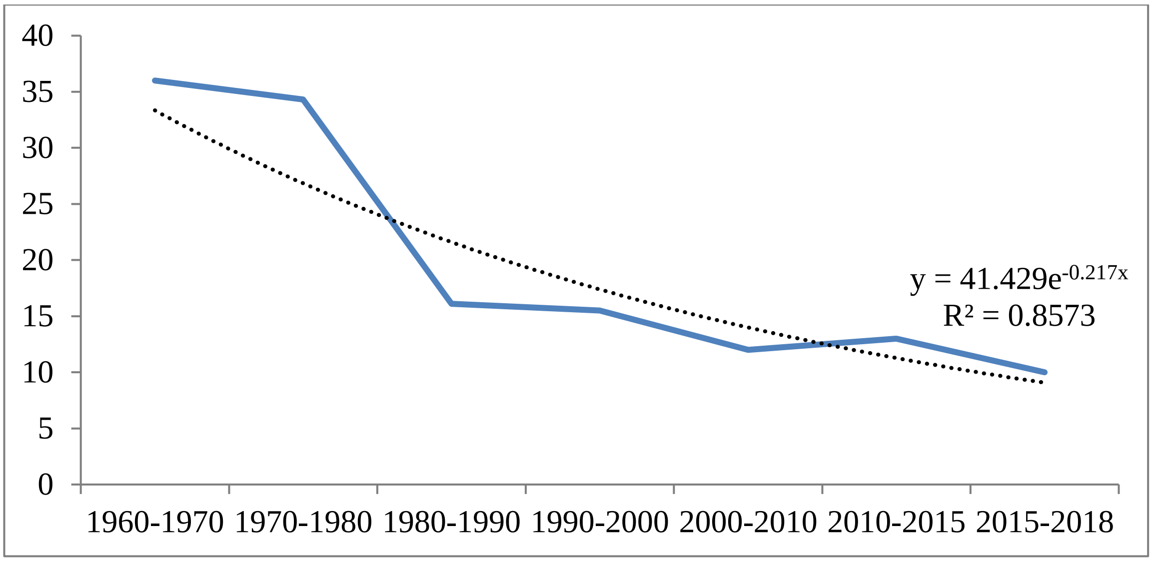
Figure 3:Agricultural GDP Versus National GDP Growth (Annual % change), 1965–2018



Source: Author's own construction based on the world bank (2016) dataset

Past studies report the contribution of the livestock sector to Kenya's GDP often ranges from 5.6% to 12.5% (Behnke–Muthami 2011), while estimates of the contribution to agricultural GDP range from 30% to 47% (Farmer–Mbwika 2016), which in turn contribute an average of about 25% to the national GDP[7]. However, the growth trends of this livestock sector over recent decades has been too negative compared to the first two decades of independent Kenya (Figure 4). For instance, in the early 1960s, livestock contribution to National GDP was 36% (Nyangito–Okello 1998) and declined to about 34% in 1970s, followed by a massive decline to 16.1% in late 1980s. Recent statistics point a further decline to 10% of the National GDP by the livestock sub-sector, yet the sector accounts for about 42% of the country's agricultural GDP, reflecting relatively low productivity (Vivien 2004, Behnke–Muthami 2011). Such trends in the growth rates for livestock contribution to the GDP shows that the dwindling tendency experienced in the sector's growth over the last few decades can best be described by a non-linear tendency – mostly exponential.

Figure 4:Share of Livestock Contribution as a Percentage of National GDP (1960-2018)



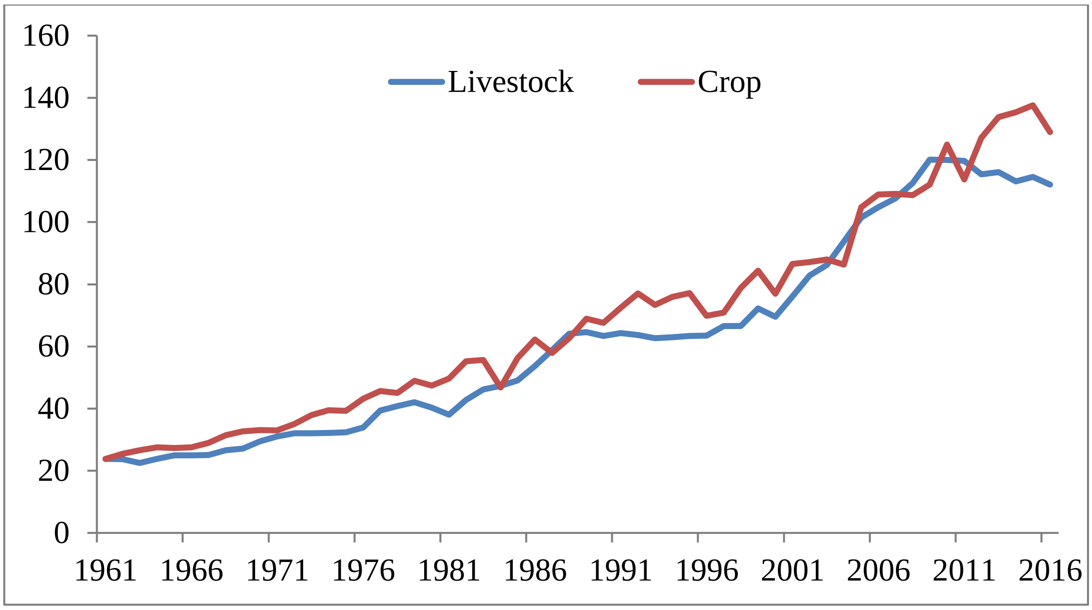
Source: Author's construction from the various literature.

Estimating the share of livestock GDP in agricultural GDP gives an indication of the relative importance of the livestock sector within the agricultural economy. Overall

[7] The discrepancy can be attributed to approach used in data capturing. The KNBS (Kenya National Bureau of Statistic) uses commodity flow approach that calculate the value of marketed agricultural production based on the value and quantity of officially recorded agricultural sales while Non-governmental organization such as IGAD (intergovernmental authority on development) uses standard practice of the production approach (that used survey) to estimating livestock GDP.

livestock output and productivity can be measured using the Livestock production index (as illustrated in Figure 5). The FAO (Food and Agricultural Organization) indices of agricultural and livestock production show the relative level of the aggregate volume of production for each year in comparison with the base period 2004-2006. Within the agricultural sector, the livestock industry is seeming to grow exponentially over the years, perhaps fuelled mainly by the expansion in demand for food of animal origin that can be attributed to population growth, urbanization and income growth.

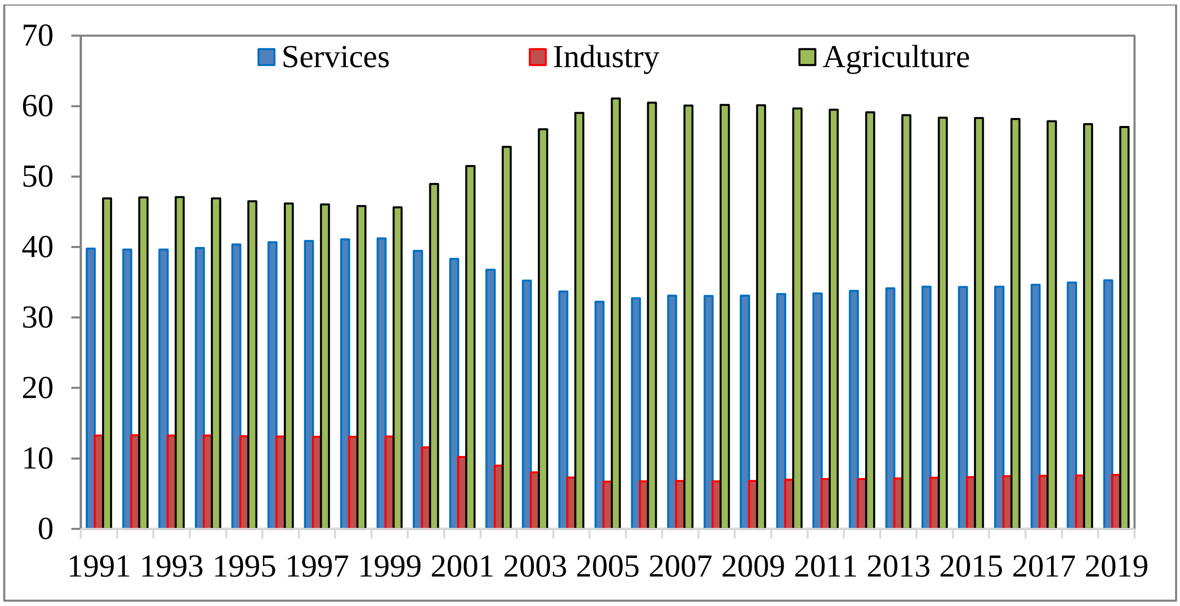
Figure 5: Evolution of the Livestock Production Index (2004-2006 = 100)



Source: Author's own construction from World bank (2016) database

Regarding employment, the livestock sector plays a crucial economic role, but much of its statistics are only published by government agencies and non-governmental organization and not independently available in different development database. However, based on GoK (2012) report, the sector provides about 88% of employment (18% of formal employment and over 70% of informal employment) and about 90% of the arid and semi-arid lands (ASALs) workforce. About 95% of ASALs household income comes from this sub-sector. These contributions can be indirectly attributed to the continues vital role agriculture sector play to Kenya national and rural employment compared to other sectors of the economy. Overall, agriculture employs more than 45% of the total population (Figure 6), and more than 70% is said to come from Kenya's rural people. This is because agriculture in Kenya is vast and complex, with a multitude of public, parastatal, non-governmental and private sectors. Service sector comes second, and the least is the industrial sector. Although Kenya is the most industrially developed country in East Africa, surprisingly, the sector has been lagging behind accounting for less than 10% to the national employment.

Figure 6: Percentage Share of Economic Sectors to National Employment (1991-2019)



Sources: Author's own construction from World bank (2016) Database.

Livestock sector also supplies the domestic requirements of meat, milk and dairy products and other livestock products while accounting for about 30% of the total marketed agricultural products. The average consumption was approximated as 15-16 kg of red meat (meat and offal from cattle, sheep, goats and camels) per capita annually (Behnke–Muthami 2011) and with a population of 38,610,097 persons, the demand was approximately 600,000 MT (GoK 2010). This demand was expected to grow at the same rate as the human population, which is 3.2 per cent (GoK 2010). The sub-sector also contributes substantial earnings to households through the sale of livestock and livestock products; and provides the raw material for agro-industries. According to KEPZA (2005), ASALs accounts for the majority of meat suppliers (60-65% of the total). The rest (20-25%) come on-hoof from neighbouring countries (Ethiopia, Somalia, Tanzania and Uganda). Culls from dairy farms contribute another 30% of beef, while ranches provide 4% of which 15% is slaughtered for home consumption. The sub-sector also earns the country substantial foreign exchange through export of live animals, hides and skins, dairy products and some processed pork products. However, the actual proportion of the contribution by the sub-sector to the economy is likely to be even higher if unrecorded slaughter, home consumption and indirect benefit[8] are all taken into account. However, recent studies on animal products demand and supply projection indicate that, unless appropriate interventional measures are introduced, the country may soon register deficit in some livestock products.

The importance of the livestock sub-sector is also positioned at Kenya's Vision 2030. Livestock production and marketing is regarded as an essential sub-sector of the agricultural sector in Kenya. The vision also highlights various specific strategies aimed at addressing the needs of the sector and key among them include transforming the critical institutions in agriculture and livestock to promote household and private sector agricultural growth; and increasing productivity of crops and livestock. The future of agricultural growth, therefore, must come from increased productivity and marketing, and the definition of livestock productivity and marketing must incorporate the livestock keepers as well as technical staff[9] and policymakers, so as to have effective livestock policies implying that understanding the production and marketing environment under which livestock are reared is prerequisite. The agricultural in Kenya is characterized by a complex structure of institutions and policies, and livestock sector-specific policies are absent or ill-functioning markets for products and production factors, implying that the values of resources used for and products derived from livestock are not necessarily reflected in market prices. There is always information asymmetry on the concept of livestock production and productivity amongst researchers and technical staff on one hand and policymakers, on the other hand, resulting in assumptions about inefficiency and low productivity especially amongst smallholders' pastoral households.

2.2. Geographical Distribution of Livestock Production in Kenya

Livestock production in Kenya is mainly concentrated in the arid and semi-arid lands (ASALs) of Kenya (Figure 7) and represents a significant national resource base of the

[8] The non-human power (draught power), by-product (e.g. manure) and the intangible non-marketed benefits from cattle in the form of financing (e.g. cementing relationship through bride payments and social links), insurance and status display roles are very much neglected.

[9] For instance, for technical staff in livestock research, livestock productivity generally focuses on improving physical production measured according to a single criterion, milk production for dairy animals and beef output for beef animals. The focus is useful especially to the technical staff, though it must be realized that farmers have multiple goals.

communities leaving in these areas. ASALs of Kenya cover about 80% of the land surface and are occupied by about 25% of Kenya's population (Elmi–Birch 2013). This implies that about two-thirds of the total landmass is ASALs and only about one-third of the total land area of Kenya is agriculturally productive and includes the Kenyan highlands, coastal plains and the lake region. The ASAL northern half of the country is so far mainly used by pastoralists for livestock keeping; sparsely populated and characterized by fragmentary infrastructure coverage. Water resources are scarce and unevenly distributed within ASALs and over time. This constrains Kenya’s agriculture potential in the ASALs and explains why the Kenyan population and its agricultural activity are heavily concentrated in the southern half of the country.

The ASALs extends from the border of Tanzania to the south and the Ethiopian and Sudanese borders to the north, Somalia to the east and Uganda to the north-western front (Figure 7). The primary ASALs counties of livestock farming in Kenya include Turkana, Wajir, Garissa, Kajiado, Narok and Marsabit among others. The leading community that practices livestock farming includes the Nilo-Hamitic groups like the Maasai, Turkana, Pokot, Borana, Rendille and Somali. The Maasai, for example, practice nomadism in the southern part of Kenya and the northern part of Tanzania. During the rains, they go down the Athi-Kapiti Plains up to Kajiado and Namanga. There are 24 million hectares in the ASAL that can be used for livestock production, but only 50 per cent of the carrying capacity of the land is currently being exploited (Odhiambo 2013).

Figure 7: Arid and Semi-Arid Lands in Kenya

Source: https://www.asalforum.or.ke

According to the National Census of 2009, livestock population in Kenya comprise of about 17.4 million cattle (14 million indigenous and 3.4 million exotic), 27.7 million goats, 17.1 million sheep, 2.9 million camels, 1.8 million donkeys and 0.3 million pigs (Table 1) (GoK 2010). Out of the national cattle herd, dairy cattle (or grade cattle) comprises of about 40% of which are pure-bred while 60% are crossbred. About 80% of grade cattle are owned by smallholder farmers and are mainly kept in areas receiving at least 800-1000 mm of rainfall per annum and where grazing is medium to high quality, and production of fodder is practised. The informal poultry sector is large (every household, even many in towns, keeps some chickens), estimated at about 25 million indigenous and 6 million commercial chicken. Bee farming is concentrated mainly in the southern arid and semi-arid lands and is estimated to be 18 million. Overall, about 75.8% of the national livestock herd is found in arid and semi-arid lands while the remaining 24.2% is found in the arable lands

Table 1: Livestock statistics for the period 2000-2009

	Arid and Semi-Arid Lands				
Livestock species	**Northern Rangelands**	**Southern Rangelands**	**Arable Lands**	**Total**	**% proportion to total livestock numbers**
Cattle	7,145,881	5,878,870	4,441,023	17,465,774	**17.3**
Sheep	10,790,468	4,681,245	1,657,893	17,129,606	**16.9**
Goats	19,164,192	6,380,963	2,194,998	27,740,153	**27.4**
Camels	2,955,212	13,466	2,233	2,970,911	**2.9**
Donkeys	1,173,376	457,334	182,503	1,813,213	**1.8**
Pigs	2,064	142,148	190,457	334,669	**0.3**
Indigenous Chicken	1,699,792	10,819,149	13,237,546	25,756,487	**25.5**
Chicken Commercial	182,199	3,596,793	2,292,050	6,071,042	**6.0**
Beehives	440,569	1,072,866	329,061	1,842,496	**1.8**
Total	43,553,753	33,042,834	24,527,764	101,124,351	**100.0**
Proportion to total Livestock numbers (%)	**43.0**	**32.8**	**24.2**	**100.0**	

Source: Author's own construction based on 2009 Kenyan livestock population census dataset (GoK 2010).

Climatically, arid and semi-arid lands of Kenya are characterized by low, unreliable and poorly distributed rainfall. They are in agro-climatic zones (ACZ) IV-VII[10] and have an average rainfall ranging from 300-800mm per year, and average annual temperatures range from 23°C to 34°C (Parry et al. 2012). The remaining climatic zones occupy 20% of Kenya. Rangelands are further characterized by sparse vegetation cover, fragile soils, high temperatures and frequent windstorms (Olang 1988). Crop production is minimal, but the rangeland supports cattle, sheep, goats and camels. It is also estimated

[10] The two extreme ACZ includes IV that is characterized by semi humid to semi-arid and VII that is characterized as very arid

that about 50% of wildlife outside the national parks is found in these rangeland areas (Ottichilo et al. 2000). Some of the naturalized herbage grass species commonly found in the Kenyan arid and semi-arid lands include *Themeda triandra, Sporobolus fimbriatus, Cenchrus ciliaris, Digitaria milanjiana, Digitaria abyssinica, Eragrostis superba, Eragrostis cilianensis, Eustachyus paspaloides, Aristida adscensionis, Aristida kenyansis, Panicum maximum, Cynodon species, Bothriochloa insculpta, Heteropogon contortus* and others. Some of the naturalized legumes include *Stylosanthes Scabra, Macrotyloma Axillare, Leucaena leucocephala*, and *Acacia species* (Orodho 2006).

2.3. Livestock production systems spotlight

Traditionally, livestock farming classification was closer to typologies and not backed by quantitative criteria, which would enable cases to be clearly allocated to one class. No attempts at developing a classification of the livestock systems by using quantitative statistical methodologies could be located in the literature, which probably relates to the lack of appropriate data sets for such approaches. Mostly, livestock production systems were purely classified as subsistence livestock farming or nomadic pastoralism (Dyson-Hudson-Dyson-Hudson 1980), and the communities used to keep livestock for subsistence, prestige and as a form of insurance against drought. However, many of the traditional livestock production systems of Kenya are now in decline. Over the years, patterns of land-use have changed in the livestock sector from, principally, nomadic pastoralism to sedentary pastoral and agropastoral production or to livestock keeping under intensive and/or commercial farming (Mwang'ombe et al. 2009, Bebe et al. 2012). The sedentary lifestyle of the pastoral communities was majorly necessitated by the response to an unprecedented growing demand for animal-sourced food fueled by, among other things rising population, income growth and urbanization.

Recently, an attempt at developing a classification of the livestock production systems by using quantitative statistical methodologies could be located in the literature (FAO 2018). The expert's and stakeholder engagement revealed that Kenyan livestock sector like in any other sub-Saharan Africa country is very heterogeneous with a diverse range of production systems functioned on farms. Variation among farms can be attributed to the vast diversity of agro-climatic conditions, livestock breeds and genetics, production practices and disparities in the scale of production. Most frequently, livestock production system has been classified based on land use by livestock, and therefore the distinction between grazing systems, mixed farming systems and industrial (or landless) systems (Seré–Steinfeld 1996) has previously been widely accepted. However, livestock production is undergoing rapid change, manifested by its growing contribution to satisfy national demand from high-value food products and in continuous adjustments at the level of resource-use intensity, size of the operation, product -and market-orientation. The most general distinction of livestock production systems in Kenya may now be distinguished as extensive (comprising of traditional pastoral or agro-pastoral and characterized by production of livestock under free-range pastoralism and ranching, and predominantly undertaken in the rangelands) and commercial (that is associated with arable farming and characterized as intensive, semi-extensive and extensive production of livestock) (Otieno et al. 2014, GoK 2019). For the purpose of this thesis, we focus on the production system in reference to significant livestock species (cattle, sheep and goat) for dairy and beef/meat production in cursory analysis highlighting only the principal features and development.

Regarding dairy animal, the intensive and semi-intensive comprises about 85% of all dairy farms (Table 2). The intensive zero-grazing system is mainly commercially oriented with a high density of animals per unit area, use of appropriate housing and high application of inputs, while the semi-intensive (semi-grazing) production systems are commonly practised by small-scale producers in dairy animal production characterized by the use of locally available forage resources with some supplementation. The scale of operations ranges from small (1-20 cows) to large scale (more than 20 cows) (Njarui 2011, Lanyasunya et al. 2006). The extensive dairy production system is a pasture-based production system dominated by exotic breeds and crosses of indigenous breeds. It is mainly practised in areas with large farms and in marginal and communal grazing areas. The scale of operation ranges from a minimum of 10 (for uncontrolled grazing) to over 50 animals (for controlled grazing).

Regarding beef/meat production, agro-pastoralists lead the list and is subsistence-based. The farms under this system keep livestock and grow crops in a complementary way – crop residue and by-products as feeds for the livestock and draught power for crop production). In this way, agro-pastoralists hold land rights and use their own or hired labour to grow crops and improve pastures for their livestock. In contrast, the pastoral system has a mobile aspect, moving the herds in search of fresh pasture and water, and the existing land and resource tenure systems are not responsive to private conservation of natural resources. The animal densities for agro-pastoral system ranges from

20TLU/Km^2 in the lowlands and 50 TLU/Km^2 in the highlands, while for the pastoral system has the lowest livestock densities of 11 TLU/Km^2. Indigenous beef cattle breeds dominate and are kept in mixed herds with other animals (Kahi et al. 2006). Ranching ranges from those that are purely commercial-oriented, whose main objective is profit-making, to community-based ranches (group ranches), which in addition to business, they safeguard community-owned land, promote sustainable use of pastures and water resources. It is reasonably labour-intensive and has the infrastructure for disease control, feeding and water storage. The average herd size is 150 animals, mainly improved Boran and exotic (Otieno et al. 2014). Intensification of beef/meat production is also taking place. Feedlot (intensive) is a re-merging purely commercially oriented beef/meat production system in which animals are kept for a short period. There are two different feedlot systems, one focusing of fattening culled dairy cows and bulls, and the other specializing in fattening beef breeds for niche/prime beef markets. This intensification is supported by increasing in the specialization of production, with a substantial shift from the backyard and mixed systems to commercial, specialized, single operations.

Table 2: Livestock Production Systems and their Proportions (stakeholders' knowledge), 2000 to 2018

Production system	**Production practice**	**The proportion of the farms (%)**
	Dairy production systems	
Intensive	Large scale	5
	Small scale	35
Semi-intensive	Semi-grazing	45
Extensive	Controlled dairy production systems	10
	Uncontrolled dairy production systems	5
	Beef/meat production systems	
Intensive	Feedlot	1
Semi intensive	Agro pastoralism	54
Extensive	Pastoralism	34
	Ranching	11

Source: Author's own compilation based on expert's and stakeholder perception, FAO (2018).

Since all these livestock production systems have different feed requirements and different intensity of production, they are operated under varying agro-climatic conditions. Thus, for policies and investments to be effective, then the multiple dimensions of livestock farming need to be taken into account. The differences in livestock production system on farms reinforces the importance of research on the technological production level or farm technical efficiency, product supply and factor input demand responsiveness and market participation behaviour. In this regard, the study focuses on beef/meat production systems under the rangelands (extensive and semi-intensive) because they support over 70% of the livestock population, the status as a priority in the current agricultural policy framework and their anticipated growth in the coming decades (GoK 2019).

2.4. Summary of the Chapter

Some important contextual issues in the livestock sector have been reviewed in this chapter. The first section focuses on the importance of livestock to the Kenyan economy. In this section, the aim was to compare trends of livestock contribution to national GDP using a literature review and analysing production and growth data available in the world bank dataset. The main observation was that there is a disappointing declining trend in livestock contribution to national GDP though the production index portrays the opposite. This means that livestock production has the potential to revitalize the agricultural sector of the Kenyan economy. Livestock is also highly prioritized for investment and economic development, as the envisaged in Vision 2030 Development Strategy for Northern Kenya.

Regarding geographical distribution of livestock production sector, it is clear that ASALs, which cover nearly 80% of the country's landmass, hold majorly of the national livestock herd. Adoption of livestock productivity policy-specific is a critical option to ASALs achievement in terms of responses to the underdevelopment of the region. The section concludes by presenting a snapshot of the cattle (beef and dairy) production systems in Kenya. This shared understanding of different livestock production systems reinforces the importance of research on the livestock production technological level or farm technical efficiency that will provide insight into the formulation of coherent and effective sector policies and investments.

CHAPTER THREE

ON MEASUREMENT OF FARM HOUSEHOLD PRODUCTION EFFICIENCY

With the diverse range of livestock production systems employing different practices and technologies being observed in Kenya, a high degree of heterogeneity is expected. Given that the livestock sector is expected to be very heterogeneous, analysis of technical efficiency (TE) in resource input use should consider that households operate in different production systems. The impacts of different technologies (assuming heterogeneous production systems) should then be compared with a model which assumes that the technology is common to all farmers. Therefore, the over the objective of this chapter is to investigate the production efficiency of smallholder farm households leaving in the southern rangelands of Kenya while considering farm uses a different technological scope. The chapter begins with a brief theoretical review on previous efficiency analysis studies with emphasis on the agricultural sector (Section 3.1). Section 3.2, provides the econometric model while Section 3.4, presents a description of the methodology that comprises data, estimation procedure and contexture variables used in the empirical analysis. Section 3.4 provides a detailed analysis that includes descriptive and empirical results. The flow of empirical results begins with a consideration of the role of the different distribution of the inefficiency error term while assuming similar technology and end with the result on the possibility of incorporation of unobserved heterogeneity. The chapter concludes with a summary of the chapter.

3.1. Theoretical review on Production Function for Efficiency Measurement

In this section, we overview the theory of production function for efficiency measurement. In order to understand the ideal behind ‘efficiency measurement’, the neo-classical production behavioural theory provides a useful standard, since it forms the foundation for a rational choice theory where profit maximization behaviour model is embedded. A production function prays a pivotal role in the theory of household profit maximization behaviour as it is a function that summarizing the process of converting factors into a particular commodity. According to Coelli et al. (2005), the production function represents the maximum level of output attainable from alternative input combinations. Further, economic theory assumes that a production function is characterized by the following regularity properties or conditions (Chambers 1988):

1. non-negativity: the value of output is a finite, non-negative real number.

2. weak essentiality: at least one input is required to produce positive output and no input implies no output.

3. monotonicity: that is, an increase in inputs does not decrease output. Thus, all marginal products or elasticities are non-negative for a continuously differentiable production function; and

4. concavity in inputs: the law of diminishing marginal productivity applies in a continuously differentiable production function. Thus, to satisfy the second-order condition for optimization, all marginal products are non-increasing.

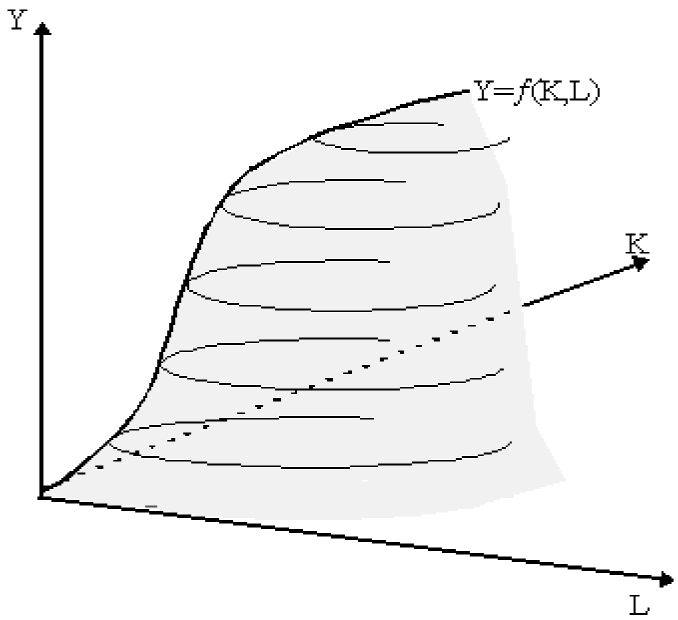
Assumption *1* defines the production function as a well-defined function of inputs, while assumption *2* simply establishes that one cannot produce something from anything. This is somewhat self-evident, at least for economists. Obviously, in other walks of life, such as in psychology, one can produce something without inputs (e.g. 'nice thoughts' can just be 'thought up' without inputs), but most examples of such things are outside the realm of economics. The monotonicity assumption (*3*) is also straightforward: increasing inputs leads to an increase in output (or, more precisely, no decrease in output). Assumption *4*, the concavity in inputs of the production function, means that the more we add a form of particular factor input, all other factors remaining constant – *ceteris paribus* – the less employing an additional unit of that factor input contributes to output as a whole. However, in practice, these properties are not exhaustive and may not be universally maintained. For example, excess usage of inputs might result in input congestion, which relaxes the monotonicity assumption. Equally, according to Coelli et al. (2005), a stronger essentiality assumption often applies in cases where each and every input included proves to be essential in a production process. Moreover, the flexibility of a production function (i.e. no restrictions imposed except theoretical consistency) is another desirable feature that allows data to capture information about critical parameters. Exact conformity with economic theory is also necessary (Sauer et al. 2006). Nevertheless, the classical production function a good, *y* can be specified in the following general form:

$$\boldsymbol{Y}_i = f\left(\mathbf{X}_{ij}; \boldsymbol{\beta}_i\right) + \varepsilon, \tag{1}$$

where Y_i is the observed scalar output of producer *i*, $\boldsymbol{X}_{ij}$ is a vector of *J* inputs used by producer i, $f(.)$ is the production function; for example, in the flexible first order Cobb–

Douglas or flexible second Translog specification, $\boldsymbol{\beta_j}$ is a vector of technology parameters to be estimated and, ε is the error term that is assumed to capture statistical noise in the model. For demonstration purposes, we adopt the representation of production technology for the one-output/two-input case imperfectly depicted in the diagrammatic form of 'hills' as presented by Pareto (1906) cited in Bruno (1987) in Figure 8. Output *Y* is measured on the vertical axis. The two common inputs in many economics' textbooks, which are marked as L and K and represent labour and capital, respectively, are depicted on the horizontal axes. The hill-shaped structure depicted in Figure 8 is the *production set*. Notice that it includes all the area *on* the surface and *in* the interior of the hill.

Figure 8: Production Function for One-output/Two-inputs



Source: Pareto (1906) cited in Bruno (1987).

A production decision is a feasible choice of inputs and output and is a particular point on or in the production hill. It will be 'on' the hill if it is technically efficient and 'in' the hill if it is technically inefficient. Properly speaking, the production function, $Y = f(.)$, is only the surface (and not the interior) of the hill, and thus denotes the set of technologically efficient points of the production set. However, such technologically efficient points can only be obtained under a maintained hypothesis that in production behaviour, economic agents are driven by the objective of profit maximization and holding other factors (such as weather, economic adversaries, etc.) constant – *ceteris paribus*. This implies that an implicit assumption of production functions is that all firms are producing in a technically efficient manner, and the representative 'average' firm (or the so-called ‘average’ practice) therefore defines the frontier (Schmidt 1986). Variations from the frontier are thus assumed to be random and are likely to be associated with mis- or un-measured production factors.

The theory of production is essentially the analysis of relevant extremums of mathematical relationships. However, the economic decision-making process can fail if marginal revenue products of some or all factors might be unequal to their marginal costs which means their allocative decision is inefficient, or failure to produce the highest possible output from a given set of inputs which imply the technical decision is inefficient. These possible scenarios brought the production function under the scrutiny of economists, and the concept of the efficiency production function that tries to quantify these extremums through statistical estimation was developed (Farrell 1957). Whereas the theoretical production function does represent the upper bound, by finding the observed upper bound of the production surface, one finds the real-world counter of the theoretical production function. Therefore, in order to conform to the current multivariate economic behaviour, this new development has generated the desire to recast the analysis of production away from the traditional classical production function approach toward a frontier-based approach that addresses efficiency. The stochastic frontier approach provides a framework where production relationship is also estimated as a conditional average (of outputs given inputs and other factors, in the case of production function) but the total deviation from the regression curve is decomposed into two terms. Estimation of the production frontier assumes that the boundary of the production function is defined by “best practice” firms.

The frontier-based approach extend the familiar classical production regression model based on the theoretical premise that a production function or its dual the cost function, or the convex conjugate of the two, the profit function, represents an ideal, the maximum output attainable given a set of inputs, the minimum cost of producing that output given the prices of the inputs, or the maximum profit attainable given the inputs, outputs, and prices of the inputs. Estimating frontier functions is the econometric exercise of making the empirical estimation consistent with the underlying theoretical proposition that no observed economic agent can exceed the ideal ‘frontier’, and deviations from this extreme represent individual inefficiencies. From the statistical point of view, this idea has been implemented by specifying a regression model recognizing the theoretical constraint that all observations lie within the theoretical extreme. Measurement of inefficiency is, then, the empirical estimation of the extent to which observed agents fail to achieve the theoretical ideal.

Since the seminal paper of Farrell (1957), TE has typically been analysed using two principal analytical frameworks. These two main frameworks include the non-parametric but deterministic approach, which includes data environment approach - DEA (Charnes et al. 1978), and free disposal hull[11] - FDH (Deprins et al. 1984), and the parametric approach which includes SFA (stochastic frontier approach that was simultaneously proposed by Aigner et al. (1977) and Meeusen–Van der Broeck (1977), distribution-free approach[12]- DFA (Khoo-Fazari et al. 2013), and thick frontier approach[13] - TFA (Berger–Humphrey 1992). Among the aforementioned TE estimation approaches, the non-parametric DEA and parametric SFA are the two widely used methods for estimating efficiency, and, therefore, in this section, we limit our discussion to these two. A detailed discussion on the distinction between parametric and non-parametric methods of frontier estimation can be found in Assaf–Josiassen (2016).

The DEA method is a non-parametric but deterministic approach for measuring efficiency. The method assumes that any deviations from optimal output levels are due to inefficiency rather than errors. The DEA model was proposed by Charnes et al. (1978), who extended the relative efficiency concept of Farrell (1957) and simultaneously incorporated many inputs and outputs. This approach involves the use of linear programming methods to construct a non-parametric frontier using sample data, and then efficiency measures are computed relative to the surface (Coelli et al. (2005). The envelopment form is generally preferred in the literature because it entails fewer constraints than the multiplier form. As Coelli et al. (2005) and Kuosmanen–Kortelainen (2012) observed, the main advantage of the non-parametric DEA form lies in its axiomatic, non-parametric treatment of the frontier, which does not require explicit *a priori* determination of a production function form but relies on the general regularity properties such as free disposability, convexity, and assumptions concerning RTS. The approach measures the efficiency of each decision-making unit (DMU) relative to the highest observed performance of all other DMUs rather than against some average. Furthermore, another advantage is its ability to simultaneously accommodate multiple

[11] FDH requires minimal assumptions with respect to production technology; for example, it does not require convexity.
[12] DFA is a method capable of incorporating probability while still preserving the advantages of a function-free and non-parametric modelling technique.
[13] TFA does not require distribution assumptions for random error and inefficiency terms but assumes that the inefficiencies differ between the highest and lowest quartile firms.

inputs and outputs in the estimation, thus providing a straightforward way of computing efficiency gaps between each DMU and efficient producers (Haji 2006).

However, as Coelli et al. (2005) observed, the non-parametric DEA form has some limitations in that its deterministic frontiers attribute all deviations from the frontier to inefficiency and ignore any stochastic noise in the data. In contrast, although parametric SFA requires an assumption about the functional form of the production function, its key advantage is its stochastic treatment of deviations from the frontier, which are decomposed into a non-negative inefficiency term and a random disturbance term that accounts for measurement errors and other random noise so that the measure is more consistent with the potential production under 'normal' working conditions. It is within this context that we situate this thesis, and a parametric SFA form was preferred to allow simultaneously estimating stochastic production frontiers, TE, and critical factors that affect TE. The method in detail will be presented in section 3.2.

In the last few decades, an enormous body of literature has progressively evolved around SFA to incorporate new advances, refinements and extensions. This thesis focuses on a few of the most recent methodological developments. The first strand of literature involves the use of SFA form that was proposed by Aigner et al. (1977) and Meeusen–Van den Broeck (1977) which allows investigation of farm-specific factors for farms operating with similar/homogenous technologies. In its original specification forms, Aigner et al. (1977) and Meeusen–Van den Broeck (1977) assumed an identical and independent half-normal and/or exponential distribution for the one-sided error terms u_i. These distributions have the regular feature of having a mode at zero, which means most inefficiency is concentrated near zero. Subsequent studies have generalized the model to allow for heterogeneity in the distribution of the inefficiency term while maintaining the assumption of half normality. For instance, Stevenson (1980) and Battese–Coelli (1995) allows the mean of the pre-truncated normal distribution of u_i to depend on the exogenous factors while Wang (2003) allows both the mean and the variance of the pre-truncated distribution of u_i to depend on exogenous factors. Greene (2003) applied the gamma model that allows both the shape and location to vary independently. Regardless of whether we allow the mean, the variance, or both the mean and the variance to depend on the exogenous factors, or both the shape and location to very independently, as observed by Wang (2003), failure to model the exogenous factors appropriately leads to biased estimation of the production frontier model and of the level of technical inefficiency, hence leading to weak policy conclusions.

The other major issue found in SFA literature concerns the type of data and the choice of functional forms considered to represent the production technology. Several different functional forms have been proposed and discussed in the literature (e.g., Chambers 1988, Giannakas et al. 2003). Two of the most common functional forms in empirical work are the second-order flexible transcendental logarithmic - typically abbreviated as "Translog" (Christensen et al. 1973), which is a generalization of the well-known first-order Cobb-Douglas (CD) functional form. Fitting a function of the CD form to the data yields fixed output elasticities across all data points while Translog form is flexible and allows for varying output elasticities. Selection of either of the two depends largely on the reliability of the econometric estimates themselves and the data type since the measurement of efficiency is also based on the notion that in a given dataset, part of the variance in total output cannot be explained by the variance in total input. In SFA literature, some of the stochastic frontier applications with cross-section data in agriculture includes Liu–Myers (2009), Otieno et al. 2014 and Asante et al. (2017) while that applied panel data includes Iraizoz et al. (2005), Hadley (2006), Barnes (2008), Lio–Hu (2009) and Zhu–Lansink (2010) and so on.

In this strand of literature, the other issue of concern is the variables for measuring efficiency and the underlying causes of inefficiency. In this regard, I review the most recent one in the livestock-related study that would help identify the variables of concern. To begin with, Asante et al. (2017) evaluated the performance of smallholder farmers in three districts of the forest–savannah transition agroecological zone of Ghana. In their study, they adopted a two-stage approach and using maximum likelihood estimation procedure; a metafrontier production framework was used both for CD and Translog functional forms nested with a half-normal inefficiency error term, and the CD form was found to be an inadequate representation of the data set. In estimating the SFA production frontier functions, variables considered were the number of animals, value of the capital assets, labour in man-days and veterinary costs and all were found to have the expected positive sign and fall between zero and one. With regards to inefficiency effect model, the study shows that small-ruminant production was influenced by factors differently across the three districts. For A-A district, off-farm income, access to market information, use of tetracyclines, and the storage of crop residue had statistically significant coefficients, indicating that these factors and usage of these products reduced inefficiency of small-ruminant outputs, except for off-farm income which had the opposite effect. In N-S district, inefficiencies of small-ruminant outputs decreased for male farmers, farmers who used tetracycline and those who stored crop residue. In E-S district, technical inefficiency tended to increase with age but decreased with farmers who were educated, participated in livestock development projects, had access to extension, used tetracycline, used ash or neem, and stored crop residue. Considering the importance of the livestock enterprise to rural livelihoods and its potential role in poverty reduction, Otieno et al. (2014) applied the same two-stage approach and first estimated a Translog in the metafrontier framework to measure the technical efficiency levels in beef cattle production in Kenya. They considered variables such as beef herd size, improved pastureland, veterinary cost and divisia index for other costs; all were found to be positive and significant for the pooled model. In the second stage of the inefficiency effect model, variables such as herd size, market access, farm size, off-farm income, farm specialization, age and present of farm managers were some of the variable thought to determine the levels of inefficiency and their effect were indifferent. Finally, Berre et al. (2017) study combined farm typology with frontier efficiency analysis in a yield gap analysis in sub-Saharan African countries, finding a more rational strategy for improving livelihoods to stimulate labour markets for off-farm income rather than the pursuit of increased crop production by closing the yield gap. All these studies use primary data and found the efficiency level to be very low. Again, the common practice of the models as they appear in the different studies assumes that the inefficiency term follows the half-normal distribution. But based on Jondrow et al. (1982), Greene (1990), Huang–Liu (1994), Kumbhakar–Tsionas (2008), and Schmidt (2011), different distributions of the inefficiency term yield different results. For instance, in Greene (1990) paper where four (that is gamma, half-normal, exponential and truncated-normal) distributions of inefficiency error term were applied, the results reflect the fact that estimates of TE can significantly depend on the distributions and it is not clear a priori the basis for choosing an appropriate distributional assumption in a specific application.

Another strand of the literature attempted to accommodate the possibility of incorporation heterogeneity in efficiency analysis. Since the presentation by Farrell (1957), the notion of technical inefficiency usually raises suspicion among neoclassical economists, particularly on how to distinguish between the heterogeneity of inputs and production conditions and inefficiency or how to account for different production technologies. Farms in different environments (e.g. production systems) do not always have access to the same technology and, therefore, assuming similar technologies when they actually differ across farms might result in an erroneous measurement of efficiency by mixing technological differences with technology-specific inefficiency. Various alternatives have been proposed in the literature that accounts for differences in technology and production environment. In the other part of the world, the issue of technological heterogeneity has been of enormous, especially using the two-stage procedure. By way of example, such studies in crop sector includes Battese et al. (1993) who used farm location in splitting wheat farmers in selected districts of Pakistan; Balcombe et al. (2007) who used plated variety to divide rice producers in Bangladesh; Fuwa et al. (2007) who used land type to divide small-scale rice farmers in Eastern India. In livestock sector, splitting a sample into groups based on some characteristic(s) and subsequently estimating separate function was done by Álvarez–del Corral (2010) using milking systems (stanchion verses parlour) in New York Dairy farms; Sauer–Morrison, (2013) who used multiple characteristics (such as intensive versus extensive and organic versus conventional production, input (labour) intensity, and production diversity) in Danish dairy farms; Bravo-Ureta (1986) who classified a sample of New England dairy farms based on the breed of the herd; Newman–Matthews (2006) who estimated different output distance functions for specialist and non-specialist dairy farms; and Moreira–Bravo-Ureta (2010), who estimated different production functions for three Southern Cone countries. In Kenya, to the best of my knowledge, separating of beef cattle production farms based on a priori characteristics is only found in Otieno et al. (2014) study. In this study, the scholar applied the regular two-stage procedure wherein the first step farms are grouped (into ranchers, nomads and agro-pastoral) using some variable and subsequently separated frontier are estimated for each group.

The use of two-stage approach was found to have a shortcoming that the information contained in a given sub-group cannot be used to estimate the technology of the farm that belongs to other sub-groups (Álvarez–del Corral 2010). This is so because farms included in the separated groups can often share some common features. Rather than using prior separators, more sophisticated statistical procedures that allow disentangling technology heterogeneity from farms technical inefficiency in a single stage are currently available, with the advantage that the limitations mentioned above can be overcome. For instance, livestock groups of farms can be defined using cluster algorithms proposed by Alvarez et al. (2008) or by applying the econometric techniques proposed by Kumbhakar et al. (2009) where a systematic approach was used to estimate the production technologies and the choice equation simultaneously, or by random coefficient models of Greene (2005), which accounts for farms' technology differences in the form of continuous parameter variation, or by the latent class models (LCM) as applied by Alvarez–del Corral (2010), and Sauer–Morrison (2013). Among the aforementioned methods of incorporation heterogeneity in the agricultural production efficiency analysis literature, LCM has increasingly been recognized as a suitable model where different production systems are utilized. For instance, Cillero et al. (2016) in the Irish livestock sector; Baráth–Fertő (2015) in Hungarian crop farms dataset; Bisimungu–Kabunga (2016) using a farm-level households' data to establish the extent of adoption of modern agricultural technologies in Uganda; Alvarez and del Corral (2010) and Alvarez–Arias (2013) using Spanish dairy farms; Kellermann (2014) using a sample of Bavarian dairy farmers to explore differences in performance of farms using exclusively permanent grassland compared to farms which do not etc.). Given that the livestock production system in Kenya operates within a complex system (Otieno et al. 2014, GoK 2019), LCM approach is ideal for simultaneously measuring and comparing the production technologies and productive performance amongst livestock production systems and explore some of their performance drivers.

This thesis is also structured to contribute to this strand of the literature by using the LCM in SFA framework in accounting for unobserved heterogeneity and therefore, I only review the most relevant papers that use this methodology. In Alvarez–del Corral (2010) study, latent class stochastic frontier (LCSF) model with a half-normal distribution of inefficiency error term was used to estimate the technology of dairy farms according to their degree of intensification. The results are compared with a model which assumes that technology is common to all farms. The empirical analysis uses data on a balanced panel of 130 Spanish dairy farms over the period 1999–2006. In their study, they tested the Cobb–Douglas against the Translog functional form to determine whether the Cobb–Douglas was an adequate representation of the data and found conclusive evidence that it was not. Although, milk per cow, milk per hectare, purchased feed per cow and cows per hectare were referred as variables that reflect the intensity of the farm system, to avoid endogeneity problems only the latter two were used as 'separating' variables. The two continuous 'separating' variables were significant and had the expected signs, being positive for the intensive group. The other variable considered included number of cows, purchased forage, expenditure on the input used to produce forage crops, land in hectares and labour, all were found to be significant. The author used Akaike's Information Criteria (AIC), and Bayes Information Criteria (BIC) tests suggested by Greene (2002) that 'test down' to show whether fewer classes are statistically supported, to determine the number of classes. From the methodological point of view, they found that the pooled model estimates a general technology which misrepresents the technology of the different groups, while using LCM model, the intensive technology was found to be more productive than the extensive one and that intensive farms are more technically efficient than extensive farms. In particular, the marginal product of purchased feed, which was a significant technological parameter, appears to be overestimated. The other technological characteristic analysed is the scale elasticity which was observed to be higher in the intensive group than in the extensive group. From an agricultural policy point of view, an important conclusion is that intensive farms have higher TE than extensive farms.

The recent trend in the intensification of dairy farming in Europe sparked Alvarez–Arias (2013) interest in studying the economic consequences of this process. However, as observed in Alvarez–del Corral (2010) study, classifying farms empirically as extensive or intensive was not a straightforward task, and therefore these authors also settled for Latent Class Models (LCM) in stochastic frontier analysis framework. This avoided an ad-hoc split of the sample into intensive and extensive dairy farms. Using the same variables and methodological approach applied in Alvarez–del Corral (2010) study, these authors estimated a single latent class model but allowed for changes of production systems over time by splitting the original panel data into two periods and find that the probability of using the intensive technology increases over time. Their estimation opens up the possibility of studying the effects of intensification not only across farms but also over time.

In another similar study, Sauer–Morrison (2013) applied a latent class modelling approach and flexible estimation of the production structure to distinguish different technologies for a representative sample of EU dairy producers, as an industry exhibiting significant structural changes and differences in production systems in the past decades. The model uses a transformation function to recognize multiple outputs; separate technological classes based on multiple characteristics, a flexible generalized linear functional form, a variety of inputs and random effects to capture farm heterogeneity; and measures of first- and second-order elasticities to represent technical change and biases. In this study, in addition to classical production factors (land, labour and capital), cost of chemical, energy, veterinary services and fodder were included. In their analysis, they included four features that are key to distinguish technologies. One important feature was the intensive or extensive nature of production, which was reflected by pasture versus purchased feed. The others were the extent of organic production the input intensity of production and finally, production diversity or specialization. The author found that primary distinguishing factor among these four – in terms of statistical significance – was specialization measured in term of amount of milk relative to total output, the other salient finding was that if multiple production frontiers are embodied in the data, different farms exhibit different output or input intensities and changes associated with different production systems that are veiled by overall (average) measures. In particular, they found that farms that are larger and more capital-intensive experience higher productivity, technical progress and labour savings, and enjoy scale economies that have increased over time.

In the Irish livestock sector, Cillero et al. (2016) observed that a high degree of heterogeneity existed amongst Irish beef farms, with a diverse range of production systems employing different practices and technologies. Such variation can compromise the estimates obtained when the stochastic frontier analysis is used to estimate the frontier under which farms in the sector operate since it relies on the assumption that all farms operate under the same technology. They implemented a Translog LCSF model using an unbalanced panel dataset in order to identify different technologies. Like in Alvarez–del Corral (2010), AIC and BIC were used to assess what model is preferred and, in this study, the LCM model with three classes is preferred over the LCM with two classes and the single frontier model, since it has the lowest AIC. In the study, variables proxying the technologies under which farms operate were included as separating variables in the parameterization of the prior probabilities. These include farm-specific mean values for the years in which they appear in the panel, and so different levels of intensity of production was captured by differences in the stocking rate, defined as the cattle livestock units per hectare and the level of specialization in breeding animals or in finishing cattle (defined as the share of calves and weanlings sold and finished cattle sold on total cattle sales respectively) are included as proxies. The significant variables affecting prior probabilities were found to be statistically significant, which is indicative of the information they contain been useful in classifying the sample. Other variables included in estimation of LCSF model were land capital, labour and variable costs which include the aggregation of feeding costs (including concentrates, pasture, winter forage, milk and milk substitutes), veterinarian costs, AI and service fees, transport expenses, casual labour and miscellaneous cattle specific variable costs; all were found to be significant at 1% lever. The empirical results obtained suggest that a single frontier model overestimates technical inefficiency compared to the model where technology heterogeneity is taken into account. Total average TE level was higher when the LCM is implemented, and technology heterogeneity is taken into account (with an average total score of 0.653 in the LCM versus 0.448 in the single frontier model). The authors also found differentiate patterns in input importance in the three classes applied, suggesting that substantial differences exist between the three technologies identified. The other element of technology characteristic investigated was return to scale, which was found to be within the range of decreasing return to scale.

3.2. The Econometric Stochastic Production Model

The departure from ‘‘average’’ practice to ‘‘best’’ practice has reinforced the importance of using stochastic frontier approach (SFA) in place of the classical production function. Since the seminal paper by Meeusen–Van der Broeck (1977) and Aigner et al. (1977), the parametric SFA has become a popular tool for efficiency measurement. A stream of research has produced many reformulations and extensions of the original statistical models, generating a flourishing industry of empirical studies. An intensive survey that presents an extensive catalogue of these formulations is found in Kumbhakar–Knox-Lovell (2000) and more recently by Greene (2012). Although SFA has been developed from isolated influences, the literature that directly influenced the development of parametric SFA has been the theoretical framework for production efficiency beginning in the 1950s (e.g. Debreu 1951). Farrell (1957) was the first to measure production efficiency empirically and suggested that it can be analysed in terms of realized deviations from an idealized frontier isoquant. Kumbhakar et al. (1991) and Huang–Liu (1994) followed, and, using SFA as proposed by Aigner et al. (1977) designed a stochastic production model for the parametric estimation of both the stochastic frontier function and the inefficiency level. To date, the SFA has become the framework of choice of many scholars (e.g. Coelli 1995, Jondrow et al. 1982, Kumbhakar et al. 2009, Schmidt 2011, Mamardashvili–Bokusheva 2014, Baráth–Fertő, 2015, Martinez et al. 2016, Bahta et al. 2018) in the estimation of TE levels for economic agents.

The SFA approach utilizes econometric techniques whose production models recognize technical inefficiency and the fact that random shocks beyond the control of producers may affect production. Unlike traditional classical production approaches that assume deterministic frontiers, SFA allows for deviations from the frontier, whose error can be decomposed to provide an adequate distinction between technical inefficiency and random shocks. Using SFA ideas proposed by Aigner et al. (1977), a stochastic frontier production function can be expressed using J inputs $(X_1, X_2, \ldots, X_J)$ to produce output Y as:

$$Y_i = f(\boldsymbol{X_{ij}};\ \boldsymbol{\beta_j})TE_i, I = 1, \ldots, n, j = 1, \ldots, J, \quad (2)$$

where Y_i is the observed scalar output of producer i, $\boldsymbol{X_{ij}}$ is a vector of J inputs used by producer I, $f(\boldsymbol{X_{ij}};\ \boldsymbol{\beta_j})$ is the production frontier, $\boldsymbol{\beta_j}$ is a vector of technology parameters to be estimated, and TE_i denotes TE defined as the ratio of observed output to maximum feasible output. If $TE_i = 1$, then the i-th farm obtains the maximum feasible output, while $TE_i < 1$ provides a measure of the shortfall of the observed output from the maximum feasible output, in other words, technical inefficiency. Inefficiencies can be due to structural problems, market imperfections, or other factors that cause economic agents to produce below their maximum attainable output.

A stochastic component is added to describe random shocks that affect the production process. These shocks are not directly attributable to the producer or the underlying technology and come from weather changes or economic adversity. We denote these effects with $exp\{v_i\}$. Each producer faces a different shock, but we assume the shocks are random and are described by a similar distribution. We can also assume that, TE_i is a stochastic variable, with a specific distribution function, common to all producers. We can write Equation 2 as an exponential $TE_i = exp\{-u_i\}$, where $u_i \geq 0$, since we required $TE_i \leq 1$. Thus, the stochastic frontier production function that assumes the presence of technical production inefficiency becomes:

$$Y_i = f(\boldsymbol{X}_i;\ \boldsymbol{\beta}_i)\, exp(\varepsilon_i)\,, \varepsilon_i = v_i - u_i, i = 1, 2, \ldots, N, \quad (3)$$

where Y_i is the observed scalar output of producer i, $\boldsymbol{X_{ij}}$ is a vector of J inputs used by producer i, $X_i \sim IIDN(\mu, \Sigma_x), f(\boldsymbol{X_{ij}}; \boldsymbol{\beta_j})$ is the deterministic production frontier, and $\boldsymbol{\beta}_j$ is a vector of technology parameters to be estimated. Term, v_i is an IID (independent and identically distributed) random error associated with random shocks, not under the control of economic agent i or the underlying technology and comes from weather changes or economic adversity. This is the 'noise' component and is assumed to be a two-sided normally distributed variable with constant variance $(v \sim N(0, \sigma_v^2))$. Term, u_i is the farm-specific technical inefficiency, $TI_i = exp(-u_i)$, where $u_i \geq 0$, since we required $TI_i \geq 0$, and is assumed to be independent of v_i and follow a distribution which is either a half-normal (Aigner et al. (1977), exponential (Meeusen–Van der Broeck 1977), truncated-normal (Stevenson, 1980), or gamma distribution (Greene 2003)[14] with variance σ_u^2. In any distribution, it follows that total variance is given by $\sigma^2 = \sigma_u^2 + \sigma_v^2$. This model is such that the possible production Y_i is bounded above by the stochastic quantity, $f(\boldsymbol{X}_i)\,exp\ (v_i)$, hence the term stochastic frontier. When the data are in logarithmic form, u_i is a measure of the percentage by which a particular farm fails to achieve the frontier or ideal production rate (Greene 2003). Following Battese–Corra (1977), the departure of output from the frontier due to technical inefficiency is defined by a parameter η given by[15] $\eta = \frac{\sigma_u^2}{\sigma^2}$, such that $0 \leq \eta \leq 1$. If the parameter $\eta = 0$, then the variance of the technical inefficiency effect is zero, and so the model reduces to the traditional mean response function, a specification with parameters that can be estimated using OLS (ordinary least squares). If η is close to one, it indicates that the deviations from the frontier are due mostly to technical inefficiency and when $\eta = 1$, a one-sided error component dominates the symmetric error component, and the model is a deterministic production function with no noise.

Since the SFA approach requires an assumption about the functional form of the production function, the next step corresponds to the selection of the functional form of the stochastic frontier production function. In the production function literature, the choice of functional form brings a series of implications with respect to the shape of the implied isoquants. In TE analysis literature earlier reviewed, there are two distinct production function forms that are widely utilized: the first-degree flexible Cobb–Douglas and the second-degree flexible transcendental logarithmic (hereafter abbreviated 'Translog') production functions. The Cobb–Douglas production function has universally smooth and convex isoquants. The alternative Translog model is not monotonic or globally convex, as is the Cobb–Douglas model, and imposing the appropriate curvature on it is generally a challenging problem. However, Translog has its strength in that it is flexible and does not require *a priori* restrictions on the technologies to be estimated (Orea–Kumbhakar 2004, Alvarez–del Corral 2010). This study adopts both functional formations (but subjects them to selection criteria) [16] and assumes that the deterministic

[14] Note, in Greene (1990) paper, all the four distributions were applied, and the results showed that the gamma model generated a significantly different set of TE estimates from the other three distributions and so very difficult to select a distribution of error term *a priori*.
[15] It is worth noting that other scholars use λ given by σ_u/σ_v in determining the contribution of technical inefficiency in stochastic production modelling.
[16] To solve this problem, one can allow for the greatest flexibility regarding the distribution shape and range of skewness for the distribution of the composed error ε, and/or compare Akaike's information Criterion

part $f(\boldsymbol{X_i};\ \boldsymbol{\beta})$ takes the log-linear form. Using SFA, we express Equation 3 using the two functional forms as:

Cobb–Douglas: $ln\,Y_i = \beta_o + \sum_{i=1}^{N} \beta_i\, ln\,X_i + \nu_i - u_i,$ (4)

Translog: $ln\,Y_i = \beta_o + \sum_{i=1}^{N} \beta_i\, ln\,X_i + \frac{1}{2}\sum_{i=1}^{N}\sum_{k=1}^{N} \beta_{ik}\, ln\,X_{ik}\, ln\,X_{\boldsymbol{ik}} + \nu_i - u_i,$ (5)

Where, following Battese–Coelli (1995) $u_i = f(Z_i) = \delta_0 + \sum_{i=1}^{M} \delta_i Z_i + \varepsilon_i\,, i = 1, 2, \ldots, M$ and Z_i represent the socio-demographic and other independent variables assumed to contribute to TI. The term, $\boldsymbol{\delta}$ is a vector of unknown parameters to be estimated and ε_i is a random variable with zero mean and finite variance σ_ε^2 defined by the truncation of the normal distribution such that $\varepsilon_i \geq -[\delta_0 + \sum_{i=1}^{M} \delta_i Z_i]$. The mean of inefficiency term, $u_i = f(Z_i) = \delta_0 + \sum_{i=1}^{M} \delta_i Z_{\boldsymbol{i}}$, is farm-specific and the variance components are assumed to be equal ($\sigma_u^2 = \sigma_\varepsilon^2$).

As Alvarez et al. (2012) and Sauer–Morrison (2013) observed, a standard limitation while using the above parametric stochastic production function (SPF) model is that the model assumes similar production technologies and no attention is paid to the possible presence of heterogeneity, particularly in the production decision process. Many case studies (e.g. Alvarez–del Corral 2010, Sauer et al. 2012, Kellermann 2014, Otieno et al. 2014, Baráth–Fertő 2015, Martinez et al. 2016, Bahta et al. 2018) have shown resource and production environments surrounding production societies are highly heterogeneous. The use of a single characteristic to cluster a sample might be challenging when heterogeneity is likely to arise from more than one factor, leading to an incomplete division of the sample. In this regard, we need to consider the possibility of production heterogeneity. To account for technology heterogeneity, several approaches on how to relax the restrictive assumption that all farms share the same production technology have been proposed in the efficiency literature. First, stochastic metafrontier approach proposed by Battese–Rao (2002) follows a two-stage process that involves first splitting the sample into groups based on some *a priori* information about farms (e.g. farm ownership, production system, farm location, etc.), and second stage estimation of separated frontier functions for each group (e.g. Battese et al. 2004, Newman–Matthews 2006, Balcombe et al. 2007, Moreira–Bravo-Ureta 2010, Otieno et al. 2014, Melo-

(AIC) among different distributions. Where AIC is an estimator of the relative quality of statistical models for a given set of data.

Becerra–Orozco-Gallo 2017).[17] However, the use of *a priori* information might be challenging in cases where heterogeneity is likely to arise from more than one factor, leading to an incomplete division of the sample (Alvarez et al. 2012, Sauer–Morrison 2013). Second, some authors allow for consideration of multiple exogenous characteristics when splitting the sample into groups by using statistical techniques such as cluster analysis (e.g. Maudos et al. 2002, Alvarez et al. 2008). The salient characteristic of the two aforementioned approaches is the use of a two-stage approach (i.e. in the first step, the sample is divided into groups, and then separate regressions are performed for each of them), which has the shortcoming that the information contained in a given sub-sample cannot be used to estimate the technology of farms that belong to other sub-samples. According to Alvarez–del Corral (2010), this limitation is critical because farms included in separate groups often share some common features.

To overcome this limitation, one option is to use Greene's (2005) approach of implementing a random coefficients model, which accounts for farm technology differences in the form of a continuous parameter variation. Another possibility is to use cluster algorithms as proposed by Alvarez et al. (2008) or apply the econometric techniques proposed by Kumbhakar et al. (2009), where a system approach is used to estimate the production technologies and the choice equation simultaneously, or by LCMs (latent class model) as applied by Alvarez–del Corral (2010) and Sauer–Morrison (2013). Although heterogeneity can be modelled using several methodological approaches, in this study, we adopted an LCM in an SFA (stochastic frontier analysis) framework because it has been increasingly recognized as a suitable way to deal with technology heterogeneity. Additionally, the comparative analysis conducted by Alvarez et al. (2012) between a two-stage SFA approach versus an LCSFA revealed that the LCSFA provided a more satisfactory separation of technologies in the sample. However, despite LCSFA proving superior, there are still very few empirical applications of the latent class in the SFA framework.

Since the introduction of LCSFA, a stream of research has produced many reformulations and extensions of the model into various sectors, generating a flourish of empirical studies. By way of example, the LCSFA was applied in agricultural-related contexts (Alvarez–Arias 2013, Sauer–Morrison 2013, Bahta et al. 2018), finance

[17] For example, Otieno et al. (2014) split the sample into three sub-samples (pastoral, agro-pastoral, and ranches) based on a single exogenous characteristic and estimated different production frontiers for each group, without considering within-group characteristics that may be unobservable.

(e.g. Brummer–Loy, 2000, Poghosyan–Kumbhakar 2010), transport (e.g. Cullmann et al. 2012) and health services (e.g. Widmer 2015). All these papers found evidence that if technology heterogeneity is not considered when estimating TE, the results could be misleading and therefore, any policy recommendation arising from them would not be accurate. In this study, we adopt the LCM in the SFA framework as was formulated in Alvarez–Arias (2013), and rewrite Equations 4 and 5 as follows:

Cobb–Douglas: $ln\, Y_i = \beta_o \big| j \; + \sum_{i=1}^{N} \beta_i | j \; ln\, X_i + \nu_i | j - u_i | j,$ (6)

Translog: $ln\, Y_i = \beta_o | j + \sum_{i=1}^{N} \beta_i \Big| j \; ln\, X_i + \frac{1}{2} \sum_{i=1}^{N} \sum_{k=1}^{N} \beta_{ik} | j \; ln\, X_{ik} \; ln\, X_{ik} + \nu_i | j - u_i | j,$ (7)

The vertical bar means that there is a different model for each class j and the other variables are as previously defined. Now, u_i, which defines the inefficiency term, can be represented by non-negative unobservable random variables associated with the technical inefficiency of production, such that for a given technology and level of inputs, the observed output falls short of its potential (Battese–Coelli 1995). This approach provides the opportunity to account for resource quality differences across farmers, along with socioeconomic and institutional differences that might affect behaviour. It is assumed that the inefficiency factors are independently distributed and that *u* arises by the truncation (at zero) of the normal distribution. Specifically:

$u_i | j = f(Z_i) | j = \delta_0 | j + \sum_{i=1}^{M} \delta_i \, Z_i | j + \varepsilon_i | j,$ (8)

Where vector Z_i is independent variables assumed to contribute to technical inefficiency, and δ is the vector of unknown parameters to be estimated. The subscript i = 1,2…M denotes farms and *j* represents the different classes. Term, ε_i is a random variable with zero mean and finite variance defined by the truncation of the normal distribution such that $\varepsilon_i \geq -[\delta_0 + \sum_{i=1}^{M} \delta_i Z_i]$ for farms in j. The *Z*-vector parameter estimate for (in)efficiency level $(\hat{u})$ is expected to have a negative (positive) sign, which implies that the corresponding variable would reduce (increase) the level of (in)efficiency (Coelli et al. 2005).

3.3. Material and Methods

This section describes the crucial materials and methods used in the measurement of farm household production efficiency for homogenous and heterogeneous technology. The section is organized as follow. Data source, sample size determination and data collection procedure are described in section 3.3.1. Section 3.3.2 presents the estimation procedures for stochastic frontier production functions, while the methods for estimating the individual technical inefficiency is explained in section 3.3.3. Method for detecting the skewness and multicollinearity and procedure for estimating the return to scare are discussed in section 3.3.4.and 3.3.5, respectively. Subsequently, the contextual variables are discussed in section 3.3.6.

3.3.1. Data source, Sample size determination, and data collection

The study relied on primary sources derived from responses from agricultural pastoral farm household residing in the southern rangelands of Kenya. The critical aspect of this study is to appropriately analyse the constraints limiting pastoral farm household in production and livestock marketing and farmers' markets participation. In order to delineate the focus of attention in this research, the study adapted Ellis (1993) definition of peasants to define smallholder agricultural pastoral farm households as a group of persons who derive their livelihoods mainly but not exclusively from agriculture, predominantly utilize family labour in farm production, and are characterized by a partial engagement in input and output markets, and are both producers and consumers of agricultural goods and services[18]. The term peasant was avoided due to the pejorative connotations usually associated with it in favour of a more neutral term, smallholder households[19]. The defined smallholder agricultural pastoral farm household conform with the recent paradigm production trend manifested by a gradual shift from the traditional nomadic pastoralism behaviour to sedentary pastoral farming[20] (Gumbo–Maitima 2007,

[18] This definition is similar to Unalan (2005) definition of agricultural household as a group of people who cook together and eat together and drawing food from a common source – share resources together and therefore for this purpose, household members are not necessarily the same as family members.

[19] Peasants term is avoided because as from the description by Handy (2009), it is derogatory since it included behavior such as a supposed reluctance to work hard, since their consumption expectations seemed to be easily satisfied; a failure to use land "efficiently" and therefore standing in the way of "progress"; having too many children; and constituting a "dangerous" class not suitable for or capable of full citizenship.

[20] A transformation from nomadic system characterized by extensive grazing on natural pasture involving constant or seasonal migration of nomads and their livestock and animal serve social needs like paying the bridal price and traditional ceremonies to sedentary pastoral farming in which farmers grow crops and improve pastures for their livestock and participate in the markets.

Mwang'ombe et al. 2009, Bebe et al. 2012). Since empirical studies on agricultural household modelling are commonly based on the premise that households behave as though they are single individuals (e.g. Becker, 1991, Umar, 2013), the assumption of a "unitary smallholder household[21]" was found convenient and appropriate in this contexts, and there is theoretical justification for aggregation individuals this way as it helps in avoiding phenomena of goal conflict. Therefore, the model of smallholder pastoral farms household behaviour hypothesized in this study describes a semi-commercial male- or female-headed family farm.

It is widely recognized among researchers that the determination of sample size and power is a crucial element in the planning of any research venture. Some of the considerations that need to be considered when determining sample size are, the sample size degree of power for hypothesis testing, the confidence interval with a specified width, or to estimate a parameter with a maximum error of estimation for specified probability. In addition, the sample size is determined by financial or logistical constraints. In determining sample size, the most common methods used are Bayesian, Frequency or Sequential approaches (highly discussed in Betensky–Tierney 1997). A Frequentist approach is the standard textbook approach to sample size determination, while Sequential and Bayesian methods are more computationally involving. Their one distinct commonality is that all are used to provide a prior estimate of parameters other than the parameter that is being either tested in the hypothesis or for which confidence interval and point estimates are to be constructed. This, coupled with the possible difficulty in justifying a selected prior distribution for parameters that must be specified, limit the number of studies in which these methods can be used. In this study, a trivial expression is presented that was used for sample size determination. The method presented is quite general and, it was hoped, to be applicable in sample determination for smallholder household under pastoral setup.

In more stringent statistical considerations and data collection procedures, sample sizes were systematically determined by employing the *Probability Proportional to Size* (PPS)[22] sampling method. The PPS involved in this study comprises of two-sequential

[21] A unitary household model commonly assumes that 'a Household' has same choices, decision making processes and pool their resources together and Households are often modeled as male headed or female headed, and analysis conducted in the same line.

[22] PPS is a sampling procedure under which the probability of a unit being selected is proportional to the size of the ultimate unit, giving larger clusters a greater probability of selection and smaller clusters a lower probability.

stages; first, the determinations of sample size for each county, and second, the distribution of the predetermined sample size in the first stage within each county. The overall sample size for the Kenya national-wide households survey consisted of 12,651 agricultural households selected from 6,324,819 households (GoK 2010) and using PPS sampling method to allocate the sampled households to all 47 counties (Appendix 2). Since we were interested with the households sampled in the southern rangelands of Kenya, then the sampling frame for this study comprises of households interviewed in Garissa, Kajiado, Kilifi, Kitui, Kwale, Lamu, Makueni, Narok, Taita-Taveta and Tana-River counties[23]. In the first stage, since the sampling frame for this study was agricultural pastoral households, and justifying a selected prior distribution for parameters proved to be problematic, the study opted for nonparametric Slovin's formula[24] to determine the sample size for each county specified as follows:

$$n = \frac{N}{1+Ne^2}, \tag{9}$$

where n_0 is the sample size, N is the total agricultural household population in each county, e is the level of precision or sampling error, which is the range in which the true value of the population is estimated. In the first stage, usually with a 95% confidence level and an error margin of less than 10%, a sample of 1961 households out of 1,295,742 households was considered representative and as observed by Nyariki (2009), an $e < 10\%$ can facilitates the collection of information on for making of valid statistical inferences. However, to account for non-responsiveness and/or incomplete data during questionnaire administration, the sample size (n) was further adjusted using a response rate r:

$$C_i = \frac{n}{r}, \tag{10}$$

where, C_i is the total number of household sampled after adjustment for the confidence level r for expected response rate and i=1,2,..10 is the total number of ASALs counties in the southern rangelands. With an overall standard margin of error of 7.29 % and at 95% confidence level, a total of 2180 smallholder pastoral household were sampled and were

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[23] These counties were selected because in general, livestock keepers are the mainstay and are less commercialized and maintain principally as a capital and cultural asset and sell only when absolutely necessary.

[24] No indication of distribution assumption required.

distributed in the ten counties found in southern rangelands of Kenya based on PPS as shown in Table 3 below.

In the second stage, the predetermined sample size distribution was confined to the prominent production systems within each county; therefore, each county's sample size was randomly spread to different areas based on the household probability population density of each production system. Unfortunately, it was not possible to stratify the samples on the basis of livestock numbers on individual properties and therefore the livestock census register list of Kenya National Bureau of Statistic of 2009 was used as it constituted the complete population listing that was available at the time (GoK 2010). The distribution of the predetermined sample size based on PPS was done by applying the following formula:

$$S_{ij} = \frac{X_{ij}}{P_{HC}} * C_i, \qquad (11)$$

Here, $\frac{X_{ij}}{P_{HC}}$ represent the probability population household density for ecological zone j in county i, S_i is the total number of individual smallholder agricultural households' selected for interview in each ecological zone j in the ith county; X_{ij} is the total number of the agricultural household farmers in each of ecological zone jth in each county i; P_{HC} is the total population of smallholders agricultural household in each county ($P_{HC} = \sum_{j=1}^{J} X_{ij}$); C_i is the predetermined sample size for county i. Appendix 1 shows the areas selected for the household baseline survey and the geo-referenced locations of the households randomly sampled in each county.

Data collection was co-funded by governments of Swedish and partly by Kenya under the Agricultural Sector Development Support Program (ASDSP). The team composing of University of Nairobi and Kenya Agricultural and Livestock Research (KALRO) staffs were involved in the data collection and together visited the 47 counties to triangulate the sample selected in consultation with the extension staff at the county level. Households identified for sampling were entered in Global Positioning System by GIS mappers who had earlier been recruited and trained for randomization, and the identified households were supplied with coupons which were to be submitted to the data clerk after a face-to-face interview. The mapping of households was done prior to the actual data collection. Enumerators and data entry clerks were recruited and trained on the survey instrument and pre-test was done before actual data collection. Since the overall objective of this study was to investigate livestock production and marketing behaviour of smallholder pastoral households, we, therefore, confined our data consideration on the households that were selected on the southern rangelands part of Kenya. Data were obtained from 2180 livestock keeping household who were distributed across the ten counties of southern rangelands of Kenya using a PPS sampling method. The sampling and data collection were done during September-October 2013 and was structured and managed in a way that ensured high data quality. Data was collected from all agro-ecological zones, but the fact that a farm belongs to which zone was not registered so only very deep, a one-by-one analysis could produce a variable. However, the manual revision of the data may cause as many biases as the lack of information. The 2180 households selected were then subjected to screening for incomplete and/or missing data of crucial variables and those not engaging in livestock production, thus reducing the number to 1288 households, and this sample size was found adequately enough to address the research questions for this study.

Table 3: Summary of the Number of Households Interviewed in each County

Counties	**P_{HC}**	***e***	***n***	**r**	**C_i**	***NHSA***	**DSF (%)**
Garissa	98,590	6.300	142	77.0%	185	114	8.9
Kajiado	173,464	6.200	250	91.4%	274	252	19.6
Kilifi	199,764	5.780	288	91.0%	317	104	8.1
Kitui	205,491	5.700	296	92.0%	321	138	10.7
Kwale	122,047	7.400	176	91.0%	204	98	7.6
Lamu	22,184	9.900	98	96.0%	102	16	1.2
Makueni	186,478	6.000	267	91.0%	293	207	16.1
Narok	169,220	6.276	244	91.3%	267	247	19.2
Taita-Taveta	71,090	9.700	102	91.0%	112	47	3.6
Tana-River	47,414	9.900	98	93.0%	105	65	5.0
Total	**1,295,742**	**7.316**	**1961**	**90.5%**	**2180**	**1288**	**100.0**

Note: P_{HC} = Total number of households in the county; DSF = Percentage Distribution of selected farmers; *e* = Margin of error; *r* = Response rate; NHSA = Number of households selected for analysis
Source: Own's computation and construction

3.3.2. Procedure for Estimation stochastic frontier models

In the case of cross-sectional data, the stochastic frontier model can only be estimated if the inefficiency effect components u_i are stochastic and have particular distributional properties (Battese–Coelli 1995). If we rewrite the stochastic frontier models (Equations 4 and 5) in matrix form as:

$$y_i = \alpha + \boldsymbol{X}_i'\boldsymbol{\beta} + \varepsilon_i, i = 1, \ldots, N ,$$

$$\varepsilon_i = \nu_i - u_i, \nu_i \sim \boldsymbol{N}(0, \sigma_v^2), \text{ and } u_i \sim \boldsymbol{F}, \quad (12)$$

where y_i represents the logarithm of the output of the *i*-th productive unit, $\boldsymbol{X}_i'$ is a vector of inputs, and $\boldsymbol{\beta}$ is the vector of technology parameters. The composed error term ε_i is the sum (or difference) of a normally distributed disturbance, ν_i, representing measurement and specification error, and a one-sided disturbance, u_i, representing inefficiency. Moreover, ν_i and u_i are assumed to be independent of each other and IID across observations. The distributional assumption, $\boldsymbol{F}$, required for identification of the inefficiency term, implies that this model can usually be estimated by maximum likelihood estimation (MLE) procedure, even though modified OLS or generalized method of moments estimators are possible (but often inefficient) alternatives (Belotti et al. 2013).

From the reviewed literature, it is clear that there is a need to investigate the role of distribution in measuring efficiency since the bases for choosing an appropriate functional form and distributional assumption of the inefficiency error term in a specific application are not clear *a priori* (Green 2002, Wang 2003). In incorporating inefficiency in SFA, Aigner et al. (1977) assumed a half-normal distribution, while Meeusen–Van der Broeck (1977) opted for an exponential one. Other commonly adopted distributions are the truncated normal with a non-zero mean (Stevenson, 1980) and gamma distributions (Greene 2003). The log-likelihood models for the four widely applied distributions in efficiency measurement literature are summarized in Table 4. In SFA, the widely canonical form of the Equation 12 model is the half-normal model, $u \sim N^+(0, \sigma_u^2)$, $\nu \sim N\,[0, \sigma_v^2]$, which has commonly been used as the default form in most statistical software (STATA, EViews, LIMDEP, etc.). In this form, the primary model estimates consist of $\beta, \sigma = \sqrt{\sigma_u^2 + \sigma_v^2}, \sigma$ and $\lambda = \frac{\sigma_u}{\sigma_v}$, and the usual set of diagnostic statistics for models fit by ML. The other common form is the exponential model, $u \sim \theta\, exp\ (-\theta u)$, $u > 0$, which has mean inefficiency $E(u) = \frac{1}{\theta}$, and standard deviation $\sigma_u = \frac{1}{\theta}$. The parameters estimated in the exponential specification are $(\boldsymbol{\beta}, \theta, \sigma_u, \sigma_v)$. Half-normal and exponential distributions have the same feature of having a mode at zero, which means most inefficiency is concentrated near zero. This may lead to significant underestimation of inefficiencies if the true inefficiency distribution has a non-zero mode.

The more flexible distributions with two or more parameters and a non-zero mean that are commonly adopted are the truncated normal ($u \sim N(\mu, \sigma_u^2)$) (Stevenson 1980) and gamma distributions ($u \sim \frac{\theta^P exp(-\theta u)u_i^{P-1}}{\Gamma(P)}$), where $u_i \geq 0, P > 0, \theta > 0$ (Greene 2003). For the normal-gamma model, the two-parameter distributional form allows both the shape and location to vary independently. The log-likelihood for this model is equal to the log-likelihood for the normal-exponential model plus a term that is produced by the difference between the exponential and gamma distributions and the normal exponential model result if P = 1. The normal-truncated normal model relaxes the implicit restriction in the normal-half normal model that the mean of the underlying inefficiency variable is zero. There are only two formulations of the normal-truncated normal model in the literature. The common one, which is applied in this study, is the extended model by Stevenson (1980) in which μ, the mean of u, is assumed to be nonzero; $u \sim N(\mu, \sigma_u^2)$ and $v \sim N\ [0, \sigma_v^2]$, and the log likelihood function is then maximized with respect to $\beta, \sigma, \lambda,$ and α. The other is Battese and Coelli's (1995) formulation, $u = \mu + w$, where w is a truncated normal, such that $w > -\mu$. These four distributions were applied to investigate the role of distributions in efficiency estimation in the livestock production for smallholder pastoral households in the southern rangelands of Kenya.

Table 4: Log-likelihood for Commonly used Distributions for SFA

Model	Log-likelihood and estimated variables
Half normal $u \sim N^{+}(0, \sigma_u^2)$	$\log L_i = 1/2\left(Log\left(2/\pi\right)\right) - Log\sigma - 1/2\left(\varepsilon_i/\sigma\right) + \log\Phi\ \left[-S\varepsilon_i\ \lambda/\sigma\right.$ $\log L_i = {}^1/_2\ (\text{Log}(2/\pi) - \text{Log}\sigma - {}^1/_2\ (\varepsilon_i/\sigma) + log\Phi[-S\ \varepsilon_i\lambda/\sigma$; Estimated parameters: $\beta,\ \sigma^2 = \sigma_u^2 + \sigma_v^2,\ \lambda = \sigma_u/\sigma_v,\ \sigma^2 = \sigma_u^2 + \sigma_v^2,\ \sigma_u = \frac{\sigma^2}{1+\lambda^2},\ \sigma_u^2 = \frac{\sigma^2\lambda^2}{1-\lambda^2}$
Exponential $u \sim \theta\ exp\ \ (-\theta u)$	$\log L_i = Log\theta + 1/2\,\theta^2\sigma_v^2 + \theta S\varepsilon_i + Log\Phi\left[-\frac{S\varepsilon_i}{\sigma_v} - \theta\sigma_v\right)$ Estimated parameters: $\beta,\ \sigma_v$, and $\theta = \frac{1}{\sigma_v}$ or $\sigma_u = 1/\theta$
Gamma $u \sim \frac{\theta^P\ exp(-\theta u)\ u_i^{P-1}}{\Gamma(P)}$ $u_i \geq 0,\ P > 0,\ \theta > 0$	$\log L_i = Log\theta + 1/2\,\theta^2\sigma_v^2 + \theta S\varepsilon_i + Log\Phi\left[-\frac{S\varepsilon_i}{\sigma_v} - \theta\sigma_v\right) + n\left[\left(P-1\right)\log\theta - Log\Gamma\left(P\right)\right] + \sum_i Logh\left(P-1,\ \varepsilon_i\right)$, where $h(r,\ \varepsilon) = \frac{\int_0^\infty z^r\left(\frac{1}{\sigma_v}\right)\varnothing\left(\frac{z-\eta_i}{\sigma_v}\right)dz}{\int_0^\infty\left(\frac{1}{\sigma_v}\right)\varnothing\left(\frac{z-\eta_i}{\sigma_v}\right)dz},\ \eta_i = -\varepsilon_i - \theta\sigma_v^2$ The exponential model result if P = 1.
Truncated-normal $u \sim N(\mu, \sigma_u^2)$	$\log L_i = -1/2\left(Log2\pi - Log\sigma - 1/2\left(\frac{d\varepsilon_i}{\sigma} + \alpha\lambda\right)^2 - \log\Phi\alpha\left(\sqrt{1+\lambda^2}\right) + \Phi\left(\alpha - \frac{\partial\varepsilon_i\lambda}{\sigma}\right)\right)$, $logL_i =$ $-{}^1/_2\ (Log2\pi - Log\sigma - {}^1/_2\left(\frac{d\varepsilon_i}{\sigma} + \alpha\lambda\right)^2 - log\Phi\alpha\left(\sqrt{1+\lambda^2}\right) +$ $\Phi\left(\alpha - \frac{d\varepsilon_i\lambda}{\sigma}\right)$, where $\sigma_u = \sigma\lambda/\sqrt{1+\lambda^2}$ and $\alpha = \mu/(\lambda\sigma)$ Estimated parameters: $\beta,\ \sigma,\ \lambda$, and α.

Note: S = + 1 for production frontier and –1 for cost frontier, and $\varepsilon_i = y_i - \beta' X_i$.
Source: Author's own construction based on literature.

With regard to the latent class stochastic frontier model that incorporate heterogeneity in the estimation, although u can take many distribution forms, we restricted our analysis to the widely used and supported latent class estimator by LIMDEP Version 11 Econometric Software: the normal half-normal and normal exponential-normal distributions (Greene 2016). Further, these distributions were preferred for parsimony because they entail less computational complexity (Coelli et al. 2005), unlike truncated and gamma, which, albeit flexible, sometimes may not be well-identified and estimated (Ritter–Simar 1997). In the LCSFA model, following Kumbhakar–Knox-Lovell (2000) formulation, the LF (latent class likelihood function) for each farm i for group j can be written as:

$$LF_{ij}(\theta_j) = f(y_i|x_i, \beta_j, \sigma_j, \lambda_j) = \frac{\Phi\left(-\lambda_j \cdot \frac{\varepsilon_i|j}{\sigma_j}\right)}{\Phi(0)} \cdot \frac{1}{\sigma_j} \cdot \emptyset\ \left(\frac{\varepsilon_{ij}}{\sigma_j}\right), \tag{13}$$

Where LF_{ij} is the likelihood function for farm i in group j, $\varepsilon_i|j = y_i - f(\beta_j' x_i), \sigma_j = \sqrt{\sigma_{uj}^2 + \sigma_{vj}^2}, \lambda = \frac{\sigma_{uj}^2}{\sigma_{vj}^2}$. $\Phi(.)$ and $\emptyset(.)$ are standard normal density and cumulative distribution functions, respectively. The LF for each farm can be obtained as a weighted average of its LF for each group j, using the prior probabilities P_{ij} of class j membership as weights:

$$LF_i = \sum_{J=1}^{J} P_{ij} LF_{ij}, \tag{14}$$

where $0 \leq P_{ij} \leq 1$, and the sum of these probabilities for each farm must be 1: $\sum_{j=1}^{J} P_{ij} = 1$. To satisfy these two conditions, the class probabilities, P_{ij}, can be parameterized as a multinomial logit model expressed as:

$$P_{ij}(\delta_j) = \frac{exp(\delta_j q_i)}{\sum_{J=1}^{J} exp(\delta_j q_i)}, \tag{15}$$

where δ_j is s a vector of parameters to be estimated, j = 1, ..., J, and $\delta_j = 0$. q_i is the vector of 'separating variables' of farm-specific characteristics that sharpen the prior probabilities[25]. However, LCM can also classify the sample into several sub-sample even when sample-separating information is not available (Orea–Kumbhakar, 2004) where the model uses the goodness-of-fit of each estimated frontier as the only additional information to identify groups but we adopted the former. The overall log LF is obtained as the sum of individual log LFs and can be written as:

$$LnLF(\theta, \delta) = \sum_{i=1}^{N} LnLF_i(\theta, \delta) = \sum_{i=1}^{N} Ln\left[\sum_{j=1}^{J} LF_{ij}(\theta_j) \cdot P_{ij}(\delta_j)\right]_i, \tag{16}$$

The log LF can be maximized with respect to the parameter set $\theta_j = (\beta_j, \sigma_j, \lambda_j, \delta_j)$ using conventional methods (Greene 2002). The estimated parameters can be used to compute the conditional posterior class probabilities. Following the steps outlined in Greene (2002), the posterior class probabilities can be obtained from:

[25] For instance, the case in Sauer–Morrison (2013), stocking rates, milk per cow or milk per land were used as separating variable that sharpen the probabilities of farms being in an intensive or extensive dairy farm in Danish.

$$P_{ij}(j|i) = \frac{LF_{ij}(\theta_j)\cdot P_{ij}(\delta_j)}{\sum_{J=1}^{J} LF_{ij}(\theta_j)\cdot P_{ij}(\delta_j)}, \tag{17}$$

This expression shows that the posterior class probabilities depend not only on the estimated δ parameters but also on the vector θ, that is, the parameters from the production frontier. This means that an LCM classifies the sample into several classes, even when sample-separating information is not available. In this case, the latent class structure uses the goodness of fit of each estimated frontier as additional information to identify classes of farms.

3.3.3. Estimating individual inefficiency

The ultimate goal of fitting the frontier models is to estimate the levels of technical inefficiency term u_i in the stochastic model using the sample observations. Unfortunately, it is not possible to estimate u_i directly from any observed sample information. In standard SFA, where the frontier function is the same for every farm, we estimate inefficiency relative to the frontier for all observations. The Jondrow et al. (1982) estimator of the conditional distribution of *u* given ε, $\hat{E}(u|\nu - u)$, where $\varepsilon = \nu_i - u_i$, is the standard estimator. Thus, a point estimate of the inefficiencies can be obtained using the mean $\hat{E}(u|\varepsilon)$ of this conditional distribution expressed as:

$$\hat{E}(u|\varepsilon) = \frac{\sigma\lambda}{1+\lambda^2}\left[\frac{\Phi\left(\frac{\varepsilon\lambda}{\sigma}\right)}{1-\Phi\left(\frac{\varepsilon\lambda}{\sigma}\right)}\right] - \frac{\varepsilon\lambda}{\sigma}, \tag{18}$$

This is an indirect estimator of *u*. Once point estimates of *u* are obtained, estimates of TE can then be derived as $Eff = exp(-\hat{u})$, where $\hat{u}$ is $\hat{E}(u|\varepsilon)$. In a traditional stochastic frontier model, the output-oriented TE can be calculated as a ratio of the observed output to the corresponding frontier output, given the available technology, using the following expression (the dependent variable expressed in the log):

$$TE_i = \frac{Y_i}{Y_i^*} = \frac{f(X_i;\beta_i)\, exp(\nu_i - u_i)}{f(X_i;\beta_i)\, exp(\nu_i)} = exp(-u_i), \tag{19}$$

Here Y_i is the observed output and Y_i^* present the frontier output. Once estimates of TE are obtained, the indirect estimator of inefficiency can be obtained using $Technical\ inefficiency = 1 - exp(-TE_i)$. This is the inefficiency parameter that enters the inefficiency effects model as the dependent variable. In the LCSF model, the calculation of TE is tedious because each farm can be assigned to several frontiers, each one with an associated probability. It is not possible to estimate u_i in LCM directly from any observed sample information. In the present case of an LCSF model, we estimate as many frontiers as there are numbers of classes. What remains an issue is how to measure the efficiency level of an individual farm when there is no unique technology against which inefficiency is to be computed. In a traditional stochastic frontier model, output-oriented TE can be calculated as a ratio of the observed output to the corresponding frontier output, given the available technology (Equation 19). In the LCSFA model, the calculation of TE is tedious because each farm can be assigned to several frontiers, each one with an associated probability. Then, based on Orea–Kumbhakar (2004), TE can be measured with respect to the most likely frontier (the one with the highest posterior probability) or using a weighted average of the TE for all frontiers with the posterior probabilities as weights. This scheme of random weighting and random selection of the so-called reference technology can be avoided by using the following expression:

$$TE_i = \sum_{J=1}^{J} P_{ij}(j|i) * TE_i(j), \qquad (20)$$

where $P_{ij}(j|i)$ is the posterior class probabilities of being in the *j*-th class for a given farm *i* defined in Equation 15, $0 < P_{ij}(j|i) < 1$ and $\sum_{J=1}^{J} P_{ij}(j|i) = 1$, while $TE_i(j)$ is its efficiency using the technology of class *j* as the technological reference.

Once estimates of TE are obtained, the indirect estimator of inefficiency can be obtained using $Technical\ inefficiency = 1 - \exp(-TE_i)$. This is the inefficiency parameters that enter the inefficiency effect model as the dependent variable.

3.3.4. Skewness and multicollinearity

The major challenge efficiency measurement analysts face often relates to skewness and multicollinearity. The one-sided distributions are expected to have positive skewness, which can be shown using Greene's (1990) third moment of ε_i given by:

$$E\{[\varepsilon_i - E(\varepsilon_i)]^3\} = -E\{[u_i - E(u_i)]^3\}, \qquad (21)$$

The positive skewness for u_i implies a negative skewness for ε_i. From equation 21, it is clear that $\hat{\mu}_{3,n} = n^{-1} \sum_{i=1}^{n} \hat{\varepsilon}_{i,OLS}^{3}$ is a consistent estimator of the negative of the third moment of u_i, which gives the sign of the skewness of u_i. The consequence of a 'wrong' skewness, as shown, for example, by Waldman (1982), is that the modified OLS and MLE estimates of the slope are identical to the OLS slope, and there are no inefficiencies, implying the mean and variance of u_i are estimated at zero. Therefore, all farms are supposed to be efficient – operating at the optimal frontier.

The other drawback in estimating the stochastic frontier model is associated with collinearity among inputs, which leads to the multicollinearity problem, and subsequent loss of estimate precision. When collinearity arises, separating the individual effects of each independent variable could be a difficult task, and the precision loss is manifested in significant estimated variances of estimates; moreover, estimated coefficients can have incorrect signs and impossible magnitudes. We applied the most common strategy for solving the multicollinearity problem by to step-by-step excluding the input whose correlation with other inputs is quite high or by eliminating an apparently insignificant variable, which can produce significant changes in estimates (Filippini et al. 2008).

3.3.5. Estimating Return to Scale (RTS)

The other technological characteristic analysed is the scale elasticity. Since classical input variables were presented as elasticities (logarithm), it is possible to calculate scale elasticity by summing up the partial differentiation with respect to each of the inputs as follows:

Classical stochastic frontier; $\frac{\partial \, ln \, Y_i}{\partial \, ln \, \boldsymbol{X_i}} = E_i = \boldsymbol{\beta_i}$; $RTS_i = \sum_{i=1}^{N} E_i,$ (22)

LC stochastic frontier; $\left.\frac{\partial LnY_i}{\partial LnX_i}\right|_j = E_k\Big|_j = \beta_k|_j + \beta_{kk}|_j LnX_{ik} + \sum_{k \neq j} \beta_{kj}\big|_j LnX_{ji},$ (23)

where RTS represents returns to scale. The elasticities are computed for each variable input with respect to output production, while the sum of all input elasticities gives a measure of RTS. For latent class model, the elasticities are computed for each variable with respect to their individual frontier as indicated by the *J* subscript, and these reflect the importance of each of the inputs in output production, while the sum of all input elasticities gives a measure of returns to scale for each farm i in each class j. It is worth noting that, in the process of computation of RTS, the coefficient for dummies were excluded given that they are shifting parameters and again, only RTS for the latent class stochastic frontier model were analysed.

3.3.6. Contextual Variables

When analysing efficiency in livestock production, beef or milk output would be considered as the dependent variable, while a number of inputs (e.g., herd size, feeds, veterinary costs, fixed costs etc.) are included as regressors in the model. However, due to measurement difficulties, previous studies have also proposed the use of proxy variables, such as value-added (e.g. Featherstone et al. 1997, Iraizoz et al. 2005) or physical weights of cattle (Rakipova et al. 2003). This study follows Rakipova et al. (2003) approach and the dependent variable *Y* stand for tropical livestock unit (TLU)[26] and comprises of cattle representing large ruminant, and sheep and goat representing small-stock ruminate. A similar approach was also applied in the study by Lekunze–Luvhengo (2016) and Manyeki–Kotosz (2019) where the number of livestock produced per year were converted to TLUs which is equivalent to physical weights approach applied in Rakipova et al. (2003) study. Different livestock species were combined into one herd, and this was necessitated because, under pastoral set-up, the three species (i.e. cattle, sheep and goat) are grazed together and shared same inputs and proved challenging to disintegrate between them.

The selected independent variables employed in testing the main hypotheses H_1 and H_2 on livestock production are summarized in Table 5 below. The selection of the main inputs for including in production function is centred around the theory of factors of production that can be traced back from Petty's Two (Land and Labour) elements theory of production, Say's Three (Labour force, Capital and Land (nature)) elements theory of production, Marshall's Four (Labour force, Capital, Land and Organization) elements theory of production, and the Xu's new development of Six (Labour, Physical, Natural, Transport and Time) forces of factors of production (Xu et al. 2009). Our understanding of the concept of factors of production is rooted for the most part in neoclassical economics, although other strains of economic theory also contribute to our current understanding.

‘‘Land’’, which was referred by Petty's like the ‘Mother or Womb of Wealth’, or designated as the origin of economic value by the physiocrats such as Quesnay, is quite a broad category as a factor of production in that it refers to all the natural resources. ‘‘Land’’, can range from land used for agriculture to that used for commercial real estate, as well as the natural resources derived from land. In this study, we were concerned with

[26] One TLUs refers to a 250 kg live weight animal: 1 cattle (cow/bull) is equivalent to 1 TLUs while 1 small ruminant is equivalent to 0.12 TLUs (ILCA 1990).

land used for agricultural, and from Say's theory, cultivated land is referred to as a critical factor among the three (Land, Capital and Labor). In many agricultural related types of research, the size of the land in hectare is commonly used as the critical factor of production (e.g. Delgado et al. 2008, Nganga et al. 2010, Alvarez–del Corral 2010, Álvarez–Arias 2013, Cillero et al. 2016). However, in the efficiency analysis, the use of imputed land rent as an input is also deemed appropriate (e.g. Hadley 2006, Barnes 2008). Further, the use of a dummy variable to indicate the presence of land as was the case in Iraizoz et al. (2005) or land quality (as was the case in Cillero et al. 2016) can also be appropriate. In this case, given that virtually all farmers sampled had some land[27], we followed the former stream and defined pastureland to include land under natural pasture, improved and woodlots in hectares (GoK 2014). Where there was no evidence that pastoralists use their *owned* land as a direct input in the livestock enterprise, the Battese (1997) formulation for cases of zero-values of some critical variables was adopted[28]. With regards to pastureland, Delgado et al. (2008), Nganga et al. (2010) and others observed that there is a strong tendency of livestock sector growing up as individual farms scale-up. These studies revealed that access to land ease the easy in which farmers can expand their enterprise by the acquisition of resources needed to expand the livestock production and productivity such as fixed inputs (that is through a loan by land acting as collateral). The same observation was found in the Otieno et al. (2014) study where an increase in the use of improved feed equivalents would lead to significant improvement in beef output. Thus, we expect a positive relationship between the size of pastureland and livestock production.

Labour, as a factor of production, involves any human input. Labour was considered to be the primary source of economic value according to early, influential political economist such as Adam Smith. The classical "labour theory of value" was an innovative theory in response to the physiocratic doctrine that only land could yield a surplus. For this study, we follow the Xu's new development theory of factors of production where the variable labour includes labour force. The various method has been

[27] Mostly household members (98.7%) had access to land and at least 40% of households had title deeds to their parcels of land, 44% owned the land but did not have title deeds or any formal document while 6.6% leased land (GoK 2014).

[28] Battese (1997) suggested that a dummy variable can be used in the incidence of the zero observations. Using Battese (1997), $ln\, Y_i = \beta_o + (\alpha_0 + \beta_0)D_{2i} + \sum_{i=1}^{N-1} \beta_i \, ln\, X_i + \beta \, ln\, X_{2i}^* + \nu_i - u_i$, where $D_{2i} = 1$ if $X_{2i} = 0$ and $D_{2i} = 0$ if $X_{2i} > 0$; $X_{2i}^* = Max(X_{2i}, D_{2i})$. This model implies that when X_{2i} for land input for farm i has a positive value, then $X_{2i}^* = X_{2i}$, but if X_{2i}has a value zero then $X_{2i}^* = 1$.

adopted in the investigation of the evolution of labour force productivity in agricultural-related research. In the study by Cillero et al. (2016), labour input was measured in total labour units working on the farm, including both unpaid and paid, while in the studies of Kibiego et al. (2015) and Bahta et al. (2018), agricultural labour was captured as the total labour cost, including permanent and temporary labour costs. Alvarez et al. (2008) and Alvarez–del Corral 2010 subsumes labour (which includes family labour and hired labour) measured in man-equivalent units, but Kellermann (2014) measure labour in man working units. Fox–Smeets (2011), showed the advantage of using the deflated wage bill as a measure of labour input compared to the number of employees or hour-based measures. In this study, we applied the hour-based approach and labour was measured in the man-working days in full-time equivalents and comprised of family and hired labour[29]. Following Kibiego et al. (2015), the use of labour on the farm is expected to increase the scale of production of the farmers, which consequently increases output and its requirements increase with the intensification.

The variable capital was first introduced in the Say's Three elements theory of production following Böhm-Bawerk (1964) suggestion that ordinary people should consider the accepted factors of production and their earnings symmetrically. However, capital has been the most controversial of factors of production and is variously defined as produced equipment; as finance used to acquire produced equipment; as all finance used to begin and carry on production, including the wage fund; and as the assessed value of the whole productive enterprise, including intangibles such as goodwill. In Cillero et al. (2016) and Bahta–Baker (2015) capital variable included fixed assets (machinery and buildings) aggregated in values according to the end of year valuation based on a replacement cost methodology. In Kellermann (2014), variable capital includes the end-of-year value of buildings, technical facilities, machinery and livestock. Increasingly, studies have come to treat any investment as a capital investment (investment in housing and equipment's was the case in Kibiego et al. (2015) in the efficiency measurement for dairy farms in Kenya). Furthermore, acquired skills have come to be viewed as analogous to physical equipment, capable of yielding their owners a return. Following this analogy Lockheed et al. (1980), designated acquired skill through education as human capital and hypothesised it to have a positive impact on efficiency. Recently, Baldwin et al. (2013)

[29] Division of labour between crop and livestock production is show in Appendix 3 and is disaggregated by gender based on the household baseline survey report (GoK 2014).

in a similar application build on a suggestion by Berndt–Fuss (1986) to account for variations in capital utilization through the share of capital income in the total value-added. Thus capital is a concept still stuck in confusion, hence here capital refers not to money (which is not a factor of production), but to value of physical resources such as machinery, equipment and buildings directly involved in livestock enterprise[30] computed in Kenya shillings at the end-of-year value and similarly to Kellermann (2014), it is expected to have a higher impact on livestock output.

Besides these conventional inputs, the fourth category applied as a control variable comprises the ingredients of the production function. In neoclassical economics, such variable includes materials, knowledge and human capital as a factor of production (Xu et al. 2009). We included a dummy variable for the case when other inputs (*material* may include expenses for forage production, veterinary services, purchased feed and other related expenses) are considered as additional factors of production (Xu et al. 2009, Kellermann 2014, Gechert et al. 2020). Such an approach is allowed especially when actual quantities of inputs are unavailable, and either a monetary equivalent or representative dummy variable for utilizing such inputs can be used (Battese et al. 1996, Murshed-E-Jahan–Pemsl 2011). As shown by Battese et al. (1996), without including these dummy variables, the estimators for the output elasticities of pastureland, labour and capital input obtained from the production function will be biased. This is because, based on Battese et al. (1996) argument, the elasticities obtained to pastureland, labour and capital inputs are assumed to be the same for farmers using these *material* inputs as those not using these inputs. Concerning the measurement of *material* inputs, our reference category is used dewormer, vaccine and acaricides (DVA) and feed and mineral supplementation (FM). We included a dummy that equals one when a study differentiates between the use of DVA and FM, zero otherwise. By use of dummy variable, we control effectively for farm-specific technology differences[31]; otherwise, our estimates of the production function parameters will generally be biased and inconsistent. However, the use of DVA and FM dummy variables as shifters of the production function is not widely used but when presented as monetary equivalent (veterinary or feed costs) in the efficiency measurement are available. For instance, in Bahta–Baker (2015) study,

[30] Machinery includes motorized asset such as Tractor/lorry/car/plough/trailer, chaff cutter, Wheelbarrow /cart(hand/donkey) etc.; equipment such as Hay baler, Cattle dip Spray pump Weighing machine, etc.; and building such bomas, Hay store, Silage pit, Borehole/dam/well, Water trough etc.

[31] More technical/skilled farmer uses DVA and FM supplement, less technical one uses no DVA and FM supplement

veterinary costs appear to have a significant impact on the profits of all herd size categories, but the result was not found to be the case for the smallest farms, probably because they use few veterinary inputs. The study by Asante et al. (2017) found that veterinary expenditures had consistently highly significant positive effects on the small-ruminant outputs, which indicates the substantial role in increasing small-ruminant productivity. Similarly, the studies by Nganga et al. (2010) and Otieno et al. (2014) showed that an increase in the use of feed and veterinary expenditure would lead to significant improvement in livestock output while in the studies by Álvarez–Arias (2013), feed per cow variable was used to measure the degree of intensification in the dairy operation. Hallam–Machado (1996) found mixed evidence since feed per cow was found to increase efficiency, while the opposite was exact for cows per hectare. Cabrera et al. (2010) found that feed per cow increases TE. Similarly, the significant positive coefficient of the *material* (that includes expenses for forage production, veterinary services, purchased feed and other related expenses) variable interacted with the time trend in Kellermann (2014) study, indicate material-using technical change. In our study, assuming the elasticities of each other variable unaltered, estimated dummies shift in the intercept.

For the inefficiency effects model, *Z's* comprises of discrete and dummy variables and are classified as household characteristics, agricultural-related institutional proxies for extension support services, proxies for market-related instructional factors and others. For household characteristic, we had discrete variables such as the age of household head in years (AGE) and the number of years in school (EDUC) while dummies variable included gender of the household head (GENDER) with 1 representing male-headed household and 0 otherwise. The age of farmers may have either a negative or positive effect on technical inefficiency. Older farmers are likely to be more or less (in)efficient, perhaps because they are likely to have more experience (Rakipova et al. 2003) while on the other hand, younger farmers, although less experienced, may be more likely to be enthusiastic and willing to learn and explore new technologies and, hence, maybe more efficient (Asante et al. 2017). Gender measured as a dummy state that males are more likely to be efficient than females, hence negative coefficient is expected. This hypothesis agrees with the Masunda–Rudo (2015), where male farmers were found to be more inefficient in dairy farming when compared to their female counterparts. Culturally, livestock production in the study locations is dominated by males, who tend to be more experienced in their production and tend to be more involved in marketing the animals than females.

There is a general expectation in the literature that education of household head or primary decision-maker in the farm should contribute to improved efficiency (Featherstone et al. 1997) hence, education is expected to have a negative effect on technical inefficiency. Various studies that have included this variable have found educated farmers are able to understand, appreciate and apply improved production practices that are likely to enhance their productive efficiency (Nyagaka et al. 2010, Nganga et al. 2010) uniquely if they are tailored towards specific production practices. However, Otieno et al. (2014), found education did not individually improve the model fit, but the inclusion of the interaction variable shows that farmers with formal education and higher income are relatively less efficient. Manyeki – Kotosz (2019) study revealed a non-linear relationship between education and inefficiency with lower education portraying a positive impact, while higher education displayed a negative effect.

With regards to agricultural-related institutional factors, all were captured as dummies and constitutes variables such as veterinary services and drug use (VDRUG), extension services (EXTSERV), agricultural researches (AGRESEARCH) and agricultural technology centres (AGTECENTRE) with 1 if the household access to VDRUG, EXTSERV, AGRESEARCH and AGTECENTRE and 0 otherwise, all these comprises veterinary supplies and advisory service and are expected to impact on inefficiency levels negatively. Veterinary services and advisory services (either through extension and agricultural research) as observed in various studies may leads to more technical inefficiency (Otieno et al. 2014, Masunda–Rudo 2015, Asante et al. 2017) which can be explained on the basis of a poor program design on the part of the extension department or a lack of a participatory approach and bureaucratic inefficiencies in delivering extension and research findings. However, agricultural research support was essential in reducing the level of inefficiency, though not significant in Manyeki–Kotosz (2019) study.

Market institutional related factors included proxy variables such as market access (MARKACCESS), input market access (INMARKACCESS) and livestock market information access (MARKINFOACCESS) with 1 if household head access to MARKACCESS, INMARKACCESS and MARKINFOACCESS and 0 otherwise, all are proxy to market performance and are expected to have a negative impact on level of inefficiency. A similar result was reported by Masunda–Rudo (2015), who found that market performance stimulates the production and hence improves productivity and profitability. Our result (Manyeki–Kotosz 2019) also found market information access negatively influences inefficiency in livestock production. Access to market information implies a farmer has the ability to obtain information on prevailing market prices, demand, and availability of livestock in the market.

Lastly, dummies for individual land ownership (LANDOWNE) with 1 if the individual household owns the land and 0 otherwise and off-farm income (OFFINCOME) with 1, if the household head has access to off-farm income and discrete variable repenting number of livestock-related technologies were categorized as others. Generally, land tenure and access rights are considered as essential prerequisites for long-term and ecologically beneficial land-related investments, technology adoption and productivity enhancement (Otieno et al. 2014), hence negative effect to inefficiency. Regarding land ownership, the hypothesised negative sign implies that land ownership policies, which prevent livestock farmers from owning the land that they use, can be very damaging, hence increase inefficiency. Off-farm income would significantly improve efficiency (Otieno et al. 2014). The significance of including off-farm income into inefficiency effect model followed Alene et al. (2008) and Otieno et al. (2014) observation that there might be considerable re-investment of such earnings in various farm operations by some livestock keepers in Kenya.

Generally, on a priori bases, the input variable X_i*'s* were expected to be positive representing the rate of change of the mean of production with respect to the *j*-th explanatory variable and a negative sign of a variables in the *Z-vector* is expected which implies that the corresponding variable would reduce the level of inefficiency (Coelli et al. 2005).

Table 5: Variables for Stochastic Frontier and Technical Inefficiency Effects Model

Variable	Variable descriptions	Sign
Variables *Xi* for stochastic frontier model		
LNR	Continuous variable for natural log of pastureland in hectares	+
LNL	Continuous variable for natural log of total man-days for both hired and family	+
LNK	Continuous variable for natural log of the total value of capital asset directly used in the livestock enterprise	+
FM	Dummy variable where 1=use feed and mineral supplements, 0 otherwise	+
VETDRUGS	Dummy variable where 1=use veterinary drugs, 0 otherwise	+
Variables *Zi* for inefficiency effects model		
AGE	Continuous variable for the age of household head in years	-
GENDER	Dummy variable where 1=Male headed household, 0 otherwise	-
EDUC	Continuous variable for the number of years in school	-
EDUC2	Continuous variable for the squared number of years in school	-
NTECHGY	Continuous variable for the number of livestock-related technologies adopted	-
GMEMBER	Dummy variable where 1=belong to farmers' group/association = 1, 0 otherwise	-
AGRIRESE	Dummy variable where 1=access to agricultural research services, 0 otherwise	-
MARKET	Dummy variable where 1=access to livestock market information systems, 0 otherwise	-
LANDOWNE	Dummy variable where 1=individual land ownership, 0 otherwise	-

Source: Author's own construction based on literature

3.4. Empirical Results, Analysis, and Interpretation

The purpose of this section is to present the research findings and to elucidate the meaning of the results obtained from the examination of the data. The section is organized into two main sections. In the first section (3.4.1), the descriptive statistics are reported and evaluated. This is followed by section 3.4.2, where results of the estimation of various econometric models are discussed starting with empirical results for stochastic frontier and inefficiency effect models for homogenous and then for heterogeneous technology.

3.4.1. Descriptive Statistics for livestock production

The summary statistics of selected technical, social and economic variables that influence livestock production is presented in Table 6. As indicated in Table 6, the mean of TLU per household was 55.91, an indication that the majority of the household are smallholder livestock farmers. This sample mean is relatively high than the total population mean (of 24.00 TLU per household) and the difference can be explained by the fact that data was subjected to screening and those not engaging in livestock production were eliminated from the analysis. The standard deviations from the means for herd sizes, land, labour and capital inputs and for other variables was very high which is a clear indication that farmers are operating at different levels of production technologies and, therefore, estimating single stochastic frontier would be misleading. The percentage use of feed and mineral supplements was reasonably high (59.2%) while the rate of use of veterinary drugs was low (28.3%).

When it comes to Z_i variables, Table 6 shows that the average age of households' head was 48.48 years with a standard deviation of 14.94, which is relatively the same as the population mean. This result indicates that most of the livestock farmers in the southern rangelands of Kenya are within the productive age bracket (between 30-50 years) suggested by Skirbekk (2003). The sample also indicates a male-headed household orientation, which concurs with the population mean. The mean years of schooling were 5.99 years with a standard deviation of 5.23 years, which implies that literacy level is low; an equivalent of primary school was the household heads' average level of education. Similar findings were reported by Ogunniyi (2010) for the livestock farmers under the same environmental condition in Nigeria. The number of technologies adopted by each farm was insignificant. The result also indicates that livestock farmers benefit from relatively better access to market information services than to agricultural-related research and services. On land ownership, the average was reasonably high (57.37%). However, the majority was informal land ownership, that is parcels with no official documentation as to "who owns" or "occupies" the land, and thus livestock farmers are naturally unwilling to improve land unless they are sure that they can reap the benefits. The other construct of transaction costs is off-farm income - an indication of endowment and wealth. Off-farm income was viewed as an alternative to livestock cash incomes and therefore expected to result in a reduction of inefficiency level. The high standard error shows high discrepancy, and this perhaps can act as an indicator that pastoral farmer operates at different levels of production if we assume that the off-farm income is reinvested in livestock production.

Table 6: Descriptive Statistics for Efficiency Measurement

Variables	Mean[1]	Std Dev	Min	Max
Variables *Xi* for stochastic frontier model				
Number of TLU produced (LNY)	55.91 (24.00)	114.49	2	1361.00
Pastureland in hectares (LNR)	285.81	1070.41	1	4999.50
Labour measured in man-days (LNL)	207.24	268.99	6.08	3239.38
Value of capital assets in KES (LNK)	35,523	208,077	150	4,160,000
Use feed and mineral supplements (FM)	0.592	0.492	0	1
Use veterinary drugs (VETDRUGS)	0.283	0.451	0	1
Variables *Zi* for inefficiency effects model				
Age of household head (AGE)	48.48 (47.50)	14.94	15	102
Gender of household head (GENDER)	0.870 (0.665)	0.336	0	1
Years of schooling of the household head (EDUC)	5.995	5.228	0	19
Number of technologies adopted (NTECHGY)	0.207	0.593	0	3
Agricultural extension services (EXTESERV)	0.464	0.499	0	1
Agricultural research services (AGRIRESE)	0.0466	0.211	0	1
Agricultural technology centre (AGRTECENTRE)	0.0085	0.092	0	1
Market information (MISACCESS)	0.457	0.498	0	1
Input Market Access (INMARKACCESS)	0.335	0.472	0	1
Land ownership by household head (LANDOWNE)	0.574	0.495	0	1
Off-farm income (OFFINCOME)	139,910	324,045	0	7,000,000

Note: [1]Number of observations =1288; Parenthesis are averages for the total population.

Source: Author's own computation from the household survey data

3.4.2. The empirical result of SFA and Inefficiency Effect Models

Our reviewed literature shows that the analysis of TE heavily relies on the choice of an econometric model used to estimate the representation of frontier production technology.

The fact that different econometric models that involve imposing different assumptions on the data and the data generating process leading to different results have been observed in the past studies (e.g. Green 1990, Schmidt 2011, Otieno et al. 2014). In the case of the SFA literature presented in this study, we find the situation that not all models are nested; hence formal testing cannot reveal the "one" right model for each dataset. In these regards, we attempt to estimates different stochastic frontier function forms and nesting the widely applied distribution of error terms in order to investigate the model that best fit our data set. The goal was to investigate the best functional form (i.e. between Cobb-Douglas and Translog) and widely applied distributions in TE analysis which will enable us to test the hypotheses that H_1**:** '*the size and access to agricultural factors of production (land, labour and livestock production supplies) positively influence livestock production of the smallholder pastoral farming, and their impact is not homogenous in the farmer population'* and H_2**:** '*human-related attributes (e.g. gender, age, education level), access to socioeconomics (e.g. land ownership, off-farm income etc.), service providers (extension, agricultural institution etc.), market factors (e.g. input markets, market information etc.) and financial institutions (e.g. credit facilities etc.) influence efficiency in the livestock production for smallholder pastoral farmers'.* We first employed Equations 4 and 5 and assumed the technologies is the same for our sampled households. The result of this analysis helps in reflecting the abilities of the models to take unobserved heterogeneity into account in order to test the second hypothesis in this group.

However, before testing this hypothesis, we had to determine the functional production form and the associated distribution that would best fit our farm-level database. We computed the AIC[32] (Akaike's information criterion) and TE for pooled data. The AIC was used because it favour's the model's goodness of fit but penalizes the number of parameters in the model; thus, it can be used to compare models with different numbers of parameters. The best model is the one with the lowest AIC. The results in Table 7 indicate a predominantly high correlation for both the CD (Cobb–Douglas) and the Translog model across various distributions, which implies that the two functional forms and the distributions fit the data well, although a more flexible Translog functional forms seem to portray higher overall TE levels. The mean correlation of TE across the different production functions and distribution forms seems to be notably uniform (Table

[32] AIC was first developed by Akaike (1974) and is founded in information theory and the statistic can be written as: $AIC = 2\kappa - 2\ln(\hat{L})$ where κ is the number of estimated parameter in the model and $\hat{L}$ is the maximum value of the likelihood function for the model.

7). The most efficient distribution is normal-gamma (GAMEFF), with mean efficiency levels of 63% and 81% for CD and Translog, respectively, followed closely by the normal-exponential (EXPEFF) and truncated-normal (TRUEFF) distributions. The lowest estimated mean efficiency recorded is for the half-normal model, with an average efficiency of 51% and 56% for CD and Translog, respectively. The likelihood ratio tests show that we cannot reject the hypothesis of the possibility of incorporation either of the four distributions. This is further confirmed by the kernel estimators for efficiency that suggest that the difference in the estimates of efficiency are quite modest (Table 8). However, based on all the TE, AIC and likelihood ratio tests, we can generally reach the same conclusion observed by Schmidt (1986) that a flexible Translog largely ‘fits’ the data better, allowing more observations to lie near the frontier, although all the model seems to best fit the data.

Table 7: Technical Efficiency Distributions Estimates for SF Models

Variable		**AIC**	LR[1]	**Mean**	**Std. Dev.**	**Min.**	**Max.**
HNEFF	CD	3309.9	25.925	0.507	0.149	0.044	0.890
	TL	3290.3	4.507	0.564	0.119	0.109	0.877
EXPEFF	CD	3273.8	61.987	0.594	0.171	0.021	0.914
	TL	3262.5	32.231	0.612	0.160	0.032	0.910
GAMEFF	CD	3272.2	65.572	0.634	0.181	0.020	0.940
	TL	3292.6	4.150	0.804	0.053	0.379	1.000
TRUEFF	CD	3276.0	61.807	0.594	0.171	0.021	0.903
	TL	3264.7	32.069	0.612	0.160	0.032	0.900

Note: TL=Translog and CD=Cobb-Douglas; [1]Likelihood ratio tests (Based on Kodde-Palm C*: 95%: 2.706; 99%: 5.412).
Source: Author’s own construction.

Table 8: Correlation matrix for average efficiency

Cor. mat.	**HNEFF**	**EXPEFF**	**GAMEFF**	**TRUEFF**
	Cobb–Douglas production model			
HNEFF	1.000	0.983	0.967	0.983
EXPEFF	0.983	1.000	0.992	1.000
GAMEFF	0.967	0.992	1.000	0.991
TRUEFF	0.983	1.000	0.991	1.000
Average cor.		0.983		
Kendall rank cor.		0.963		
	Translog production model			
HNEFF	1.000	0.984	0.906	0.984
EXPEFF	0.984	1.000	0.905	1.000
GAMEFF	0.906	0.905	1.000	0.905
TRUEFF	0.984	1.000	0.905	1.000
Average correlation		0.984		
Kendall rank correlation		0.950		

Source: Author’s own construction.

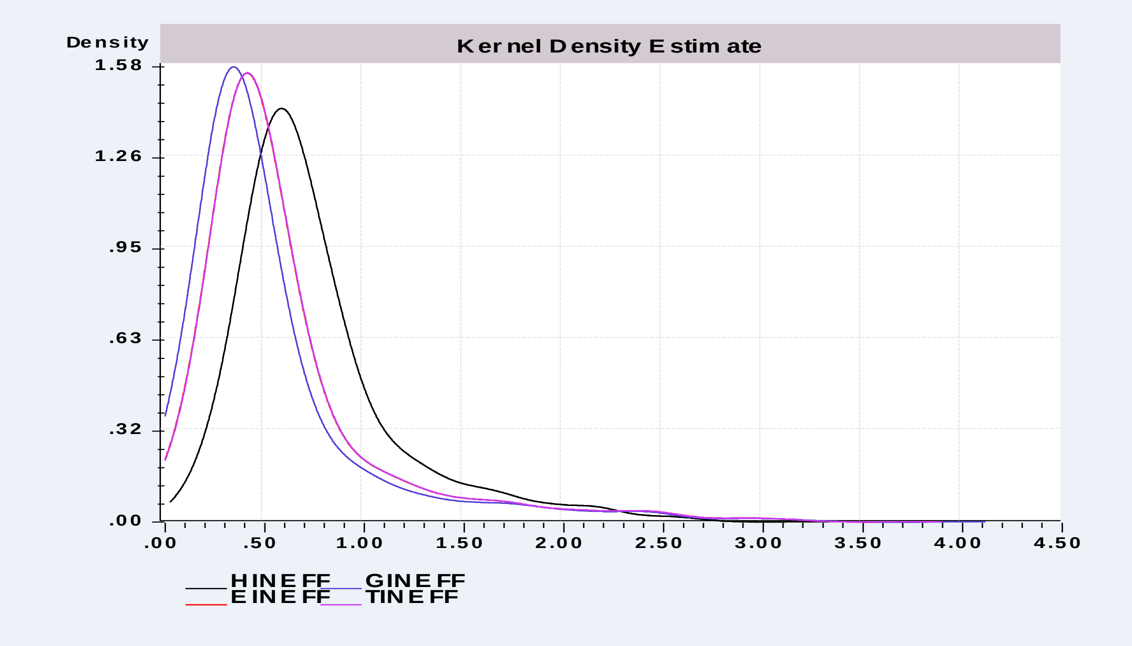
We also computed the inefficiency distributions for the frontier Cobb–Douglas and Translog function and plotted kernel density estimators for the four distributions in order to compare them. The positive skewness for u_i in all cases implies a negative skewness for ε_i (Table 9). It is, therefore, clear from the statistical result that $\hat{\mu}_{3,n} = n^{-1}\sum_{i=1}^{n}\hat{\varepsilon}_{i,OLS}^{3}$ is a consistent estimator of the negative of the third moment of u_i, which gives the sign of the skewness of u_i. The consequence of a 'wrong' skewness would mean that the modified OLS and MLE estimates of the slope are identical to the OLS slope, and there are no inefficiencies, implying the mean and variance of u_i are estimated at zero (Waldman 1982). All model portrayed a kurtosis value greater than 3, implying that the distributions have a high peak and flat tail. The standard chi-squared test for normality is based on the skewness and kurtosis measures. All inefficiency distributions for Translog production function is highly and positively skewed, so the significant departure from normality in the left figure is to be expected. The final Kernel density plot (Figures 9 and 10) shows more graphically how different distributions of inefficiency error term can change the estimates. The means and variances of the four distributions under Cobb-Douglas seem to be virtually the same, but for the Translog function is considerably indifferent. The kernel density plot confirms this.

Table 9: Inefficiency Estimate for the Stochastic Frontier Production Functions

Variable		**Skewness**	**Kurtosis-3**	**Chi^2 normality test**
HNEFF	Cobb-Douglas	1.9765	4.6555	62.2583
	Translog	2.0282	5.2784	74.6005
EXPEFF	Cobb-Douglas	2.7536	8.6248	178.8365
	Translog	2.8585	9.3190	204.7089
GAMEFF	Cobb-Douglas	2.8704	9.3833	207.2759
	Translog	3.2202	21.4226	885.5445
TRUEFF	Cobb-Douglas	2.7302	8.3832	170.6973
	Translog	2.8536	9.2900	203.5761

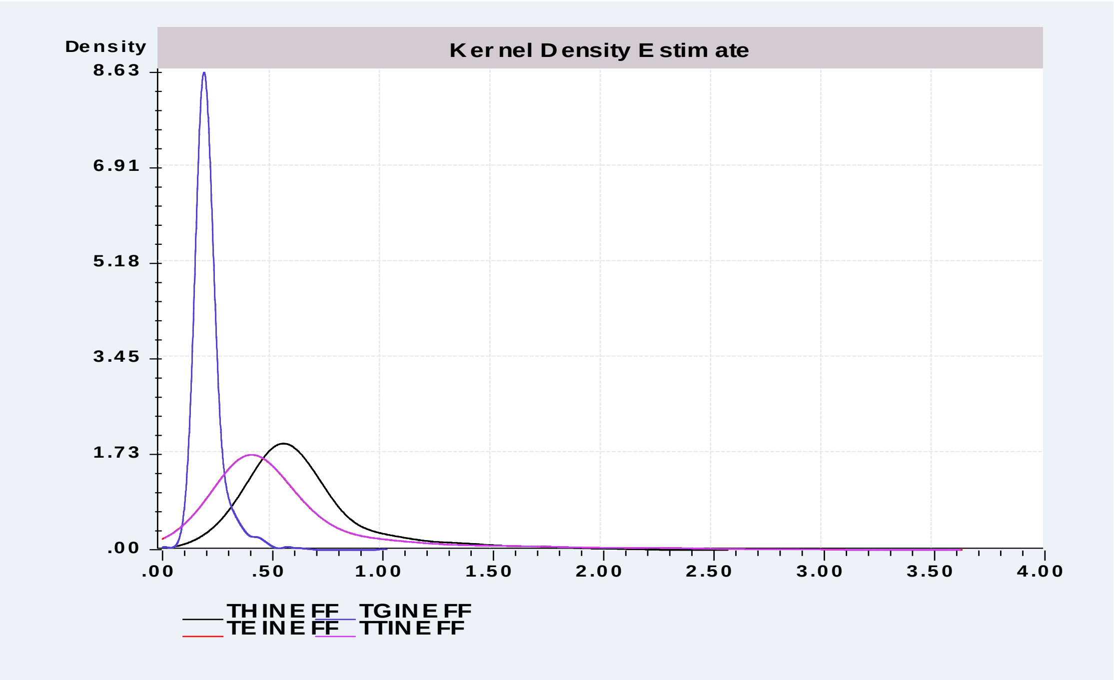
Source: Author's own construction.

Figure 9: Inefficiency Estimate of Distribution based on Cobb-Douglas Function



Source: Author's own construction based on the data analysis

Figure 10: Inefficiency Estimate of Distributions based on Flexible Translog Function



Source: Author's own construction based on the data analysis

Having confirmed that virtually all the model and distributions of inefficiency error term specified best fit the data, the next phase of analysis involves testing the hypothesis earlier stated vie the variables presented in Table 5. The first part of this hypothesis is to confirm whether livestock farmers are indeed inefficient in the allocation of the resource currently at their disposal. To do so, first, we estimated stochastic Cobb-Douglas model (Equation 4) for the four types of distributions of the inefficiency error term. Table 10 summarizes the estimation results of the stochastic Cobb-Douglas production function for the four distributions. The technical inefficiency of the sampled farmers is more than 0 across all distribution, indicating that all the farmers are producing below the maximum efficiency frontier. A range of technical inefficiency is observed across all distribution where the spread is relatively large (36-49%). The implication of the result is that TE in livestock production could be increased by 36-49 per cent through better use of available resources, given the current state of technology. Same high levels of inefficiency among nomadic and pastoral system but less in ranches of Kenya were observed by Otieno et al. (2014). The magnitude of the mean technical inefficiency reflects the fact that most of the sample farmers carry out livestock production under technical conditions involving, either inefficient allocation of available resources or use of inefficient tools, unimproved pasture lands and so on.

The presence of inefficiency error term in the model was also tested. This was done using the likelihood ratio statistic, based on Kodde–Palm (1986), which is a chi-square distribution under the null hypothesis that there has not been an effect of inefficiency and the presents significant values at the 1% level in all distributions, indicate the effects of inefficiency in the model. The estimate of parameter η, which measures the variability of the inefficiency error versus the composite error, indicates that about 46.38–99.7% of the total variance of the composite error of the four types of function distributions is explained by the variance of the inefficiency terms. This represents the importance of incorporating inefficiency into the production function. The terms relative to inefficiency assume a temporal pattern of behaviour represented by sigma(u). If it assumes a null value, it is considered that the inefficiency does not vary – also called persistent inefficiency. The estimates of sigma squared (σ^2) for all the distributions are significantly different from zero at the 1% level of significance. This indicates a good fit and correctness of the specified distributional assumptions of the composite error term, suggesting that the classical production function is not an adequate representation of the data.

Table 10 also shows the significant factors that influence livestock production. The significant variables are labour resources (LNL), the size of agricultural pasture land

(LNR), direct capital inputs (LNK) estimated as the value of capital assets used directly in livestock production (LNK) and the purchase of feed and minerals (FM) – all assuming the expected positive signs. The results are robust in the sense that they are similar for the four widely applied distributions and the three classical factors of production of (labour, land and capital) in the livestock industry are positive and significant at the 1% level. The most considerable elasticity observed is that of labour input. This indicates the intense relationship that exists between livestock production and labour, independently of the utilization of other factors that, *ceteris paribus*, would contribute significantly to livestock productivity. The size of the pastureland variable reveals the second significant elasticity, confirming the importance of agricultural pastureland in size and quality to the execution of livestock investments, which account for the most significant share of the data analysed. A similar correlation between farm size and livestock production has been demonstrated in past studies (e.g. Delgado et al. 2008, Nganga et al. 2010). Capital input displays a significant positive effect, implying that increasing the usage of these inputs would yield more output as postulated by theory, assuming that producers are rational (Coelli et al. 2005, Otieno et al. 2014). The use of FM in livestock production revealed a weakly significant effect while the use of VETDRUGS did not, although both of them have the expected positive sign. This result confirms the Nganga et al. (2010) finding where the cost of the feed was found to be the most important variable determining profit efficiency.

Lastly, the sum of elasticities slightly above unity, indicating that on average, the constant returns to scale property of the Cobb-Douglas specification fits the data. The input elasticities fulfil the regularity condition of monotonicity which implies the production frontiers are non-decreasing in inputs (Coelli et al. 2005).

Table 10: Parameter Estimate for the Cobb–Douglas Stochastic Frontier Model

Parameters	Normal-half normal	Normal exponential	Normal gamma	Normal–truncated normal
Technical Inefficiency	0.492 (0.149)	0.406 (0.171)	0.366 (0.181)	0.407 (0.171)
Con.	0.0114	-0.272**	-0.354**	-0.264
	(0.141)	(0.133)	(0.169)	(0.174)
LNL	0.577***	0.620***	0.627***	0.616***
	(0.0194)	(0.0203)	(0.0196)	(0.0198)
LNR	0.213***	0.200***	0.198***	0.200***
	(0.0143)	(0.0143)	(0.0113)	(0.0114)
LNK	0.0800***	0.0749***	0.0742***	0.0746***
	(0.0127)	(0.0121)	(0.0112)	(0.0114)
FM	0.0983*	0.1048**	0.1052*	0.1047*
	(0.0518)	(0.0493)	(0.0551)	(0.0556)
VETDRUGS	0.0837	0.0465	0.0413	0.0467
	(0.0537)	(0.0512)	(0.0561)	(0.0573)
Return to scale	1.052 (0.0341)	1.0462 (0.0329)	1.0457 (0.0626)	1.042 (0.0353)
AIC	3309.9	3273.8	3272.2	3276.0
Variance parameters for compound error				
Sigma(u)	0.937	0.596	0.601	11.643
Sigma(v)	0.667	0.641	0.642	0.642
$\sigma^2 = \sigma_u^2 + \sigma_v^2$	1.322***	0.767***	0.774***	135.968***
$\lambda = \sigma_u/\sigma_v$	1.406	0.930	0.937	18.134
$\eta = \sigma_u^2/\sigma^2$	0.664	0.464	0.467	0.997
Likelihood Ratio test for inefficiency: sigma(u)=0				
Chi-sq[1]	25.925***	61.983***	65.572***	61.807***

Note: ***, ** and * ==> significance at the 1%, 5% and 10% level; [1] Kodde-Palm C*: 95%: 2.706; 99%: 5.412.

Source: Author's own construction.

Turning to Translog specification, the number of parameters estimated practically 'explodes' as the number of production factors considered in addition to the technical inefficiency component increases (Table 11). Again, the analysis shows a relatively high technical inefficiency level (19-43%) across the different distributions indicating that there is considerable room for improvement in livestock production. The likelihood ratio statistic presents a significant value at 1% and the 5% level, indicating the effects of inefficiency in the model. For the Translog models, the estimated component η indicates the presence of inefficiency in the analysed sample that ranges between 6.63% and 99.63% of the total composite error variance of the production function, thus revealing the importance of incorporating inefficiency into the production function. Once more, the estimates of sigma square (σ^2) for all the distributions are significantly different from zero at the 1% level of significance, implying a good fit and correctness of the specified distributional assumptions of the composite error term for the Translog production model.

With regards to influencing agricultural factors of production, the analysis shows robust results across the different distributions considered. This is clearly demonstrated by the significances of similar variables across the four distributions. The statistical significant parameters at different levels of significance are primarily related to the critical traditional production variables and their association as well as the measures of the purchase of livestock feed and minerals (FM) and veterinary drugs (VETDRUGS) expressed by the dummy variables. Here, the labour input records the highest significant elasticity. The coefficients for LNLLNR (the interaction between the log of labour and the log of pastureland size) and LNRLNK (the interaction between the log of land and the log of capital) are positive and statistically significant at different levels. The positive coefficients estimate for LNLLNR, and LNRLNK indicates that labour and pastureland size and pastureland size and capital complement one another in livestock production, thereby resulting in an increase in the livestock production, so the costs can be reduced by mixing them. Additionally, there is strong empirical evidence indicating the decreasing returns to labour (inverse U) in the livestock production output, as the coefficient of ½*LNR*LNR is negative and statistically significant while the returns to capital are increasing (U-formed) though not significant. The elasticity with respect to the size of pastureland also indicates decreasing returns, given the statistically significant negative coefficient of ½*LNR*LNR.

Table 11: Parameter Estimates for the Translog Production SF Model

Parameters	**Normal–half normal**	**Normal exponential**	**Normal gamma**	**Normal–truncated**
Technical Inefficiency	0.436 (0.120)	0.388 (0.160)	0.196 (0.053)	0.388 (0.160)
Con.	-0.513 (0.692)	-0.825 (0.651)	-0.728 (0.992)	-0.819 (0.837)
LNL	1.047*** (0.161)	1.047*** (0.152)	1.088*** (0.198)	1.044*** (0.170)
LNR	0.127 (0.0981)	0.141 (0.0951)	0.0886 (0.0950)	0.141 (0.0900)
LNK	-0.0475 (0.109)	-0.0188 (0.103)	-0.0733 (0.126)	-0.0176 (0.110)
LNL*LNR	0.0277** (0.0112)	0.0141 (0.0118)	0.0409*** (0.00827)	0.01420* (0.00774)
LNL*LNK	-0.00067 (0.0100)	-0.00568 (0.00986)	0.00410 (0.00984)	-0.00562 (0.00830)
LNR*LNK	0.0132* (0.00728)	0.0139* (0.00709)	0.0128** (0.00646)	0.0139** (0.00557)
½*LNL* LNL	-0.109*** (0.0295)	-0.0822*** (0.0294)	-0.138*** (0.0288)	-0.0817*** (0.0252)
½*LNR*LNR	-0.0402*** (0.00923)	-0.0309*** (0.00929)	-0.0462*** (0.00839)	-0.0310*** (0.00779)
½*LNK*LNK	0.00786 (0.0104)	0.00719 (0.0101)	0.00787 (0.0101)	0.00699 (0.00911)
FM	0.108** (0.0519)	0.115** (0.04964)	0.0967* (0.05516)	0.116** (0.0555)
VETDRUGS	0.104* (0.0538)	0.0569 (0.0521)	0.1317** (0.0608)	0.0561 (0.0588)
AIC	3290.3	3262.5	3292.6	3264.7
Variance parameters for compound error				
Sigma(u)	0.757	0.551	0.221	10.827
Sigma(v)	0.728	0.662	0.831	0.663
$\sigma^2 = \sigma_u^2 + \sigma_v^2$	1.104***	0.742***	0.740***	117.670***
$\lambda = \sigma_u/\sigma_v$	1.0398	0.831	0.266	16.340
$\eta = \sigma_u^2/\sigma^2$	0.520	0.409	0.0663	0.996
Likelihood Ratio test for inefficiency: sigma(u)=0				
Chi-sq[1]	4.507**	32.231***	4.151**	32.061***

Note: ***, ** and * ==> significance at the 1%, 5% and 10% level; [1] Kodde-Palm C*: 95%: 2.706; 99%: 5.412.

Source: Author’s own construction.

The next phase of analysis involves testing the second part of the hypotheses, which was done through estimating technical inefficiency effect model of equation 4 and 5 to establish the underlying causes of technical inefficiency. In other words, the equation was used to identify the determinants of inefficiency in livestock production by testing the hypothesis that household socio-economic factors and farm characteristics are not statistically crucial in explaining technical inefficiency using the p-value of the statistic.

The null hypotheses to test the individual significance of the variables can be stated as βj = 0 for each of the j explanatory variables. In a one-step stochastic frontier production estimation, the parameter for the inefficiency level ($\hat{u}$) usually enters the model as the dependent variable in the inefficiency effect component of the model, and, intuitively, as Coelli et al. (2005) observed, a negative sign of the element of the δ vector is expected, which implies that the variable would decrease inefficiency. The selection of variables for estimating the inefficiency effect model started with a test of multicollinearity through the computation of several collinearity diagnostic measures including variance inflation factors (VIF), tolerance, eigenvalues, condition index, and R-squared (Appendix 4.1). All the independent variables exhibited $VIF_i < 5_i$ (with an average VIF of 3.15) and conditional index of 7.3721 (which is less than the critical value of 30), it was concluded that there was no multicollinearity and therefore all these variables were eligible for inclusion in the model estimation (Appendix 3.1). The next stage involves the estimation of the inefficiency model. Table 12 presents relatively similar (robust) results for all the models across different distributions, with gender (GENDER), high levels of education (EDUC2) of the household head, access to market information (MISACCES), the number of technologies adopted (NTECHGY), land ownership (LANDOWNE) and off-farm income (OFFINCOME) having the expected negative sign, implying that they would significantly reduce inefficiency, while lower levels of education (EDUC), age of the household head in years (AGE) and general market access (MARKETAC) would increase inefficiency.

The negative relationship of gender with the level of inefficiency implies that male-headed households are less inefficient in livestock farming when compared with their female counterparts. Similar results were reported by Masunda–Rudo (2015). Perhaps this is true since livestock farming is labour intensive and generally, in the pastoral set-up, is considered as men's domain and because women's status in pastoral societies is usually inferior to that of men and women's labour is associated with the domestic sphere. Farmers' education level (EDUC) has the expected positive influence on the inefficiency level, concurring with the findings of Nganga et al. (2010) and Otieno et al. (2014). The positive sign for the length of education denoted by the variable EDUC in inefficiency could similarly be explained by the high level of illiteracy experienced by pastoral communities (as indicated in Table 6 above). As the average number of years of schooling increases, (as indicated by the incorporated control (EDUC2) variable), the efficiency increases, which concurred with Kibaara (2005) finding. This could perhaps be explained by the observation that a high education level, particularly in livestock farming techniques, is said to be an essential factor that could improve efficiency since it contributes to the improvement of the managerial capacity of farmers, hence easing their access to modern technologies.

Market information, especially on livestock prices, negatively influences inefficiency in livestock production. Similar results were reported by Masunda–Rudo (2015), who found that market performance stimulates the production and hence improves productivity and profitability. This study also found that an increase in the amount of improved agricultural technology (NTECHGY) decreases the inefficiency of pastoral households, which is consistent with Hussien’s (2011) findings. Regarding land ownership, the negative sign implies that land ownership policies, which prevent livestock farmers from owning the land that they use, can be very damaging. Livestock farmers are naturally unwilling to improve land unless they are sure that they can reap the benefits. Off-farm income was found to be negatively related to the inefficiency in livestock production, and, based on this finding, we can argue that there is considerable reinvestment of off-farm earnings in farm production. These results are in line with those of Hussien (2011) for crops and livestock in Ethiopia and Otieno et al. (2014) for beef cattle in Kenya.

The evidence on the effect of farm households’ ages on inefficiency is ambiguous. Positive effects on inefficiency may be due to older farmers’ resistance to change and unwillingness and inability to adopt technological innovations (Masunda–Rudo 2015). Moreover, as observed by Nganga et al. (2010), older farmers who are at or near their exit stage may reduce their commitment to livestock farming and profit maximization as other priorities appear. The estimated relationship between market access and inefficiency is positive, a result that was also observed by Kibiego et al. (2015) in the dairy industry in Kenya. Market access is associated with the distance to the livestock market and can be considered as a proxy for transaction costs. The farther away a pastoral household is from the livestock market, the more difficult and costlier it would be to become involved in input and output markets. The overall marginal effects associated with inefficiency for the sample analysed range from 20 to 49%, an indicator of the amount lost due to the misallocation of the productive factors at the farmers’ disposal.

Table 12: Determinants of Inefficiency among Smallholder Livestock Farmers of Kenya

Parameters	**Half-normal**	**Exponential**	**Gamma**	**Truncated**
_cons	0.392***	0.321***	0.176***	0.322***
	(0.0165)	(0.0238)	(0.00738)	(0.0237)
AGE	0.000645***	0.000958***	0.000275***	0.000954***
	(0.000222)	(0.000319)	(0.0000993)	(0.000319)
GENDER	-0.0269***	-0.0354***	-0.00984**	-0.0353**
	(0.00985)	(0.0140)	(0.00440)	(0.0140)
EDUC	0.0106***	0.0135***	0.00460***	0.0135***
	(0.00208)	(0.00299)	(0.000929)	(0.00298)
EDUC2	-0.000495***	-0.000619***	-0.000221***	-0.000618***
	(0.000129)	(0.000185)	(0.0000576)	(0.000185)
OFFINCOME	-0.00704**	-0.00903*	-0.00258*	-0.00904*
	(0.00330)	(0.00504)	(0.00147)	(0.00503)
MARKETAC	0.0435***	0.0588***	0.0187***	0.0588***
	(0.00835)	(0.0119)	(0.00373)	(0.0119)
AGRIRESE	-0.0137	-0.0224	-0.004822	-0.0224***
	(0.0155)	(0.0223)	(0.00690)	(0.0222)
MISACCES	-0.0216**	-0.0328**	-0.0100**	-0.0327**
	(0.00966)	(0.0137)	(0.00432)	(0.0137)
NTECHGY	-0.0167***	-0.0182**	-0.00656***	-0.0182**
	(0.00547)	(0.00799)	(0.00244)	(0.00797)
LANDOWNE	-0.0111*	-0.0161*	-0.00445	-0.0160*
	(0.00655)	(0.00940)	(0.00293)	(0.00938)
Sigma	0.115***	0.160***	0.0514***	0.160***
	(0.00229)	(0.00357)	(0.00102)	(0.00356)
Wald chi^2 (10)	102.46***	83.85***	87.64***	83.97***
Marginal effects	0.436	0.384	0.196	0.384
AIC	-1883.326	-1138.624	-3948.201	-1140.689

Note: ***, ** and * imply significance at the 1%, 5% and 10% level.
Source: Author's own construction.

The next level of analysis involved examining the possibility of incorporating the unobserved heterogeneity that exists among pastoral livestock producer of the southern rangelands of Kenya. A stochastic frontier latent class model (Equation 7) was applied using an extensive household farmer-level data, and the results are then compared with a model which assumes that the technology is common to all farmers. Our empirical analysis was only based on the flexible Translog functional form in order to avoid imposing unnecessary *a priori* restrictions on the technologies to be estimated (Orea–Kumbhakar 2004, Alvarez–del Corral, 2010), and also, from our recent study where both functional forms were tested, the flexible Translog functional forms were found to be adequate representation of the dataset (Manyeki–Kotosz 2019). Further, it also allows the relevance of input interactions when explaining production. Is also worthy to note that we only considered two distributions (half-normal and exponential) because they are the only one supported by the LIMDEP 11.0 statistical software that we used for analysis.

However, before estimating LCSF model, one has to address the problem of determining the number of classes, and this was done by allowing the data the opportunity to determine the adequacy of the independence assumption of the inefficiency error term between half-normal (HN) and normal-exponential (NE) models. In this study, the likelihood ratio test and Akaike information criterion (AIC) statistics[33] were applied since they are the most widely used criteria in standard latent class models (e.g. Orea–Kumbhakar 2004, Álvarez–del Corral 2010). AIC statistics were used because the criteria favour the model's goodness of fit but put a penalty on the number of parameters in the model and thus, it can be used to compare models with the different number of parameters. The best model is the one with the lowest AIC. The AIC values for the two type of model distributions decrease as the number of classes increases from one to three (Table 13).

Regarding likelihood ratio test, the test involves comparing the log-likelihoods of the two models, and the test statistic is distributed Kodde–Palm chi-squared, with degrees of freedom equal to the number of parameters that are constrained. In our case, the likelihood ratio test begins with testing the null hypothesis relating to the adequacy of the Translog stochastic frontier model relative to the OLS model with normal errors (row labelled 1). The tests involve the null hypothesis ($H_0: \sigma_u^2 = 0$) against the alternative hypotheses ($H_0: \sigma_u^2 > 0$) and the less restrictive Translog stochastic frontier model was found to fit the data significantly (at 1% level) better than the OLS model; thus, we rejected the hypothesis. This means that the log-likelihoods of the two models (a model with normal error and one with two error terms) are, a statistically significant difference. The next level involved comparing log-likelihoods of a more restrictive model (m1) with a less restrictive model (m2) in a sequential order, and if this difference is statistically significant, then the less restrictive model (the one with more variables) is said to fit the data significantly better than the more restrictive model. Based on likelihood ratio tests, and applying the testing 'down' strategy suggested by Greene (2002), against the testing 'up' from *J*-1 to *J which is* not a valid approach, we can begin the specification search with *J** = 4 and testing down from 4 to 3, 3 to 2 and 2 to 1 classes, results strongly

[33] The formula was $AIC = -2 * \log LF(j) + 2k$ where k is the number of parameters $LF(j)$ is the value of the LF for *J* groups.

suggested that J < 4 and rejects models with 2 and 1 classes. Applying both AIC and likelihood ratio test statistics lead us to the conclusion that a model with 3 class stochastic frontier with inefficiency component of the composite error through a half-normal random variable is the preferred model for this data. This is because, as the number of classes' increases more than three, it seems there being precision loss in estimates for a four-class HN model, perhaps due to multicollinearity problem associated with collinearity among inputs due to parameter outburst or as suggested by Kumbhakar–Knox-Lovell (2000), Orea–Kumbhakar (2004) and Alvarez–del Corral (2010), we take this as evidence that a model with more than three classes is over specified.

Table 13: Latent Class Selection Criterions for Stochastic Frontier Analysis

		Half normal Model			**Normal-Exponential Model**		
Classes	**Par**	**AIC**	**LLF[1]**	**LR test[2]**	**AIC**	**LLF[1]**	**LR test[2]**
1	14	3284.9	-1628.457	8.406	3252.4	-1612.188	40.945
2	32	2406.9	-1171.429	914.057	2359.9	-1147.961	928.454
3	50	1079.5	-489.735	1363.387	2307.4	-1103.716	88.491
4	68	2896.0	-1380.010	-1780.55	2210.7	-1037.353	132.724

Note: Par=Number of parameters; [1]Log likelihood function; [2]Likelihood ratio test {Chi-sq=2*[LogL(m2)-LogL(m1)}, always based on Kodde–Palm chi2 C*: 95%: 2.706, 99%: 5.412.
Source: Own author computation.

The estimated class probabilities and the main features of livestock farms in each class are summarized in Table 14. Although the results show the overall posterior class probabilities are on average relatively high (over 91.7%), the highest-class membership is found at class 3 where the prior class probability is high and posterior class probability is relatively high. Table 14 also displays TE with respect to each farm's most likely frontier, based on the estimated posterior probabilities which indicate how close on average the farm operate with respect to their frontier; these scores cannot directly be compared across classes (Álvarez–del Corral, 2010, Kellermann 2014). The result shows that farms in class 3 are on average operating closer to their own frontiers, with average TE score of 0.9686 while farms in class 2 were operating slightly above average (0.5348). Farms in class 1 obtained the lowest TE score on average, meaning these farms have the broadest scope for improvement (about 0.6446).

Table 14 also contains descriptive statistics for the selected farm characteristics that were examined to differentiate classes further and possibly classify farms into different production systems. In general, the units considered were small-to-medium-to-large-scale livestock farms which are different from the informal criteria adopted by Otieno et al. (2014) where farms were classified as either nomad, agro-pastoral and ranches without considering the technological differences within them. The last three rows (labour units per TLU, stocking rate and capital units per TLU) refers to variables which were introduced to reflect the intensity of the farm system.

The classification resulting from the probabilities shows that the largest group membership (class 3) is mainly formed by relatively small-scale holding farms, having on average medium farm size (ha) and TLUs and characterized by lower level of labour- and capital-intensive use perhaps due to higher unpaid family labour component, and using the same on farms in an effort to reduce production costs. We can refer to this group as a small-scale production system. A detailed examination of the other two groups' membership allows us to identify two more different types of livestock production systems. The second type is formed by medium-scale holding farms (class 1), having on average the high stocking rate and lower use of DVA and mineral supplements than farms in class 3. This class signifies relatively small farms (with an average land size of over 44.70 hectares) that also use relative labour- and capital-intensive production system, which is generally associated with a decrease in factors marginal productivities on-farm, hence relatively less efficient than farms in class 3. The third type includes a semi-commercial large-scale livestock production system (class 2) which is characterized by high use of farm inputs and relatively low stocking rate. The farms that belong to this class seemed to be specialized in intensive livestock production and displayed by the high use of capital assets, relatively high levels of labour resource use and a high degree of animal health care (as manifested by high on average DVA use), though not in competitive way which reduce the efficiency. The semi-commercial large-scale farms are also expansive in terms of land in hectares but relatively more extensive in terms of live animal production. In our view, the explanation for this result is that marginal increases of land are unlikely to be an option for farms and therefore, farmers who wish to increase production need to use more feed and mineral supplement (FM), increase usage of animal health services (DVA) and in some cases buy more productive animals, thereby becoming more intensive.

Table 14: Average Farm Class Characteristics based on Latent Class in SF Framework

	Latent Class Model			
Parameters	**Class 1**	**Class 2**	**Class 3**	**Full Sample**
Observations	252	223	813	1288
Technical efficiency	0.355	0.535	0.969	0.774
	(0.768)	(0.281)	(0.0128)	(0.444)
Prior probability[1]	0.388	0.207	0.405	1.000
Posterior	0.969	0.829	0.954	0.917
	(0.104)	(0.156)	(0.0559)	(0.103)
Livestock numbers	79.429	56.072	48.568	55.905
(LTUs)	(166.260)	(132.531)	(84.872)	(114.490)
Labor (Man-days)	284.075	337.185	147.784	207.242
	(209.521)	(299.092)	(258.156)	(268.988)
Capital (Kenya	56,775.63	46,808.25	25,950.33	35,592.64
shillings)	(355,063.77)	(215,143.65)	(131,216.77)	(208813.03)
Farm Size (hectares)	44.698	1051.412	150.548	285.811
	(318.52)	(1962.84)	(730.76)	(1070.41)
DVA (Veterinary	0.913	0.834	0.876	0.876
Drugs)	(0.283)	(0.373)	(0.330)	(0.330)
Feed and Mineral	0.337	0.448	0.487	0.451
supplements	(0.474)	(0.499)	(0.500)	(0.498)
Labor units per TLU	3.5765	6.0136	3.0426	3.7067
	(1.2602)	(2.2568)	(3.0418)	(2.3495)
Stocking rate (TLUs	1.9547	0.0587	0.3549	0.2152
per hectare)	(0.5742)	(0.0743)	(0.1278)	(0.1177)
Capital units per TLU	714.78	834.81	534.28	1636.59
in KES	(2135.59)	(1623.35)	(1546.08)	(1823.85)

Notes: [1]Prior class probabilities at the data means; Standard deviation in the parenthesis.

Source: Authors' computation using data using household data

We now compare the LCM with a stochastic frontier, which we labelled the 'pooled frontier' because it includes all observations without considering any kind of individual heterogeneity. In order to avoid the possible endogeneity problems, the ratios, namely labour units per TLU, stocking rate (TLUs per hectare) and capital units per TLU, were not considered. Since output and input variables were normalized by their means and all classical factors expressed in natural logarithms prior to estimation, then coefficients of classical factors and their association can be interpreted as elasticities. Empirical results obtained are displayed in Table 15, that shows how the parameter estimates for pooled stochastic frontier model are quite different compared to when the presence of multiple technologies is taken into account; therefore, there were two kinds of differences to be analysed – difference across models (pooled model versus LCM) and differences across classes. Although, overall the empirical results are robust in the senses that the estimates for majority of factors inputs employed across the single frontier and LCM were significant at either 1% and 5% level, differentiated patterns in input importance can be observed in pooled model and in each of the three classes, suggesting that significant differences exist between the three technologies identified. In classes 1 and 3, the size of labour (LNL) has a clear substantial impact on output production than the rest of inputs while it had an opposite effect for farms in class 2. For farms in class 2, pasturelands (LNR) appears to have a more significant impact. This implies that farms in class 2 would obtain the highest returns from labour, while those in classes 1 and 3 would obtain high returns from pasture lands. Farms in class 1 and 3 also obtain the highest returns for DVA and feed and mineral supplement (FM). The results also display a decreasing return for capital (LNK) for farms in classes 1 and 2 respectively, albeit at a high decreasing rate in class 2.

Regarding the associations and multiples of production input factors, the significant positive parameter estimates for the interaction between logs of labour and capital (LNL*LNK) indicates that labour and capital, can be a compliment for one another for farms in classes 1 and 3; so costs can be reduced by mixing them. The statistical results also show that livestock productivity would increases if pastureland and capital (LNR*LNK) and labour and pasture lands (LNL*LNR) are used together for farms in class 2 and 3, respectively. Additionally, there is empirical evidence of increasing returns (U-formed) to pastureland (0.5LNR*LNR) for farms in classes 1 and 3 while for farms in class 1 and the single frontier is decreasing returns (inverse U). Moreover, the positive significant coefficient of 0.5LNK*LNK, for farms in class 1 and 2, shows an increasing return to capital, indicating that livestock farmers in the Kenyan rangelands are slowly shifting from subsistence to a commercial production system; the same conclusion found in Otieno et al. (2014) study. The elasticity with respect to the multiple of labour input for farms in class 2 display a decreasing return to labour, given the statistically significant negative coefficient of ½*LNR*LNR – a result that clearly confirms that farms in class 2 are labour-intensive (Table 14). For demonstration purposes, the elasticities obtained when a pooled frontier is estimated are displayed in column 2 of Table 15. It can be seen how the averaged output elasticities obtained, assuming a homogenous technology for all farms are quite different than when the presence of multiple technologies is taken into account in the estimation. Of particular concern are the land and capital inputs elasticity and the association of the two, which is significant for all classes in the LCM model and insignificant when a single frontier model is assumed.

Regarding variables used to sharpen the prior probabilities of class membership, the sign of the coefficient obtained points the direction of the effect of a given separating variable on the probability of a farm being classified in each class, with class 3 being the reference category. The coefficient of the stocking rate and capital unit per TLU for farms in class 1 and labour units per TLU for farms in class 2 were statistically significant in affecting prior probability, which proves our hypothesis that farm size, labour and capital assets play an essential role in the establishment of the three classes. This result implies that an increase in pasture farm size and labour would reduce the probability of a farm ending up in class 2 and 1 respectively, while an increase in capital, would increase the probability of farm ending in class 1.

A comparison of the TE estimates for pooled frontier and the LCSF model show that the average TE estimates of the later (about 0.774 in Table 14) are nearly one and half times more than that of the former specification (about 0.544 in Table 15), thus confirming the observation by Álvarez–del Corral (2010), Alvarez et al. (2012), and Sauer–Morrison, (2013) that a single frontier specification would yield biased estimates of technological characteristics if the unobserved differences of technology are not taken into account. The effects of these omissions might inappropriately be branded as inefficiency for farms in class 3 and efficiency for farms in class 1 and 2 (Table 15). Again, following from the LCSF specification, there is a substantial difference in efficiency levels among classes with average TE for farms in class 3 being 0.969; it reduces to 0.535 and 0.355 for farms in classes 2 and 1 respectively in that order. The estimated TE levels are relatively lower than those obtained by Otieno et al. (2014) where a meta-frontier model was used, perhaps due differences in the size of data points used between the two studies.

When it comes to the estimated η and λ components which indicates the presence of inefficiency in the analysed sample, all models revealed the importance of incorporating technical inefficiency term in the production function at 1% level since $\lambda > 1$. Even though farms in class 3 operated at slightly lower below their frontier as indicated by the computed term η, the presence of $\lambda > 1$ in all cases means that technical inefficiency components is an essential phenomenon in Kenya livestock industry and must be included in the production models (Otieno et al. 2014). The estimates of sigma square (σ^2) for a pooled frontier and LCM models are all significantly different from zero at 1% level of significance, implying a good fit and correctness of the specified distribution assumptions of the composite error term. Lastly, the log-likelihood test and AIC statistics indicate that the latent class stochastic frontier Translog production function constitutes an appropriate approximation for our livestock production analysis.

Table 15: Parameter Estimate for Latent Class Stochastic Frontier Model

Parameters	**Pooled Frontier**	**Class 1**	**Class 2**	**Class 3**
Observation	1288	252	223	813
_Cons	-0.421	-2.523*	3.958**	-1.106***
	(0.690)	(1.334)	(1.545)	(0.0380)
LNL	1.0564***	4.224***	-1.0828***	1.0155***
	(0.160)	(0.238)	(0.274)	(0.0088)
LNR	0.143	0.0634	1.166***	-0.0581***
	(0.0978)	(0.295)	(0.0812)	(0.0061)
LNK	-0.0768	-1.766***	-0.564***	0.0259***
	(0.108)	(0.191)	(0.189)	(0.0061)
LNL×LNR	0.0238**	-0.387***	-0.0014	0.0178***
	(0.0111)	(0.0156)	(0.00448)	(0.0012)
LNL×LNK	-0.0029	0.0465***	-0.0212*	0.0129***
	(0.0100)	(0.0146)	(0.0127)	(0.0009)
LNR×LNK	0.0123*	0.0044	0.0292***	-0.0054***
	(0.0073)	(0.0214)	(0.0066)	(0.0005)
0.5LNL×LNL	-0.102***	-0.552***	0.267***	-0.0385***
	(0.0294)	(0.0314)	(0.0348)	(0.0024)
0.5LNR×LNR	-0.0394***	0.760***	-0.1541***	0.0027***
	(0.0093)	(0.0499)	(0.0083)	(0.0006)
0.5LNK×LNK	0.0119	0.180***	0.089***	-0.0081***
	(0.0105)	(0.0161)	(0.0132)	(0.0007)
FM	0.183***	0.571***	-0.419***	0.0374***
	(0.0554)	(0.0802)	(0.0760)	(0.0038)
DVA	0.0634	1.7385***	-0.05806	-0.0067
	(0.0770)	(0.0711)	(0.0841)	(0.0047)

Table 15: Parameter Estimate for Latent Class Stochastic Frontier Model (continued)

Estimated prior probabilities for class membership				
Constant	-	-0.0416	-0.671***	-
		(0.111)	(0.151)	
Labor units per TLU	-	0.0110	-0.970***	-
		(0.267)	(0.285)	
Stocking rate (TLUs	-	-0.241*	-0.0688	-
per hectare)		(0.129)	(0.141)	
Capital units per TLU	-	1.589***	-0.361	-
		(0.5640)	(1.2369)	
Efficiency analysis				
Technical efficiency	0.544	0.355	0.535	0.969
	(0.130)	(0.768)	(0.281)	(0.0128)
Variance parameters for compound error				
Sigma(σ)	1.0781***	2.170***	1.0790***	0.0460***
	(0.00070)	(0.107)	(0.0505)	(0.00439)
Sigma(u)	0.668	2.152	1.0775	0.0354
Sigma(v)	0.495	0.277	0.0574	0.0293
$\sigma^2 = \sigma_u^2 + \sigma_v^2$	1.162	4.709	1.164	0.00211
$\lambda = \sigma_u / \sigma_v$	1.162***	7.772***	18.784***	1.208***
	(0.0796)	(0.753)	(1.998)	(0.312)
$\eta = \sigma_u^2 / \sigma^2$	0.574	0.984	0.997	0.593
Estimated prior probabilities for class membership				
Prob.	-	0.3883	0.2069	0.4048
Test statistics				
Log likelihood test[1]	8.406***		1363.387***	
AIC	3284.9		1079.5	

Notes: ***, **, * Significance at 1%, 5%, 10% level; Standard Deviation in the parenthesis; [1]Based on Kodde-Palm chi2 C*: 95%: 2.706, 99%: 5.412.

Source: Own author computation.

The other technological characteristic analysed is the scale elasticity. The Translog form is flexible and allows for varying output elasticities. Again, the Translog functional forms also allow for a certain degree of technological heterogeneity, as the production elasticities for the individual firms vary according to their level of input use (Sauer-Morrison 2013). To calculate output elasticities, we first partially differentiate the LCSF model (equation 7) with respect to each of the classical factor of production variables using Equation 22. Control dummies variables were excluded given that they are shifting parameters, and coefficient attached to them are referred to as differential intercept coefficients. Then, the returns to scale (RTS) is defined as the sum of the input elasticities ($RTS_i|_j = \sum_{j=1}^{J} E_i|_j$). Note, the elasticities are computed for each variable with respect to their individual frontier as indicated by the *J* subscript, and these reflect the importance of each of the inputs in output production, while the sum of all standard input elasticities gives a measure of returns to scale for each farm's i in j. Table 16 presents the elasticities of the three inputs (labour, land and capital represented as LNL, LNR and LNK respectively) which were calculated by multiplying the elasticity of each observation times its arithmetic mean. The row labelled RTS displayed scale elasticity (Table 16).

There are two kinds of differences to be analysed: differences across models (single frontier model versus LCMSF) and differences across classes. The differences in the elasticities across classes are evidence of different technological characteristics between the three technologies identified. For all elasticities, with exception to land input in class 1 and 3 and capital in classes 3, have the expected positive signs at the means and different from zero. In Class 1, all these factors' elasticities are very close to zero, so an increase in the standard inputs has no impact on the production. In class 2, just as expected in theory, all inputs portrayed a positive contribution to livestock production while in class 3, only labour input matters. The output elasticity with respect to labour is more than twice as large in class 3 as it is in class 2 and a single frontier. On the other hand, the output elasticity of pastureland and capital is always more significant in class 2. These different elasticities imply significant differences in the marginal productivity of inputs across the three technologies; thereby, the classification was useful. In terms of elasticity of scale, the differences were conspicuous with farms in classes 2, and 3 operating on average in an increasing return to scale meaning their scale is more than adequate (Coelli et al. 2005) while farms in class 1 presented a decreasing return to scale. The scale elasticity for farms in class 1 is very close to zero giving the possibility that farms in this class may have not yet exhausted their scale of production. The scale elasticity is higher for farms in class 2. The scale elasticity obtained assuming a single frontier for all farms can be misleading for farms in class 1 which might inappropriately be branded on average under close to constant returns to scale.

Table 16: Output Elasticities for the Classical Factors of Production

With respect to:	Latent Class Frontier Class 1	Class 2	Class 3	Single Frontier
LNL	0.00077	0.4514	1.1693	0.5545
	(0.0822)	(0.0862)	(0.0033)	(0.0603)
LNR	-0.0211	0.6394	-0.00511	0.2341
	(0.1087)	(0.0302)	(0.0024)	(0.0363)
LNK	0.0737	0.2592	-0.00046	0.0596
	(0.0688)	(0.0616)	(0.0024)	(0.0392)
RTS	0.0534	1.3501	1.1637	0.8482
	(0.0865)	(0.0593)	(0.00267)	(0.0453)

Notes: Parenthesis are the standard deviations.
Source: Authors' own computation using analysis result of household data

The next phase of analysis involved investigating the underlying causes of technical inefficiency for different classes and compare them with homogenous technology. Since most of the estimates for sigma squared (σ^2) were significant, they confirmed that the frontier model is stochastic (rather than deterministic), and the need to include technical inefficiency error term was necessary. Moreover, the significant value of λ implies that the 50.65%, 24.09%, 39.14% and 62.03% discrepancies between the observed value of livestock output and the frontier output for single frontier and LC frontiers classes 1, 2, and 3 respectively (Table 17), can be attributed to failures within the farmers' control and this necessitated the analysis of the determinants that may cause this underlying deviation To ensure consistent estimates of inefficiency effects model in Equation 8, the one-stage approach proposed by Coelli et al. (2005) was adopted over the alternative two-stage analytical process. In one-step LCSF, the parameter for inefficiency level usually enters the model as the dependent variable. Intuitively, a negative (positive) sign of an element of the δ vector in Equation 8 implies that the variable reduces (increases) technical inefficiency (Brummer–Loy 2000, Coelli et al. 2005). In order to estimate the inefficiency effect model of Equation 8, a step by step process of deletion of highly insignificant variables (obviously by a cross-check on p-value and standard deviation) was adopted, and this reduced the number of variables included in the estimation of the inefficiency effect model to fourteen as shown in Table 17.

Causes of inefficiency analysis results in Table 17 show that the effect of the covariates examined is not the same across the single stochastic frontier model and the classes of the LCSF model. Most of the results for the pooled data model are statistically significant with education level squared (EDUC2) of household head, access to drugs, agricultural research, input market and off-farm income having the expected negative sign signifying that they would significantly reduce inefficiency while access to extension services and land ownerships (LANDOWNE) portray an opposite effect on inefficiency. When we adopt an LCSF model, access to drugs and markets significantly reduces inefficiencies for farms in class 1 than in classes 2 and 3. Gender of household head, land ownership for the and access to input markets has the opposite effect on inefficiency for farms in class 2, while farms in class 3, access to input markets would increase inefficiency. Hence, for efficient production of livestock in the study area, these factors with positive effect must be addressed, and their effects reduced to a bare minimum.

In explaining the significant covariates that reduce inefficiency effects between the single stochastic frontier and LCSF model, the results of the study reveal farmers' education level (a proxy to household characteristic variables) had non-linear influence to livestock performance, dominantly negative impact in the single frontier and in classes though insignificant. Since education is not significant in the classes, its overall impact is weak and contradictory in different groups. Regarding single frontier, the result of this variable seems to be consistent with Nganga et al. (2010) and Otieno et al. (2014) who found a significant negative influence of formal education on efficiency. Perhaps this suggests that highly educated people (among pastoral and agro-pastoral communities) may practice less professional farming because they consider agriculture to be relatively less rewarding than other economic sectors.

The results of this study also show that one of the essential avenues for reducing inefficiency is to address the institutional factors such as markets, market information and agricultural-related, which were captured as dummy since they constitute proxies to transaction costs and these institutional factors are thought as transaction cost minimizing arrangements. For instance, access to drugs, research and technology services constitutes the key agricultural institution related factors that were significant in reducing levels of inefficiency. Of particular prominent among this category of variables is access to drugs which is significant in all cases, but with an apparent high magnitude for farms in classes 1. This is true because farms in this class were found to be capital intensive. Differences pattern between the single frontier and LC model can also be seen with references to market access with this variable being significant in the LC model but insignificant when homogenous technology is assumed. Thus, policies focusing on ensuring institutional efficiency in agricultural and livestock markets might be effective measures. This can be done through suitable policy formulation, implementation, proper supervision of livestock production programs, the effective extension services, proper market information systems and an institution of pro-pastoral Livestock Input Subsidy Program to improve resilience to erratic droughts experienced in these areas.

The other construct of transaction costs is off-farm income. Off-farm income was viewed as an alternative to livestock cash incomes and therefore expected to result in a reduction of inefficiency level. The significance of off-farm income under single frontier and expected negative sign for farms in classes 2 and 3 seems to suggest that, as noted by Alene et al. (2008), there might be considerable re-investment of such earnings in various farm operations by some livestock farmers in Kenya. This result on off-farm variable suggests that formulation and judicious enforcement of a policy targeting injecting capital resources into the livestock industry or provision of affordable microloans in remote rural areas would help in improving efficiency in livestock production. Other essential variables for policy concern, though not significant, is the number of technologies adopted. In Kenya, since the rural areas where over 78% of smallholder farmers live is characterized by higher illiteracy levels compared to urban centres, adoption of new ways of farming is challenging. Therefore, pastoralists resolve to use their own experiences and knowledge, which they have used for generations and thus, low productivity (Irungu et al. 2006). Adoption of enhancing livestock technology may, in turn, alleviate the current problem of food insecurity and lead in the long run to economic development.

Lastly, the variance parameter (sigma) is statistically significant at the 1% level for single and LC frontier models. The sigma values indicate the goodness of fit and correctness of the distributional form for the composite error term for the inefficient effect model for the pooled data and latent class model. The tests result of Wald chi2(11), and log-likelihood refers to the joint significance tests of the parameters of the variables that explain technical inefficiency. The result rejects the hypothesis that the parameters are simultaneously equal to zero ($H_0: \delta_i = 0$) at 1% or 10% except for class 3 where it fails to reject.

Table 17: Determinants of Inefficiency among Smallholder Livestock Farmers of Kenya

Parameter	Pooled data	Latent class model Class 1	Class 2	Class 3
Observations	1,283	251	222	810
Technical inefficiency	0.507	0.241	0.391	0.620
	(0.192)	(0.200)	(0.166)	(0.0049)
Household characteristics				
AGE	-0.0004	0.0008	0.0007	-7.48e-06
	(0.0004)	(0.0020)	(0.0008)	(1.16e-05)
GENDER	0.0140	0.1105	0.0715**	0.0007
	(0.0165)	(0.0975)	(0.0362)	(0.0005)
EDUC	0.0072**	0.0049	-0.0023	-2.86 e-05
	(0.0035)	(0.0186)	(0.0075)	(0.0001)
EDUC. squared	-0.0004*	-9.34e-05	0.0001	-9.07e-07
	(0.0002)	(0.0011)	(0.0004)	(6.90e-06)
Institutional related factors				
VDRUG	-0.0592***	-0.517***	-0.0762**	-0.0025***
	(0.0169)	(0.0969)	(0.0329)	(0.0005)
EXTESERV	0.231*	0.130	-0.0363	0.0026
	(0.129)	(0.297)	(0.0732)	(0.0022)
AGRESEARCH	-0.214*	-0.193	0	-0.0016
	(0.127)	(0.327)	(omitted)	(0.0023)
AGRTECENTRE	-0.189*	0	-0.264	0
	(0.1065)	(omitted)	(0.236)	(omitted)
Market institution and information				
MARKACCESS	0.0270	-0.479***	-0.104*	-0.0015*
	(0.0259)	(0.183)	(0.0601)	(0.0008)
INMARKACCESS	-0.0498**	0.0662	0.0893*	0.0013*
	(0.0218)	(0.1407)	(0.0534)	(0.0007)
MARKINFOACCESS	-0.0093	0.1975*	0.0449	-0.0002
	(0.0194)	(0.1197)	(0.0359)	(0.0007)
Others				
NTECHGY	-0.0132	-0.0284	-0.0050	-0.0001
	(0.0093)	(0.0433)	(0.0218)	(0.0003)
LANDOWNER	0.0294***	0.0897	0.0435*	-0.0002
	(0.011)	(0.0600)	(0.0243)	(0.0003)
OFFINCOME	-0.0768***	0.0047	-0.0171	-0.0001
	(0.0144)	(0.101)	(0.0483)	(0.0004)
_Cons	0.601***	0.406**	0.363***	0.623***
	(0.0322)	(0.196)	(0.0756)	(0.0010)
Marginal effect	0.504	0.0071	0.386	0.620
Disturbance Standard Deviation and tests				
Sigma	0.189***	0.276***	0.165***	0.0048***
	(0.0040)	(0.0299)	(0.0089)	(0.0001)
Wald chi2	78.53***	34.76***	18.59	45.54***
Log likelihood	342.885	140.693	95.481	3180.932
AIC	-653.769	-251.386	-160.962	-6331.864
BIC	-571.258	-198.504	-109.921	-6261.408

Notes: ***, **, * Implies significance at 1%, 5%, 10% level; Parenthesis is standard deviation.

Source: Authors' computation using data using household data

3.5. Summary of the chapter

The objective of this study was to investigate the production efficiency of smallholder farm households leaving in the southern rangelands of Kenya while considering farms uses a different technological scope. Using Cobb-Douglas and Translog in the framework of SFA and nesting the widely used distributions for inefficiency error term, the picture that emerges from this analysis is one of general average technical inefficiency in livestock production in the study area. The distribution of the technical inefficiency suggests that potential gain can be achieved through improved agricultural-specific efficiency factors such as land, labour and capital. Equally, the likelihood ratio statistic test that is based on the null hypothesis that there has not been an effect of inefficiency, the presence of significant values at the 1% level in all distributions, indicate the effects of inefficiency in the model. Under heterogeneous technology, **v**arious hypotheses tested established the model fit. The notion on poolability of the group frontiers is rejected, suggesting that there are significant differences in the input parameters. The variation of TE score between the three classes indicates the presence of livestock production heterogeneity justifying the estimation of a stochastic latent class model. The distribution of the technical efficiency between classes suggests that potential gain can be achieved through indifferent improvement in agricultural-specific efficiency factors of production. The estimated η and λ components, which indicates the presence of inefficiency revealed technical inefficiency term is an essential phenomenon in livestock production at 1% level since $\lambda > 1$. Again, there is also indifferent between classes with regards to the effect of significant factors such as the number of livestock production technology adopted by the majority of the farmers, education level, low levels of formal education, access to markets, access to veterinary drugs and off-farm income that influenced the level of technical inefficiency. With all the aforementioned facts**,** there is sufficient evidence to support the claim *that the size and access to agricultural factors of production (land, labour and livestock production supplies) positively influence livestock production of the smallholder pastoral farming and their impact is not homogenous in the farmer population.* Factors that can reduce the level of inefficiency under homogenous are gender and education level of the household, off-farm income, number of technologies adopted by the majority of the farmers, and nature of land ownership while under heterogeneous technologies they are class-specific. Thus, we can partially support the hypothesis that *Human related attributes (e.g. gender, age, education level), access to socioeconomics (e.g. land ownership, off-farm income etc.), service providers (extension, agricultural institution etc.), market factors (e.g. input markets, market information etc.) and financial institutions (e.g. credit facilities etc.) influence efficiency in the livestock production for smallholder pastoral farmers,* and thus we can accept the hypothesis

CHAPTER FOUR

FARM HOUSEHOLD LIVESTOCK PRODUCTS SUPPLY AND FACTOR INPUTS DEMAND RESPONSIVENESS

Despite there being incredible challenges in enhancing livestock development in Kenya, the livestock products supply, and factor input demands responsiveness was isolated as the main constraints facing the smallholder pastoral households. While the available studies have given some insight into output-price responsiveness (e.g. Nyariki 2009, Manyeki et al. 2016), they have not extended the understanding of factor substitution/complementarity in the livestock sector fully. The study on farm household livestock products supply and factor demand responsiveness are, therefore, designed to address how the law of supply and demand affect the output and factor input market of livestock sector in Kenya with particular references to southern rangelands? The discussion in the next sections proceeds with a theoretical framework (section 4.1) that set the empirical model used in analyses. The data and estimation procedure are then presented in the methodology section, followed by the analysis and discussion of results. The summary of the main findings concludes the chapter.

4.1. Theory and empirical review of the Supply and Factor Demand

Theoretically, there are many ways to derive supply and factor demand model from a given technology and a given endowment of variable and fixed factors of production in the neoclassical framework. A review of the theory of production with an emphasis on its use in supply and factor demands derivation and response analysis conducted is provided in various microeconomic textbooks. In order to derive factor demand equation, the common practice has been to formulate a transformation function[34] dependent on factor quantities, a vector of output levels and the production technology and then empirically derive factor demand equations from the first-order conditions of cost minimization. For supply response equation, the profit maximization is assumed, and the output supply response equations derived from the first-order conditions. Such an approach is referred to as positive or econometric approach and is broadly classified into two sub-groups: the primal approach and the dual approach (Sadoulet–de Janvry 1995). The alternative is

[34] In a standard microeconomic theory, a transformation function provides a direct or primal or description of production technology. It describes the maximum amount of one output that can be produced for a given levels of production of the remaining outputs and for a given levels of input usage.

normative approaches that typically combine historical and artificial (generated) data and impose behavioural assumptions in programming models that attempt to determine optimal choices, i.e. "what ought to be" (Shumway–Chang 1977). The primal approach involves estimation of the structural production function or frontier from cross-sectional or time-series data, and profit-maximizing marginal conditions are imposed to derive the supply and demand equations. The problem associated with this method includes simultaneity bias that occurs between inputs and outputs since the two jointly determined unless experimental data is used. The other alternative to primal or dual methods is ad hoc specification of supply response (including partial adjustment and expectations formation) and this employ the Nerlovian's supply response models.

In our case, producer response is determined by two elements which include the technological relationship between combinations of inputs and the resulting level of output, and producers' behaviour in choosing inputs (given market prices and fixed factor availability). Integration of these two features leads to (a) definition of the output supply and factor demand that can be determined from profit-maximizing or cost-minimizing functions and (b) to a direct method by which optimal decisions on output supply and factor demand can be determined. The latest development that is based on duality theory provides such a simple approach and ensures researcher that it is in fact theoretically sound since it reduces the problems of solving first order conditions by directly specifying suitable minimum cost functions or maximum profit functions rather than production or transformation functions and therefore was found to be ideal for this study (Sadoulet–de Janvry 1995). Moreover, it's increasing in popularity in use in the field of applied economic analysis is because it allows greater flexibility in the specification of factor demand and output supply response equations and permits a very close relationship between economic theory and application (Diewert 1971, Lopez 1982, Sadoulet–de Janvry 1995). This is because the ingenuity of duality models is that it incorporates a behavioural assumption (profit maximization), and readily available data can be incorporated to obtain unobservable demand and supply parameters and fundamental technological. Therefore, the use of duality allows estimation of models consistent with neoclassical theory and provide a beneficial relationship and smooth transition to conducting economic assessments of policies and regulations. Additionally, the duality approach has the ability to accommodate multiple outputs as well as a multiple-input framework (Tocco 2013).

The theoretical background on how to apply duality to empirical studies are fully explained and proven in Shepard (1953, 2015), Diewert (1982) and Debertin (2012) and the concept behind dual theory implies that the shape of the total variable cost function is closely linked to the shape of the production function that underlies it. That is to say, if input prices are constant, all the information about the shape of the variable cost function is contained in the equation for the underlying production function. Moreover, if the variable cost function and the prices for the inputs are known, so is the shape of the underlying production function. Therefore, in the dual theoretical framework, two short-run versions of duality can be generated, if it is assumed that either output level or input levels are assumed to be known and constant. In the former case (i.e., constant output), objective function simplifies to the minimization of cost subject to the requirement of generating the given output level. In the latter case of known and fixed input levels, the objective function simplifies to maximization of revenue subject to the use of the given input levels. In either case, corresponding marginality conditions may be derived for these short-run variants of the profit maximization or cost minimization problem.

In the agricultural product supply and inputs factor demand responsiveness analysis, there are relatively few studies which have made use of derived supply and factor demand model in estimation output and factor demand responses using profit function. Looking at the studies which relied on a profit function, McKay et al. (1982) examined the flexibility of production and the bias of technical changes in the wheat/sheep zone of Australia by estimating the system of derived output and input share equation from a Translog variable profit function. This analysis was undertaken from three outputs (sheep and wool, crops and beef cattle and farm output) and five inputs (labour, materials and services, livestock, capital and lands). In this study, the supply response of each of these three significant groups of farm outputs has been inelastic. Sheep production enterprise has been complementary with cropping while crop and beef cattle outputs have not been complementary. The demands for materials and services inputs have been elastic while the elasticity of demand for labour has been approximately unity. Wool and other sheep output have been relatively labour-intensive while crops have been relatively capital intensive. Livestock activities (sheep and cattle) have been relatively land-intensive.

In the same spirit, Fisher–Munro (1983) observed that most of the supply elasticity estimates reported for Australian agriculture are derived from equations estimated using time series data and incorporating *ad hoc* assumptions about price expectations. The authors' aim is to compare previously obtained supply elasticity estimates with those derived using theoretically more acceptable survey data on both producers' intentions and price expectations. Surveys were conducted in three regions in New South Wales; namely, the Southern Tablelands, the South-West Slopes and a portion of the Western Division centred in Cobar. The results of the research show that there are no significant differences between the supply elasticities derived using the traditional time series approach and those obtained using the survey data. This finding is reassuring, given the cost of collecting survey data.

In the USA, Shumway–Alexander (1988) estimated supply equations for five outputs and demand equations for four inputs in ten agricultural production regions, using annual time. The authors employed a Normalized Quadratic profit function to assess the differences in the responses across USA regions to market stimuli, government intervention, and changing technology. The author found that there was an extreme diversity across regions in terms of own-price elasticities, with hired labour exhibiting the most significant variation. The same results hold for cross-price elasticities, with regions differing in their responsiveness to market stimuli and governmental intervention, as also supported by the output supply elasticities with respect to diversion payments. A study by Huffman–Evenson (1989) present estimates of supply and demand elasticities for USA multiproduct cash grains farms and place particular emphases on the input and output bias effects caused by research, extension, and farmers' schooling. The authors employed a multi-output Normalized Quadratic profit function with USA repeated cross-sections in forty-two states over the period 1949-74. These authors found a biases effects of agricultural research in favour of fertilizer and against farm labour that are consistent with the induced innovation hypothesis. Moreover, the estimated shadow values had a positive value for public crop research and farmers' schooling, with the social return of 62% and 15% respectively, whereas private crop research and extension are slightly negative.

Despite the increase in movement from the 'primal approach' based on the production function, to the 'dual approach' use of duality over the last three decades, in Kenya, the only study that has so far applied this concept was carried out by Olwande et al. (2009) in crop industry. This author aimed at assessing how responsive maize output is to price and non-price factors and how sensitive fertilizer and labour demand are to prices and non-price factors using cross-sectional farm-level data. The study employed normalized restricted Translog profit function to estimate maize supply and variable input demand elasticities. Results show that maize price support is an inadequate policy for expanding maize supply. Fertilizer use was found to be particularly important in the decisions on resource allocation in maize production. However, the negative cross-price elasticities of fertilizer and labour demand suggest that fertilizer and labour are more of complementary inputs than substitutes in maize production of the fixed inputs, the land area was found to be the most critical factor contributing to the supply of maize.

4.2. Theoretical Model of Output supply and factor input demands

In this study and in pursuit of our theoretical foundation of profit maximization in the context of bounded behaviour, the dual framework was assumed to be output-oriented, and therefore the theoretical premise was based on the profit function that was assumed to represents an ideal, the maximum profit attainable given the inputs, outputs, and prices of the inputs. Supply and factor demand functions, from which output supply and input demand responsiveness are estimated, are then derived analytically. The reason for using profit maximization approach over the cost minimization approach is that the latter assumes that output levels are not affected by factor price changes and, thus, the indirect effect of factor price changes (via output levels) on factor demands are ignored (e.g. Olwande et al. 2009, Debertin 2012). In addition, the inclusion of output levels as explanatory variables in cost minimization function may lead to simultaneous equation biases if output levels are not indeed exogenous. The profit function approach overcomes most of these problems, although it requires a stronger behavioural assumption. The factor demands estimated using a profit function framework allow one to measure input substitution and output scale effects of factor price changes. Additionally, one can measure the cross effects of output price changes on factor demands and vice versa as well as output supply responses and their cross-price effects. Finally, the profit function framework allows the estimation of multi-output technologies in a much simpler way than a cost function or a transformation function. To examine the smallholder pastoral livestock producers behavioural on output and input use, particularly on their responsiveness, farmers were assumed to maximize restricted profit function conditional on a convex production possibility set or technology T expressed by

$$\pi(P, W; Z) = \underset{Q,X}{Max}\{pQ - wX | F(Q, X; Z) \in T\}, \qquad (24)$$

Subject to the constraint that $\pi = R - C \geq \pi^*$

where $R = pQ$ is the gross receipts, and $C = w(.)$ is the cost structure functional form. Term Q and X are vectors of quantities of outputs, and variable inputs and P and W are the corresponding vectors of output and input prices respectively; Z denotes the quantity of fixed factors inputs (e.g. land, capital). The profit function $\pi(.)$ is assumed to be non-decreasing in p, non-increasing in w, linear homogeneous and convex in p and w. The function $\pi = R - C \geq \pi^*$ shows the farmer specific minimum acceptable profit level π^* referred to as lower bound and capture the satisficing behaviour due to information asymmetry in the market.

In this profit function, the main impediments are the variable inputs costs structure, $w(.)$ given the independency of the production possibility sets and, therefore, the concept of normalized restricted profit function was adopted. This is because normalized restricted profit function applies to cases in which some commodities such as livestock product outputs and labour input prices are restricted to vary within a closed convex set in addition to the case in which some commodities such as land and capital assets are restricted to be fixed. Normalization has the purpose of removing any money illusion (in other words, producers respond to relative price changes) and, also reduces the demand on degrees of freedom, by effectively reducing the number of equations and parameters to estimate. In the case of a single output, a normalized restricted profit function (defined as the ratio of the restricted profit function to the price of the output), π*, can be specified. In the case of multi-output normalized profit function, the numéraire is the output price of the nth commodity and following Fare–Primont (1995), the restricted profit function was specified as:

$$\pi_i^* = \pi_i^*(P^*, W^*; Z), \tag{25}$$

where normalized profit, output prices and input prices are defined by $\pi_i^* = \pi/p$, $P_i^* = P_i/P$ and $W_i^* = W_i/P$ respectively. Here, *P* is the minimum acceptable price for cattle and sheep and goat outputs (shoat hereafter) for a satisficing smallholder household *i* – referred to as farm gate price. Differentiating the normalized profit function with respect to prices of outputs and inputs, respectively (applying Hotelling's Lemma) would yield the supply function of output and demand functions for input.

To implement this process empirically, it is necessary to first specify a form for the profit function. In the literature, the are several flexible functional-forms that give a second-order Taylor approximation to an arbitrary (true) functional form such as Translog by Christensen et al. (1973), generalized Leontief by Diewert (1973), symmetric generalized McFadden by Diewert–Wales (1987) and normalized quadratic by Lau (1976) and permits the application of the duality theory for a more disaggregated analysis such as livestock sector of Kenya. To formulate an effective livestock production and marketing policies, one needs reliable empirical knowledge about the degree of responsiveness of demand and supply for factors and products, to relative prices and technological changes. And, the normalized Translog version of the profit function was considered to be one of the general functions for the approximation of production and cost function and simultaneously for estimation of output supply and factor demand responsiveness since they are closely interlinked to each other. The logarithmic Taylor series expansion of normalized profit function (Equation 25) can be written as:

$$Ln\pi_i^*\left(P_i^*, W_j^*; Z_k\right) = \alpha_0 + \sum_{i=1}^{N} \beta_i LnP_i^* + \sum_{j=1}^{M} \gamma_j LnW_j^* + \sum_{k=1}^{K} \delta_k LnZ_k + \sum_{i=1}^{N} \sum_{j=1}^{M} \vartheta_{ij} LnP_i^* \, LnW_j^* + \sum_{i=1}^{N} \sum_{k=1}^{K} \theta_{ik} LnP_i^* \, LnZ_k + \sum_{j=1}^{M} \sum_{k=1}^{K} \xi_{jk} LnW_j^* \, LnZ_k + \frac{1}{2}\left(\sum_{i=1}^{N} \sum_{h=1}^{N} \tau_{ih} LnP_i^* LnP_h^* + \sum_{j=1}^{M} \sum_{l=1}^{M} \phi_{il} LnW_j^* \, LnW_l^* + \sum_{k=1}^{K} \sum_{u=1}^{K} \psi_{iu} LnZ_k \, LnZ_u\right), \quad (26)$$

Where, subscripts *i*, stands for output and run from 1 to N; [35], subscripts *j* and *l* stay for variable inputs (prices) and run from 1 to M; [36], subscripts *k* and *u* stay for fixed inputs and run from 1 to K;[37] P_i and W_j are output and input prizes respectively; Z_k denotes the quantity of factor k that are assumed to be fixed in the short term (e.g. area of pasture land, the value of capital assets=Household income). π_i^* is the restricted profit of *i*-th product normalized by the average product price P_i; P_j^* is the normalized price of multi-output technologies, normalized by the output price P_i, that is, $P_j^* = P_j/P_i$ where *i*, *j*= cattle price, sheep and goat price; $\boldsymbol{P}^*; \boldsymbol{W}^*; \boldsymbol{Z}$ are vectors of these variables; Coefficients α_{i0} , β_{ij} , γ_{ik} , δ_{ih}, ϑ_{ijk} , θ_{ijh}, ξ_{ikh} , τ_{ijl}, ϕ_{ikm}, and ψ_{ihn} are parameters to be estimated and *Ln* = natural logarithm.

Using Hotellings Lemma, the first-order derivatives of Equation 26 with respect to normalized prices of variable outputs i yield a system the output supply *(Y)* equations:

$$Y\left(P_i^*, W_j^*; Z_k\right) = \frac{\partial Ln\pi_i^*\left(P_i^*, W_j^*; Z_k\right)}{\partial LnP_i^*} = \beta_i + \sum_{j=1}^{M} \vartheta_{ij} LnW_j^* + \sum_{k=1}^{K} \theta_{ik} LnZ_k + \sum_{h=1}^{N} LnP_h^* + \varepsilon , \qquad (27)$$

Further, a system of inverse input demand equations that represent technological change is obtained by differentiating Equation 26 with respect to normalized variable

[35] In our case $N = 3$, because we have three outputs: cattle, goat and sheep.
[36] In our case $M = 1$, because we have only one variable input: Labour.
[37] In our case $K = 2$, because we have two fixed inputs: Pastureland area and Household income.

input prices W_i^* and fixed factor Z_k, yielding a system of inverse variable inputs equations X and shadow-value equations, Q expressed as:

$$X(P_i^*, W_j^*; Z_k) = -\frac{\partial Ln\pi_i^*(P_i^*, W_j^*; Z_k)}{\partial LnW_i^*} = \gamma_j + \sum_{i=1}^{N} \vartheta_{ij} LnP_i^* + \sum_{k=1}^{K} \xi_{jk} LnZ_k + \sum_{l=1}^{M} \phi_{il} LnW_l^* + e, \quad (28)$$

$$Q(P_i^*, W_j^*; Z_k) = -\frac{\partial Ln\pi_i^*(P_i^*, W_j^*; Z_k)}{\partial LnZ_k} = \delta_k + \sum_{i=1}^{N} \theta_{ik} LnP_i^* + \sum_{j=1}^{M} \xi_{jk} LnW_j^* + \sum_{u=1}^{K} \psi_{iu} LnZ_u + \eta, \quad (29)$$

These systems of supply and demand response Equations 27 to 29 show the relation between output supply and input demand to the output prices, input prices and the quantities of fixed factors respectively. To exhibit the properties of a well-behaved profit function, Equation 26 must be non-decreasing in output price ($\beta_i \geq 0$, for *i*=cattle, sheep and goat outputs), non-increasing in input prices ($\delta_k \leq 0$, for *k*=pasture land, capital and labour and $\gamma_j \leq 0$ for labour price) and symmetry constraints are imposed by ensuring equality of cross derivative (e.g. $\vartheta_{ij} = \vartheta_{ji} \quad \vartheta_{ij}$for all *i*, *j*; *i* ≠ *j*, $\theta_{ik} = \theta_{ki}$ for all *i*, *k*; *i* ≠ *k* and $\xi_{jk} = \xi_{kj}$ for all *j*, *k*; *j* ≠ *k*). This implies that all own price responsiveness (elasticities) are expected to be positive for output supply and negative for input variable costs, and less than unity. However, the cross-price elasticities are expected to be indeterministic such that a negative sign implies a degree of substitutability with a positive sign indicate a degree of complementarity. The homogeneity and adding-up are automatically maintained by constructing a normalized Translog profit function. Similarly, the output supply functions (Equation 27) and inputs demand functions (Equation 28-29) exhibit theoretical restrictions reflecting the properties of the profit functions.

The empirical model consists of Equations 27 to 29 with symmetry imposed and truncated normal distribution which is the probability distribution of a normally distributed random variable with mean μ and standard deviation σ appended error terms $\{\varepsilon, e, \eta\}$ that are identically independently distributed. In total, a system of five (two supply and three input demand) equations were derived from the normalized profit function, and the variables were converted to logs before subjected to analysis. The five equations considered included two output supply – cattle and a composite of sheep and goat (shoats hereafter) and three inputs demand – one variable input presented by hired labour and two fixed inputs presented by a total area under pasture measured in hectares and farm capital asset expressed in monetary value.

4.3. Materials and Methods

This section provides materials and methods applied in analysing farm household livestock products supply and factor inputs demand responsiveness. The discussion proceeds in the next sections with the data and sample size used in this analysis. Section 4.3.2 follows with the procedures for estimation supply and factor demand responsiveness and the section 4.3.3 concludes with the discussion on the contextual variable for hypothesis testing.

4.3.1. Data Source and Sample Size

The dataset used was the Kenyan Household Survey which was a nation-wide survey of rural households that was conducted during September-October 2013. The sampling frame comprises of 1512 households interviewed in Garissa, Kajiado, Kilifi, Kitui, Kwale, Lamu, Makueni, Narok, Taita-Taveta and Tana-River counties. These counties were deemed representative of many livestock production zones in Kenya. For this study, quantities of outputs and inputs variable were extrapolated based on the current market values as of 2013. More details on the sampling procedures and data collection are discussed in section 3.3.3 of chapter 3.

4.3.2. Procedure for Estimating the Supply and Factor Demand Responsiveness

In order to estimate the supply and factor demand model from a farm-level data, a two-stage approach was used. In the first step, it was necessary to assume a stochastic structure and assumed that any deviations of the observed profit, output supply and input demand from their profit-maximizing levels were due to random errors in optimization and that the disturbances were additive and followed a multivariate normal distribution with a zero mean (μ) and a constant contemporaneous covariance matrix (Σ) expressed in shorthand notation as $X \sim N(\mu,\Sigma)$. By taking the first-order derivative using Hotelling's Lemma, we derived five equations from the normalized profit function.

In the second phase of analysis involved the estimation of derived output supply and input demand equations and a truncated regression analysis was adopted. Truncation is mainly a characteristic of the distribution from which the sample data are drawn whose value is either bounded below or above (or both). For this study, to avoid bias in the estimation, sample selection was determined solely by the value of x-variable. A maximum likelihood estimation technique was used, and the truncated normal distribution is the probability distribution of a normally distributed random variable with mean μ and standard deviation σ, and therefore the density of the truncated normal distribution of the i-th observation was expressed by:

$$L_i = \frac{\frac{1}{\sigma}\phi\left(\frac{y_i - x_i'\beta}{\sigma}\right)}{\Phi\left(\frac{x_i'\beta}{\sigma}\right)}, \quad (30)$$

where ϕ and Φ are the density and distribution functions of the standard normal distribution.

The log-likelihood function is given by:

$$LogL(\beta,\sigma) = \sum_{i=1}^{N} LogL_i = -\frac{N}{2}[Log(2\pi)] + Log(\sigma^2) - \frac{1}{2\sigma^2}\sum_{i=1}^{N}\varepsilon_i^2 - \sum_{i=1}^{N} Log\left[\Phi\left(\frac{x_i'\beta}{\sigma}\right)\right], \quad (31)$$

Where the values of (β, σ) that maximize LogL are the maximum likelihood estimators of the truncated regression. Using the parameter estimates, and assuming output prices and input prices are defined by $\bar{x}_j = {}^{P_i}/_{P}$ and $\bar{x}_j = {}^{W_i}/_{P}$ respectively, the own-price responsiveness was calculated at the population means using:

$$e_{ij} = \beta_{ij} * \frac{\bar{x}_j}{\bar{y}_i} \text{ for } i = j, j = \text{cattle, sheep, goat, labour and land,} \quad (32)$$

And the cross-price responsiveness:

$$e_{ij} = \beta_{ij} * \frac{\bar{x}_j}{\bar{y}_i} \text{ for } i \neq j,\ j = \text{cattle, sheep, goat, labour and land,} \quad (33)$$

For own price response, e_{ij} represent the per cent change in quantity demanded (supplied) of input (output) of type *i* in response to a 1% change in the prices of input (output) of type *i*. Likewise, for the cross-price response, e_{ij} represent the per cent change in quantity demanded(supplied) of input (output) of type *i* in response to a 1% change in prices of input (output) type *j*, holding all prices of other than of the *j*-th input (output) constant. Positive (negative) value of *cross-price elasticities* indicated that *i* and *j* are substitutes (complements). Additionally, following Färe et al. (1986), we estimated responsiveness of scale[38] via the output-oriented measure of scale elasticity.

[38] Responsive of scale is based on functional form of the production function and it exhibit increasing, constant and decreasing if scale elasticity is greater, equal or less than one respectively.

4.3.3. Contextual Variables

The list of variables used for econometric estimation of the livestock products supply and input demand responsiveness was based mainly on work by Fisher–Munro (1983), Abrar et al. (2002) and Olwande et al. (2009). The variables are grouped into three categories: output variables that include number of livestock tropical units supplied in the market which represent the endogenous variable; output price variables that include the average live animal selling prices in KES (Kenya shillings) and resource input variables that include both fixed factor (pasture land in hectares) and variables factors (labour cost and disposable income in KES). It's worth noting that for the output variables neither could cattle, sheep and goat output be divided between adults and young once or male and female. Hence, only TLUs could be used to calculate cattle sheep and goat outputs. The average cattle, sheep and goat output prices were also derived implicitly by dividing the value of sales by the quantity of each output sold which meant that the output prices for each cross-sectional unit were different, thus accounting for price variation between farmers. Other variables were taken the way they were presented by the farmers during the interview. The variables and their definition are presented in Table 18 below.

Regarding the expected sign, as found in our earlier case study (Manyeki et al. 2016) and in Nyariki (2009) study in Kajiado, own price is expected to influence the decision of the farmer to sell positively. Fisher–Munro (1983) study on supply response in the Australian extensive livestock and cropping industries found that the decision-maker intention to increase cattle numbers was influenced by price for beef price, sheep products prices and proportion of the improved pasture on the land property. There was also an incidence of an unexpected negative sign on the influence of pastureland variable to the number of cattle sold in some region. Significant cross-elasticity effects were apparent in the estimates in Fisher–Munro (1983) study; they indicate competitive relationship, for example, between beef and sheep products. Freebairn (1973), in his study of the New South Wales livestock sector, also found positive cross-price elasticities between beef and wool, and beef and lamb products. This implies that if a livestock product has several alternative production possibilities available, then response elasticities with respect to price changes of these products prices will be higher than when fewer alternatives are available. However, a study by Abrar et al. (2002) found cross-price elasticities been more critical determinants of supply and input demand decisions than own prices. Their study also found price elasticities were also found to be all less than unity. The influence of labour cost in livestock off-take is expected to be positive.

The study by Olwande et al. (2009) found labour demand to be inelastic to changes in the wage rate and having an elastic own-price elasticity.

In general, the pastureland variable represented technological change was regarded as crucial in production decisions and was hypothesised to have positive. The study by Freebairn (1973), Malecky (1975) and others have found it to be a significant explanatory variable in livestock response studies. Technological improvements help reduce production cost and increase profit, thus stimulate higher supply. Labour is an essential factor of production in the livestock industry and arises in the price leads to an increase in the production costs and vice versa. Households' income was computed by including monetary income items and benefits in kind connected to employment relationships[39]. This variable was expected to be positive because the more the household income the high the likelihood that, part of the income will be invested in livestock production which would add to the livestock available for sale (Bebe et al. 2003).

Table 18: Definition of Price and Non-Price Variables for Model Estimation

Variables	Definition, expected supply elasticity and measurements
Output quantity variables	
Cattle	Total numbers of cattle sold in the last one year
Sheep	Total numbers of sheep sold in the last one year
Goat	Total numbers of goat sold in the last one year
Output price variables	
Goat prices	Average selling market price in Kenya shillings with expected positive own price elasticity on supply
Sheep prices	Average selling market price in Kenya shillings with expected positive own price elasticity on supply
Cattle prices	Average selling market price in Kenya shillings with expected positive own price elasticity on supply
Resource inputs variables	
Labour	Total labour (hired and family labour) in man-days utilized for livestock production with its supply elasticity expected to be positive.
Pastureland area	Land area under pasture in hectares with its supply elasticity expected to be positive.
Disposable Income	Household income in Kenya shillings with its supply elasticity expected to be negative.

Source: Author’s construction based on the literature

[39] This capture total on-farm income, total non-farm and off-farm income, bank savings and livestock off-take etc.

4.4. Empirical Results, Analysis, and Interpretation

The valuable discussion of empirical results in this section is organised as follows. Sample characteristics from the survey are described in section 4.4.3, while, empirical results on livestock products supply and factor input demand responsiveness are extensively discussed in section 4.4.2.

4.4.1. Descriptive Statistics for supply and factor demand in livestock production

Table 19 presents the average values of variables at that period of study time. The statistic presented in Table 19 was captured on recall based on the last one year from the time of the interview. For instance, during the survey, the households were asked to indicate the number of cattle, sheep and goat that they sold in the last year. The data indicate that the off-take rates ranged between 20-40 per year of different livestock species and were selling at about KES 3000 (USA Dollar 35.12) and KES 20,000 (USA Dollar 342.41)[40] for small stocks and cattle respectively. The significant standard deviation implies that the farmers operated at different levels of production, which tend to affect their outputs. The average pastureland size of sample properties was reasonably high; implying that the majority of the household had set aside high pastureland for livestock production. Mean annual labour was about 261 man-days which included the total man-day employed in livestock from production to marketing. The mean annual income for the household was KES 124,450 (US Dollar 1,457.09). This was included to capture off-farm income-earning opportunities which include business in farm produces although it is worth noting that off-farm employment is relatively rare in Kenya, is distributed in an uneven manner and access to it depends strongly on education and place of residence.

[40]US Dollar to Kenyan Shilling by 31 March 2013 was 1 USD = 85.41 KES.

Table 19: Sample Means of Variables used in Supply and Demand Equation

Variables	**Mean**	**Std Dev.**	**Min.**	**Max.**
Output quantity variables				
Cattle	21.262	54.982	1	958
Sheep	39.853	77.646	1	890
Goat	23.076	42.860	1	670
Output price variables				
Goat prices	3,021.526	1073.988	88.889	13,500
Sheep prices	3,013.775	1502.957	100	15,000
Cattle prices	20,509.62	8887.737	450	61,666.67
Resource input variables				
Labour (Man-days)	261.2956	179.8822	1	1220
Pastureland area	259.825	1051.783	1	5009
Household Income	12,4450	299,712.6	0	7,000,000

Source: Author's own construction

4.4.2. The empirical result on Livestock Products Supply and input demand Responsiveness

Smallholder pastoral households in the southern rangelands of Kenya routinely make decisions as to whether to sell livestock, the principal form of wealth in the region. Under the maintained hypothesis that market behaviour is driven by a household's objective of maximizing profit it enjoys, one cannot ignore the effect of input prices on output and demand for inputs. However, this has not been taken into account by these previous studies. Under this sub-topic, the hypothesis to be tested as earlier stated was H_3: *'the supply of livestock products is not affected by price and non-price input incentives (e.g. such as the size of pastureland, income and labour inventory)'*. To test this hypothesis, we estimated the derived supply Equation 27 with respect to normalized prices of livestock product outputs presented in Table 18 using STATA software (StataCorp 2012).

Parameter estimates from the derived system of output supply and input demand are given in Tables 20 to 23. With three outputs and two inputs in the model, only 6 and 5 parameters respectively are freely estimated. Tables 21 and 23 gives the elasticity computed (with their corresponding standard error) of the three outputs supply and three input demand equations for the farm-household data. In all cases, the output and inputs prices were normalized and directly included in the equations. In Table 20, the results of the coefficient estimate for output supply and labour demand are found to be robust in all cases. The signs of the own-price coefficient estimate for the livestock supply are all theoretically consistent and significant at 1% and 5% level (Table 20), with a positive supply elasticity (Table 21). The result indicates that the own prices are inelastic for goat and sheep. The most inelastic being sheep followed by the goat. The own-price elasticity is relatively elastic for cattle; a result that concurred with the finding of Nyariki (2009) and Manyeki et al. (2016) in Kajiado District in Kenya. The only explanation for this finding is that producers respond to an increase in prices accompanied by diverting resources into increasing cattle herds in anticipation for a better price in future. However, it is worth noting that sheep and goat are less responsive to own-prices elasticity than cattle which can be associated to longer production cycle in cattle that tends to make producers more responsive to changes in cattle prices.

Cross-price elasticities were found to be in the inelastic range in all cases which indicate that a price change will result in a relatively small uptick in supply of livestock products. This result confirmed Abrar et al. (2002) finding where cross-price was found to be an essential determinant of the decision to supply than own-price. The cross-price elasticities indicate that cattle can be a substitute for sheep and goat, and sheep and goat a complement for cattle. This confirms Freebairn (1973) finding that the more possible alternatives available to a product, the larger response a product in question has with respect to the prices changes of alternative products. Moreover, cattle output is less price responsive to goat and sheep prices than the goat, and sheep output is to cattle prices. The only cross-price elasticity that was significant was between cattle and goat prices and sheep and goat prices. The cross-price elasticities for sheep and goat are similar (as they are both negatives), while those between cattle and goat and cattle and sheep output are indeterministic. The possible explanation to this is that the goat meat prices at the consumption level are high and a slight increase in the price of goat prices would reduce the demand compressing the producer prices, and this would result into reduction in the supply. The high price would make the consumer shift to cattle meat, thereby increasing the demand for the cattle meat. Subsequently, the prices of cattle meat will increase, and that would result in an increase in the supply. The sheep quantity is more than thirteen-time as sensitive to the goat output prices than goat quantity is to sheep output prices.

Outputs response to variable input was measured by the cost of labour normalized by output price of type *i*, the individual household income and the size of improved pastureland in hectares. Based on the magnitude of the elasticities, a slight change in labour price would have a more significant effect on output level than pastureland improvement price in all the livestock type. Labour price had a cross-relation to herd size and the more the labour costs, *ceteris paribus*, the large the herd size and this would translate to more livestock available for marketing. The livestock supply equations have unexpected negative elasticity with respect to household income. The possible explanation to this negative result on output supply on all livestock products is that the elasticities were estimated from survey data; only the short-run response is captured. However, in long-run, a sign switch is expected, and a policy incentive that would increase capital investment to the bottom of the income pyramid such as the poor farmers who, in the absence of formal insurance markets, tend to diversify including keeping livestock to achieve a balance between potential returns and the risks associated with climatic variability and market and institutional imperfections would improve livestock off-take. As observed by Bebe et al. (2003), enhancement of capital resources at livestock farmers level through either injecting of capital resources into the livestock industry or provision of affordable microloans in remote rural areas would provide households with an incentive to invest in livestock because of the broad spectrum of benefits these provide, such as cash income, food, manure, draft power and hauling services, savings and insurance, and social status and social capital.

The most critical fixed input in terms of livestock output response is the size of improved pastureland. The variable was specified as the total hectares of (natural or improved) land pasture and in this case, captured technological change that is regarded as valuable in production decisions. The livestock supply response with respect to pastureland was found to be very significant and positive as expected, which is consistent with theory. This finding confirms Freebairn (1973), Malecky (1975) and others where pastureland was found to be a significant explanatory variable in livestock response studies. In relative terms for the three type of enterprises, cattle output supply is almost twice as sensitive to the size of the improved pastureland. The high magnitude on the pastureland variable for cattle output supply possibly may be associated to the fact that cattle being the primary beef producer in Kenya is pasture-based and hence dependent on land availability (Kahi et al. 2006). Based on the pastureland elasticities, red meat would expand by about 2-4% if the pastureland area under livestock production were to increase by 100%. This, however, need not imply support for a general policy of increasing the size of holdings so that more land can be allocated to livestock production. It may be that following the recent trend of land subdivision experienced in the rangelands of Kenya, there are many small-holding farms, which strangles the carrying capacity of rangelands, leading to uneconomical production systems. Land policies that prevent undesirable land fragmentation and protect holders of large tracts of land should be encouraged.

The elements in the row labelled ‘all’ in Table 21 are the sum of the individual effects of output prices and inputs on livestock products supply, which reflects the output supply response to a change in all exogenous variables combined usually referred to as scale elasticity. Generally, the scale elasticities for the three livestock products were less than one (though not less than zero, giving the possibility of free disposal), which indicate a decreasing return to scale. Under decreasing returns to scale, it means that an equiproportional increase in factor inputs results in less than a proportional increase in output. However, goat output seems to be more responsive to factor inputs than cattle and sheep output are. This is so because, in pastoralist areas, where frequent droughts and diseases are experienced, goats are becoming attractive since they are less susceptive, can easily be de-stocked during drought and re-stocked afterwards, hence reducing the losses due to starvation (Degen 2007). The estimates of sigma square (σ^2) are significantly different from zero at 1% level of significance, implying a good fit and correctness of the specified distribution assumptions of the composite error term. The Wald Chi-square value (Wald chi2(6)) showed that statistical tests are highly significant (P < 0.000), suggesting that the model had strong explanatory power.

Table 20: Output Supply Response Parameter Estimates for Smallholder Livestock Farmers

Parameter	**Cattle**	**Goat**	**Sheep**
_cons	-2.676	-3.480**	-1.210
	(2.317)	(1.692)	(1.533)
Cattle prices	0.492**	0.241	0.232
	(0.239)	(0.221)	(0.267)
Goat prices	-0.284*	0.634***	-0.718***
	(0.177)	(0.198)	(0.215)
Sheep prices	-0.150	-0.108	0.400**
	(0.149)	(0.143)	(0.161)
Labor cost	0.299***	0.363***	0.340***
	(0.0802)	(0.0801)	(0.0897)
Household income	-0.143***	-0.0949***	-0.105***
	(0.0311)	(0.0302)	(0.0342)
Pastureland area	0.134***	0.197***	0.163***
	(0.0471)	(0.0426)	(0.0509)
Sigma	0.821***	0.781***	0.868***
	(0.0489)	(0.0463)	(0.0539)
Wald chi2(6)	65.41***	73.63***	54.98***
Log likelihood	-176.041	-167.439	-168.420

Note: * *p* <0.10, ** *p* <0.05, *** *p* <0.001; Standard deviation in the parenthesis.
Source: Author’s own construction.

Table 21: Livestock Products Output Supply Elasticities

With respect to:	Cattle	Goat	Sheep
Cattle Price	0.689	0.077	0.108
	(0.911)	(0.299)	(0.443)
Goat Price	-0.0052	0.565	-0.081
	(0.023)	(0.780)	(0.435)
Sheep Price	-0.0015	-0.006	0.221
	(0.010)	(0.089)	(0.276)
Labor Cost	0.120	0.375	0.440
	(0.454)	(1.366)	(1.394)
Household Income	-0.156	-0.058	-0.042
	(0.197)	(0.092)	(0.064)
Pastureland	0.040	0.028	0.027
	(0.040)	(0.053)	(0.041)
All (Output effect)	0.686	0.981	0.673
	(0.273)	(0.447)	(0.442)

Note: Standard deviation in the parenthesis.
Source: Author's own construction.

The hypothesis (H_4) set before holds that *'factor demand for livestock production is not affected by price factors and non-price input incentives (e.g. such as the size of pasture land, income and labour inventory'* was also tested using Equations 28 and 29. Tables 22 and 23 contain the parameter estimates and price elasticities for the factor demand system, respectively. The inputs demand elasticities in Table 23 were computed by employing the estimated coefficients in Table 22. All factor input demand elasticities were found to be in the inelastic range with exceptional to that of cattle output prices and labour cost which was elastic for land demand in cattle and goat production enterprises respectively concurring with the finding in Olwande et al. (2009) study. Estimates for the labour input demand equations were robust, though less precise in many cases than that of pastureland counterpart. With regards to output prices, all production enterprise showed an elastic response of pastureland demand to cattle output price, yet labour demand was reasonably responsive to cattle output prices in the cattle production enterprise. The situation with regards to goat and sheep output prices on factor demands is opposite except for labour and land demand response to goat and sheep output prices respectively which is relatively inelastic. The pastureland response in the goat and sheep production enterprise are similar and relatively elastic. A similar finding was reported in Freebairn (1973) and Malecky (1975) study where the size and quality of pastureland were found to influence livestock production and off-take significantly. Our analyses also show that an increase in sheep and cattle output prices puts substantial positive pressure on pastureland demand, and indeed, this can explain the high effect shown on sheep and cattle supply. Increases in goat output price would encourage the expansion in demand for labour under goat production enterprise while it would result in a reduction in pastureland demand in all cases.

When it comes to labour cost, labour demand is inelastic to changes in the labour price, having a positive own-price elasticity estimate that is not consistent with economic theory. This is because despite livestock farming is one of the leading sources of employment in Kenya; young people are often said to prefer employment in non-farm sectors, perhaps due to low returns and lack of prestige associated with agriculture compared to white-collar jobs (Afande et al. 2015). If this is a general phenomenon in all livestock production areas, then 'surplus' labour available in the agricultural areas of Kenya will only be attracted to livestock production, if it is, by an increase in wage rates. The situation is the opposite with a relatively elastic response of pastureland demand on labour costs in the goat production enterprise, but an inelastic response to in the cattle and sheep production enterprises. This high elastic of labour costs on pastureland demand equation for goat production possibly may be associated to the fact that goats are browser unlike cattle and sheep, which are heavy grazers. The results have important implications for agricultural research and development policies for developing countries such as Kenya. The availability of labour is a more severe constraint owing to its relatively low elasticities but very significant across all livestock type.

As expected, household income in both demand equations is positive in all cases with a relatively low negative effect on labour demand recorded in cattle production enterprise (Bebe et al. 2003). The income effect can be observed under two scenarios: if a household aggregate level of income increases or if the relative cost of expanding pastureland or wage for labour decreases. Both situations increase the amount of discretionary income available, so does the quantity of pastureland and labour. Factor demands in sheep production enterprise were relatively more responsive to changes in household income. The estimates of sigma square (σ^2) are significantly different from zero at 1% level of significance, implying a good fit of the specified distribution assumptions of the composite error term and the Wald chi2(5) showed that statistical tests are significant suggesting that the model had strong explanatory power.

Table 22: Parameter Estimates of Input Demand Equations for the Livestock Production

	Cattle		Goat		Sheep	
Variables	**Land**	**Labour**	**Land**	**Labour**	**Land**	**Labour**
_cons	-11.549***	-0.568	3.283	0.936**	-0.552	1.945
	(4.0423)	(0.620)	(3.265)	(0.417)	(2.684)	(0.406)
Cattle prices	1.484***	0.391***	1.119**	-0.341***	1.347***	-0.444***
	(0.412)	(0.0639)	(0.446)	(0.0549)	(0.457)	(0.0689)
Goat prices	-0.380	-0.465***	-0.156	0.292***	-1.266***	-0.380
	(0.315)	(0.0512)	(0.382)	(0.0488)	(0.361)	(0.0546)
Sheep prices	0.230	-0.177***	-0.256	-0.168***	0.222	0.178***
	(0.267)	(0.0436)	(0.302)	(0.0352)	(0.280)	(0.0425)
Labour cost	-0.086	0.939***	-0.269*	0.979***	-0.108	1.0293***
	(0.144)	(0.0234)	(0.159)	(0.0200)	(0.156)	(0.0238)
Household income	0.0128	-0.0031	0.0427	0.0199***	0.0477	0.0298***
	(0.0564)	(0.0091)	(0.0596)	(0.0075)	(0.0600)	(0.0091)
Sigma	1.455***	0.243***	1.506***	0.196***	1.490***	0.231***
	(0.0928)	(0.0143)	(0.0979)	(0.0116)	(0.0999)	(0.0142)
Wald chi2(5)	18.73***	2030.10***	9.84*	2991.53***	16.53***	1925.97***
Log likelihood	-254.143	-0.473	-253.841	30.086	-234.621	5.877

Note: * *p* <0.10, ** *p* <0.05, *** *p* <0.001; Standard deviation in the parenthesis.
Source: Author's own construction.

Table 23: Factor Input Demand Elasticity for Livestock Production

	Cattle		Goat		Sheep	
With respect to:	**Land**	**Labour**	**Land**	**Labour**	**Land**	**Labour**
Cattle Price	2.322	0.059	0.882	-0.021	0.833	-0.018
	(3.436)	(0.096)	(3.959)	(0.108)	(2.126)	(0.034)
Goat Price	-0.006	-0.001	-0.594	0.085	-0.255	-0.006
	(0.017)	(0.006)	(0.618)	(0.142)	(0.565)	(0.017)
Sheep Price	0.002	-0.0002	-0.189	-0.002	0.401	0.029
	(0.008)	(0.0005)	(0.467)	(0.028)	(0.685)	(0.071)
Labour Cost	-0.047	0.016	-1.185	0.088	-0.322	0.086
	(0.114)	(0.017)	(2.371)	(0.048)	(0.970)	(0.079)
Household Income	0.011	-0.0003	0.008	0.004	0.047	0.003
	(0.017)	(0.0005)	(0.013)	(0.006)	(0.081)	(0.007)

Note: Standard deviation in the parenthesis.
Source: Author's own construction

4.5. Summary of the chapter

This study applied duality theory to sequentially analyse livestock products supply and input responses of the household livestock farmers. Using Hotelling's Lemma approach to a normalized Translog profit function, a system of supply and inverse factor input demand equations were derive used and separately analysed using a farm-level database. It is clear from the above discussion that livestock product supply response to own price is elastic, statistically significant and theoretically consistent. Equally, it is also clear that at least one non-price incentive considered, positively influence livestock supply. This is especially portrayed by labour cost, which shows a cross-relationship to herd size. As such, there is sufficient evidence to reject the claim that *'the supply of livestock products is not affected by price and non-price input incentives (e.g. such as the size of pastureland, income and labour inventory)'.* With regards to factor input demand responsiveness, own price seems to put a substantial pressure to input factor demands. Factor incentive such as labour cost and household income influence input demand decision. Since at least one-factor influence input demand decision, the hypothesis that '*factor demand for livestock production is not affected by price factors and non-price input incentives (e.g. such as the size of pastureland, income and labour inventory)'* can also be rejected.

CHAPTER FIVE

ON THE ANALYSIS OF FARM HOUSEHOLD LIVESTOCK MARKET PARTICIPATION

While there is a general agreement that improving market access of smallholders has a high potential for economic development and poverty reduction, there remain multiple challenges in making progress. One of the critical challenges facing smallholder agricultural households market participation is imperfect or incomplete markets for some goods and factors, which are then non-tradable. Several studies have attempted to address this challenge aiming at identifying the constraints and the corresponding interventions that are important for improving access to markets by the smallholder. However, until now, there is limited available empirical evidence on pastoral livestock farmers' market participation casting some doubt on attempts to facilitate national "self-sufficiency" in livestock commodities or, more generally, to induce vigorous supply response or broad-based rural welfare gains through trade and price policy instruments instituted in Kenya three decade ago. The present study attempts to contribute to this information gap with a particular focus on the pastoral livestock marketing in the southern rangelands of Kenya. The chapter begins with a review of the theory of marking participation. This is followed by a review of the literature on theoretical and empirical models, data and estimation procedures. Next, a detailed discussion of the main results that entails descriptive statistics, analysis of factors determining the probability and level of market participation is presented. The chapter concludes with a summary of the main findings.

5.1. Theory of Market Participation

The theory of market participation has developed various theoretical approaches, and key among the critical ones includes asset-based approach (ABA), transaction cost approach (TCA) and agricultural developmental approach (ADA) (summarized in Table 24 below). The ABA is well discussed by Boughton et al. (2007), who held that market participation depends fundamentally on households' initial asset endowments with market-based development strategies favouring initially wealthier household. As Barrett (2008) put it, those with access to adequate assets and infrastructure and faced with appropriate incentives stand a high chance of actively engaging in markets, while those who lack one or more of those three essential ingredients mainly do not. In short, the ABA refers to the uses of the current value of a farmer tangible net asset as the critical determinant of market participation. The approach conceptualizes farm families having dynamic collections and assortments of assets that can mitigate many production and marketing risks, generate a surplus to meet household expenditure needs, and can be used to design diversified farming enterprises so as to reduce vulnerability and build up farm resilience (Milestad–Darnhofer 2003, Darnhofer et al. 2010). The ABA also provides a useful reasonableness check when reviewing the value derived under the income or market approaches. Empirically, Boughton et al. (2007) found that as the market share of agricultural output increases, input (asset) utilization decisions and output combinations are progressively guided by profit maximization objectives. This process leads to the systematic substitution of non-traded inputs with purchased inputs, the gradual decline of integrated farming systems, and the emergence of specialized high-value farm enterprises. However, the costs and returns of market participation, and thus the marginal response of participation and sales volumes to household asset endowments, vary by market types[41].

The agricultural developmental approach views market participation as both a cause and a consequence of economic development[42] (Barrett 2008). According to this concept, markets offer agricultural households the opportunities in twofold; first to specialize according to comparative advantage and second in enhancing resource-use efficiency, thereby enjoy welfare gains from trade. Recognition of the potential of markets as engines of economic development and structural transformation gave rise to a market-led paradigm of agricultural development during the 1980s (Reardon–Timmer 2006) in which market liberalization policy agendas were widely promoted in sub-Saharan Africa (SSA) and other low-income regions. Furthermore, as households' disposable income increases, so does the demand for a variety of goods and services, thereby increasing demand-side market participation, which further increased the demand for cash and thus supply-side market participation. The standard process of agrarian and

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[41] Darnhofer et al. (2010) hypothesized that participation in higher return markets may require different asset portfolios (amount and types of asset) than does participation in less remunerative markets.

[42] Cause of Economic Growth because markets participation may stimulate an increase in aggregate demand of products (inputs and outputs) which may further stimulate a rise in agricultural output if the economy has unused resources. And, consequence of economic growth because an increase in agricultural output can improve income and living standards of people. Further, higher agricultural output and incomes increase government tax revenue (both foreign and domestic), making it easier for governments to finance measures to reduce poverty, increase health care provision and raise educational standards, without having to raise tax rates.

rural transformation, therefore, involves households' transition from a model of subsistence, in which most inputs are provided for, and most outputs consumed internally, to a market engagement mode, with inputs and products increasingly purchased and sold off the farm.

The transaction cost approach which is part of the New Institutional Economics (NIE) postulates that economic activity does not occur in a frictionless environment, but rather are always accompanied by the transaction costs of carrying out the exchange which are directly influenced by the efficiencies of the institutions (Omamo 1998, Key et al. 2000, Renkow et al. 2004). From the time, Williamson (1993) coined the phrase new institutional economics in order to distinguish it from the old institutional economics pioneered by Commons and Veblen; the NIE has gained popularity in explaining farmer market participation in different production enterprises (Williamson 2000, Alene et al. 2008, Ouma et al. 2010). The old institutional school pioneered by Commons and Veblen argued that institutions were a key factor in explaining and influencing economic behaviour. However, the critics to this school of thought argued that it operated outside neoclassical economics since the school did not provide any quantitative theory from which reliable generalizations could be derived, or sound policy choices could be made.

NIE acknowledges the critical role of institutions but argues that one can also analyse institutions within the framework of neoclassical economics (Williamson 2000). In other words, under the NIE, some of the assumptions of neo-classical economics (such as perfect information, zero transaction costs, full rationality) are relaxed but the assumption of self-seeking individuals attempting to maximize an objective function which is subject to constraint(s) still holds (Alene et al. 2008, Ouma et al. 2010). The NIE represents thus an expanded economics that focuses on the choices people make, while at the same time it allows for factors such as occurrence of information and human limitations on the processing of information, evolution of norms, and willingness of people to form bonds of trust which all contribute to cost of exchange or transaction costs. TCA is, therefore, predominantly concerned with economizing these transaction costs. The costs of exchange depend on the efficiency of institutions of a country that includes the legal system, political system, social system, educational system, culture, financial system, market system, and so on. In effect, it is the institutions that govern the performance of an economy and more importantly, agricultural householder market participation.

Table 24: Theoretical Approaches and Hypothesis in Market Participation analysis

Theoretical framework	**General statement of the hypothesis in market participation analysis**	**Main literature source**
Asset-based approaches	Market access depends on households' initial asset endowments with market-based development strategies favouring initially wealthier household	Milestad–Darnhofer 2003, Boughton et al. 2007, Darnhofer et al. 2010
Transaction cost approach	Market participation depends on the status of institutions and institutions are transaction cost minimizing arrangements, which may change and evolve with changes in the nature and sources of transaction costs	Coase 1937, Williamson 1993, Omamo 1998, Williamson 2000, Key et al. 2000, Renkow et al. 2004, Alene et al. 2008, Ouma et al. 2010
Agricultural developmental approaches	Market participation is viewed as both a cause and a consequence of economic development	Reardon–Timmer 2006, Barrett 2008

Source: Author's own construction based on the literature.

Market participation of agricultural farm households in domestic and regional livestock markets in most developing countries especially SSA remains low (Coulter–Onumah, 2002, Poulton et al. 2006) and this has been attributed to poor market access (Makhura et al. 2004, Kydd–Dorward 2004). The majority of an agricultural farm household in SSA are located in remote areas with poor transport network, and market infrastructures, contributing to the high transaction costs faced. In addition, they lack reliable market information as well as information on potential exchange partners. All these contribute to the high cost of exchange or transaction costs, and as observed by Omamo (1998) to some extreme cases, the markets can be said to be "missing". Therefore, policies that aim at addressing these constraints have to address transaction costs. As a result, TCA framework seems ideally suited to explain the marketing participation behaviour of agricultural pastoral farm households in the southern rangelands of Kenya who are undergoing a gradual shift from pastoral livelihoods to commercial agro-pastoral land-use systems and non-traditional lifestyles (Bebe et al. 2012) and faced with production and marketing uncertainties. The agricultural pastoral farm household's decision to participate in the market can be similarly understood, based on farm behavioural approach model in TCA framework.

Transaction cost approach has been utilized in a number of studies to explain the market participation behaviour of small-scale farmers and those poor in resources in developing countries. It endeavours to determine the factors influencing the decision of these farming households to participate in the output market for agricultural products, that is, the decision to sell or not to sell. In the context of this study, those factors that influence the decision to participate as well as the level of participation are commonly referred to as transaction costs. Although transaction costs in the context of Coase and Williamson are used to identify alternative modes of governance or economic organization; the approaches have well been used in investigating the organization of individual transactions in product markets. The purpose here is not to attempt an exhaustive review but instead discusses the various empirical applications of TCA to the small-scale farmers' market participation in developing countries.

The concept of transaction costs was first empirically applied by Staal et al. (1997) to determine the smallholder market participation in east Africa. In their study, one of the hypotheses was to confirm the notion that high transactions costs for dairy production and marketing limit participation by an asset- and information-poor smallholders of East Africa. This assertion was investigated by the authors in a case study for Kenya and Ethiopia, where smallholder dairy is much more prevalent than in the rest of Africa. The authors applied a transaction cost approach to this analysis and conducted a survey that targeted the milk marketing value chain actors – farmers, self-help groups and dairy cooperatives in the two counties. The authors found that transactions costs in east African dairy are high, as evidenced by the low percentage of milk production that is commercialized in Kenya and Ethiopia. Second, the size of the dairy operation, and its proximity to urban markets, influence the products and market channels used by producers to market dairy products. The authors also observed that transactions costs increase with distance, and this they attributed it to increased costs of information and risk of dairy product spoilage before a buyer is found. The prices received by producers were also found to decrease with distance and appear to vary considerably depending on the size of sales and the flexibility of contractual relationships between producer and consumer. Finally, the study also found that producers with a higher degree of capital intensity per cow tend to be able to secure higher prices per litre than those with lower capital intensity. This is an indication of an underlying explanation of differential transactions costs faced by different producers: differential access to assets (and probably to differential information), which may translate into a higher market influence. The authors conclude that, in both countries, government intervention in cooperative formation and decision-making appears to transcend that of necessary to protect cooperative members and their customers and therefore recommended a more detailed study of the structure and determinants of transactions costs and their impacts on the behaviour of economic agents.

A similar study on live animals was undertaken by Bellemare–Barrett (2006) in the southern and northern part of Ethiopia and Kenya. The authors were interested in assessing whether market participation and volume decisions are made simultaneously or sequentially. The authors developed a two-stage econometric method to test these two competing hypotheses regarding household-level marketing behaviour. The first stage models for the household's choice referred to whether to be a net buyer, autarkic or a net seller in the market. The second stage models the quantity bought (sold) for net buyers (sellers) based on observable household characteristics. Using household data from Kenyan and Ethiopian livestock markets, the authors find evidence in favour of sequential decision making. The authors found that prices matter to the extent of participation and that fixed transactions costs matter both in the participation and in the extent of participation decisions, thus offering additional evidence in favour a well-known behavioural anomaly. Fixed transaction costs of market participation and the complex property rights in animals that accompany cultural livestock gifting and lending institutions impede market participation.

A study by Alene et al. (2008) seeks to estimate the effects transaction cost has on relative price and non-price factors on smallholder marketed surplus and inputs that formed the key determinant to market participation among maize producers in Kenya. A selectivity model was used that accounts for the effects of transactions costs, assets, technology, and support services in promoting input use and generating a marketable surplus. In this study, output supply and input demand responses to changes in transactions costs and price and non-price factors were estimated and decomposed into market entry and intensity. The authors found that while transactions costs indeed have significant adverse effects on market participation, institutional innovations such as group marketing are also emerging to mitigate the costs of accessing markets. In addition, the authors found that output price has no effect on output market entry and only provides incentives for increased supply by sellers. On the other hand, the authors revealed that both price and non-price factors have a significant influence on the adoption and intensity of input use. In conclusion, the authors suggest that although other policy options that would enhance public service delivery and promote input use and marketed surplus, better price policy would induce greater input-output market participation among smallholders in Africa.

Ouma et al. (2010) employed a bivariate Probit model to jointly and separately estimate banana market participation decisions of buying and selling households in Rwanda and Burundi using household survey data. Selectivity bias was corrected for estimating the transacted volumes using Heckman's procedure. The authors found that transaction cost-related factors such as the geographical location of households, market information sources, and travel time to the nearest urban centre influence market participation. Non-price-related factors such as security of land tenure, labour availability, off-farm income, the gender of the household head, and years of farming experience had a significant influence on the transacted volumes. Output prices had a significant correlation with sales volume, indicating price incentives increased supply by sellers. Generally, the findings suggest that policies aimed at investments in rural road infrastructure, market information systems, collective marketing, and value addition of banana products may provide a potential avenue for mitigating transaction costs and enhancing market participation and production of marketed surplus by rural households.

In the current debates over the privatization of the parastatal such as Kenya Creameries Company, new knowledge about smallholder participation in dairy could be an essential contribution. Burke et al. (2015) undertaken a study using a triple-hurdle approach, a modification of double hurdle model, to identify the factors associated with Kenyan smallholder farmers choosing to participate in dairy production and the role that these producers choose to play (or not) in the marketplace. The authors describe a version of the ordered Tobit model referred to as triple-hurdle model that includes non-producers. They performed a likelihood ratio test, and it showed the latter to be a significantly better fit to their data. The authors found that of the ongoing rural electrification, training, and improved grazing practices are important factors contributing to farmer participation. They also found that expected net sales are significantly higher when farmers have access to informal private markets. They concluded that triple-hurdle model was better for their case because the population of interest included non-producer, but in case all were producer, then the preferred model would be double-hurdle.

The recent endeavour by developing countries to commercialize livestock industry has resolved that, for smallholder livestock farmers to benefit from their livestock, they need to participate in the market fully. Such an initiative requires intervention strategies by government and development agencies. Based on this notion, Kgosikoma–Malope (2016) developed a study that aimed at identifying the determinants of market participation by smallholder livestock farmers in Botswana that would limit the initiative of commercialization. The theory behind their study was that when producers are faced with high transaction costs, they may not get the benefits of trade and thereby choose not to participate in the markets which subsequently results in low off-take rates. The authors employed a Logit model framework to identify factors that determine whether smallholder farmers will participate in the market or not. The results of their analysis revealed that although household characteristic such as the age of household head negatively and significantly affects market participation, (implying that older farmers are less likely to participate in the market), major institutional limitation facing smallholder livestock farmers is the requirement that the animals should have a bolus (for traceability) and veterinary permits.

5.2. Market participation model

Pursuant to the underlying theoretical background of TCA in NIE framework, the study considers livestock farmers' participation in the market and adopting Alene et al. (2008) theory, theorizes that the household pastoral farmers always tend to avoid participation in the market if transaction costs are high. As a result, the reduction of transactions costs as a means of increasing market participation is identified as a goal of development policy. Therefore, in this context, those factors that influence the decision to participate as well as the level of participation are commonly referred to as transaction costs. These costs are attributable to endogenous factors related to household characteristics and other factors, which are exogenous to the household. The choice to participate in the market is always influenced by expected net returns that are assumed to be guided by transaction costs. As Boughton et al. (2007) pointed out; positive net returns result in participation while negative net returns lead to non-market participation.

This inherent tendency of households participating in the market only when net return is positive falls under the neoclassical theory of the firm that assumes rational behaviour of economic agents whose ultimate goal is to maximize profits in the short or long run. However, this assumption is now criticized by economists who have studied the complex organization and objectives of corporations and in particular the existence of a 'divorce of ownership and control' that is common to most modern firms (e.g. Simon 1957, Kaufman 1990). These scholars argued that there are often good reasons to depart from pure profit maximization because many economic agents did not have sufficient information to make pure judgments about the profit-maximizing choice and therefore operated under uncertainty while others pursue self-interest rational behaviour. Rather than maximize, the economic agents often satisfice when making decisions. Satisficing behaviour as earlier discussed involves settling for a good enough option not necessarily the very best outcome in all respects within the threshold of acceptability levels of profit, a type of rationality referred as 'bounded rationality[43]' (which is highly discussed by Glenn 2006).

The idea behind 'bounded rationality' can be expressed by extending the neoclassical production theory that provides a useful standard for profit maximization analysis for economic agents' behaviour to include the transaction cost approach. The neo-classical starting point supposes that the agricultural pastoral household earns its income from the production and possible selling of a livestock product Q, and faces a parametric price for the livestock product P. Under the assumption of perfect competition in the product market and factor markets, the theoretical supply function can be derived from the following profit optimization condition:

$$Max\pi = PQ - \bar{c}(\mathbf{w}, Q), \tag{34}$$

where, π represent the profit the pastoral livestock farmer receives, and $\mathbf{w}$ represent a vector of factors prices.

In specifying theoretical framework to be applied in the analysis of smallholder livestock market participation, 'bounded rationality' is expressed by extending this neo-classical theory that provides a useful standard for profit maximization analysis to include transaction costs. Following Alene et al. (2008), we maintained the hypothesis that market behaviour is driven by a household objective of maximizing profit it enjoys, and thus focus attention on a choice problem that relates optimal and of course, non-negative quantities sold, Q_s to household attributes and the environmental factors that condition

[43] Concept that decision makers have to work under three unavoidable constraints: (1) only limited, often unreliable, information is available regarding possible alternatives and their consequences, (2) human mind has only limited capacity to evaluate and process the information that is available, and (3) only a limited amount of time is available to make a decision.

market behaviours. Bounded rationality is then expressed by assuming complexity in the transaction cost function that includes observable and non-observable costs associated with livestock marketing, making farmer unable to evaluate and process the information that is available in time – the so-called cognitive limitations of their minds. For a representative smallholder household, we assumed that the cost function (C) may depend on household-specific characteristics that includes education attainment, gender, household size and age reflected in the vector (H), household endowment such as land size and livestock number reflected in the vector (E), information asset such as television and mobile phone reflected by vector (IF), and institutional factors represented by livestock prices, access to extension service, access to market information, access to financial institution and group affiliation reflected in vector (IS) and others such as off-farm sources of income or liquidity which may be earned or unearned (K) and household wealth index reflected by vector (O):

$$C = c(H, E, IF, IS, K, O), \tag{35}$$

The smallholder households' choice to maximize profit (π), subject to the complex cost function represented as:

$$Max\ f(\pi) = PQ_s - c(H, E, IF, IS, K, O), \tag{36}$$

Subject to the constraint that $\pi = R - C \geq \pi^*$

where P and R present the livestock products prices and gross receipts respectively, while π^* is the farmer specific minimum acceptable profit level – referred to as lower bound.

In this profit function, transaction costs are the major impediments and determinants of market participation. In the southern rangelands of Kenya, livestock market exists, but the gains for a particular household may be below or above cost, with the result that some households will use the market while others will not. The definition of market failure is thus household-specific and not commodity-specific as the same commodity can be tradable for one household while being a non-tradable for another. Another impediment in solving Equation 36 is that smallholder does not possess perfect knowledge of the transaction costs to contain in the cost function constraints in this theory. This information asymmetry forces the farmer to have only two decisions; first, the decision whether or not to participate in the livestock market and second, the number of livestock to supply in order to maximize household welfare given the fixed and variable transaction costs faced by the household. The two decisions may be made in a single (simultaneous) or a sequential two-step process. In the sequential process, the farmers decide whether or not to participate in the market and, if they choose market participation, the next step in the decision about the quantity to sell. Increasing research on sequential decisions on market participation has been done (e.g. Holloway et al. 2005, Bellemare–Barrett 2006, Boughton et al. 2007, Omiti et al. 2009). Simultaneous decision-making means that the farmers make choices about market participation and quantity at the same time (Abdoulaye–Sanders 2005, Chirwa 2005). The previous study explicitly tests whether or not farmers make sequential or simultaneous decisions and finds the evidence necessary to support sequential decision making and this form the premise for this study. This is because pastoral households make the discrete participation decision at home, not yet knowing information available only at the market. In the second stage, those households that have chosen to participate in the market proceed to market received additional information and would make their continuous sales.

With the aforementioned theoretical background in place, the next step involves econometric model specification. There is a considerable amount of studies on agricultural household market participation that have mainly modelled both/either output and/or input market participation decisions as a single or sequential two-step decision process. Table 25 below summarizes some of these researches in agriculture and the econometric approach employed in analysing market participation decision by household farmers in Africa. These studies have used either the sample selection model of Heckman of 1979, the Tobit model of 1958 or the double-hurdle models developed by Cragg (1971).

Table 25: Review of Econometric Models for agricultural product market participation

Literature source	Product and Country	An econometric model for estimating: Market participation	Degree of participation	
Boughton et al. (2007)	Crop (maize, cotton, and tobacco) in Mozambique	Probit	Lognormal censored distribution	Heckman two-stage
Omiti et al. (2009)	Crop industry in Kenya	Probit model	Truncated normal regression	Double-hurdle
Bellemare-Barrett (2006)	Livestock cross-border of Ethiopia and Kenya	Type II Tobit models	Censored Tobit	Ordered Tobin two-stage
Burke et al. (2015)	Dairy in Kenya	Ordered probit	Truncated normal regression	Triple hurdle
Makhura et al. (2004)	Maize in South Afrika	Probit models	Lognormal censored distribution	Heckman two-stage
Alene et al. (2008)	Maize in Kenya	Probit models	Lognormal censored distribution	Heckman two-stage
Olwande-Mathenge (2011)	Maize zone in Kenya	Probit models	Truncated normal regression	Double hurdle
Holloway et al. (2005)	Dairy in Ethiopian highlands	Non-zero-censored Tobit	Zero Censoring Tobit	Double hurdle
Abdoulaye-Sanders 2005	crop in Niger	Standard simultaneous structural equation	-	Single-stage OLS
Chirwa 2005	Maize in Malawi	Bivariate probit	-	Single-stage MLE

Source: Author's own construction based on the literature

The sample selection model of Heckman is ideally used to deal with non-random samples as a result of survey design, non-response on survey questions, sample attrition or the specific attributes of the variable being analysed. Heckman model also addresses the problem associated with the zero observations generated by non-participation decisions, arguing that estimation on a selected subsample as is the case with Tobin model (i.e., censored estimation) results in sample selection bias. The model overcomes these aforementioned problems by undertaking a two-step estimation procedure (known as Heckit). This is done by computing a selection term or Mills ratio from the first equation (selection model) and including it as a regressor to correct for self-selection in the second stage regression involving observations from the selected sample usually referred (Dow–Norton 2003, Wooldridge 2010). This selection bias was viewed by Wooldridge (2010) as the omitted variable in the selected sample, which is corrected by this procedure. The model also assumes that different sets of variables could be used in the two-step estimations.

As opposed to the Heckman model, the Tobin models are a type of corner solution outcome (sometimes referred to as censored regression model) and accounts for the clustering of zeros due to non-participation. The Tobit estimator fits conceptually well when we think of decisions on market participation and degree of participation in livestock markets as being made simultaneously. However, a main limitation with the Tobit model is that it assumes that the same set of parameters and variables determine both the probability of market participation and the level of transactions and the model is also too restrictive as it assumes that all the zeros to be the respondents' deliberate choices.

The Double Hurdle (DH) or 'Two-stage' model was proposed by Cragg (1971) which is modification of the Tobit model to overcome the restrictive assumptions inherent in Tobin model associated to too many zeros in the survey data by giving special treatment to the participation decision and also allow different mechanisms to determine the discrete probability of participation and the level of participation. In this model, two hurdles must be crossed, which are decisions to participation and the level of participation. The decision to participate in livestock market and supply is assumed sequential and therefore, DH models was found ideal as it allows for a separation between the initial decisions to participate ($Y>0$ vs $Y=0$) and the decision of how much Y given $Y>0$. Further DH model is appropriate for analysing the possibility that the factors influencing a farmer's decision to participate in the livestock market may not affect the quantity sold. In addition, the model allowed the researcher to consider that the same factor can potentially affect participation and the amount sold in different ways. Although more recently Burke et al. (2015), tried to modify Tobin model and described a triple-hurdle model of the ordered

Tobit model that includes non-producers[44], the focus for this analysis was purely on farmers engaging on livestock producing since our target was to provide an insight into those factors that would influence their decisions on market participation and, therefore, DH model was appropriate, and we restricted our review on DH specification.

The DH model applied in this research is a parametric generalization of the Tobit model, in which two separate stochastic processes determine the decision to participate and the level of participation. The first equation in the DH model relates to the decision to participate and can be expressed in Probit formulation as follow:

$$P(Y_i = 1|X_i) = P(Y_s > 0) = f(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots \beta_K x_K + \varepsilon_i)$$
$$P(Y_i = 1|X_i) = f(X_i \beta_i) + \varepsilon_i \tag{37}$$

where $f(.)$ is a function taking on values strictly between zero and one $(0 < f(X_i \beta_i) < 1)$ for all real numbers. Where *Y* takes the value of one if a household made any positive decision to participate in the livestock market and zero otherwise. *X* is a matrix of factors (transaction and other non-transaction cost factors which includes household characteristics, household endowment, transport assets, information assets, institutional asset etc.) that affect the discrete probability of participation by pastoral farmers and β_i is a vector of parameters; ε is normally distributed disturbance with mean zero and standard deviation of σ and captures all unmeasured variables

The second hurdle, which closely resembles the Tobit model, is expressed by a truncated regression function. The main advantage of the truncated normal distribution over the lognormal mostly applied under Heckman procedure is that it nests the usual Tobit Model thus allowing us to test the restrictions implied by the Tobit hypothesis against the two-step model (Wooldridge 2010). The model was specified as follows:

$$Q_i^* = Z_i' \gamma_i + \mu_i,$$
$$Q_i = Q_i^* > 0 \text{ and } Y_i > 0$$
$$Q_i = 0 \text{ Otherwise,} \tag{38}$$

[44] Insights of Burke et al. (2015) Triple-Hurdle model for market participation includes: first stage, the probability of producing or not producing (addressed by Probit model); second stage include households producing, but also being a net buyer and producing, but not participating in the market – mostly referred as autarkic and producing and selling (addressed by ordered Tobin model) and third stage level (intensity) of participation (addressed by two lognormal models that integrate the net volumes bought/sold for net buyers and net sellers).

here, Q is the proportion of the number of livestock sold; i= Cattle, sheep and goat (shoats henceforth); Z define the matrix of factors that determine the intensity of participation and $\gamma_i$is a vector of parameters; μ is the random disturbance for unit i for intensity equation.

The decisions by pastoral household whether or not to participate in the market and about how much livestock to supply to market can be jointly modelled if they are made simultaneously and independently if they are made separately or sequentially. If the independence model applies, the error terms are distributed as follows: $\varepsilon_i \sim N(0,1)$ and $\mu_i \sim N(0, \sigma^2)$. If both decisions are made jointly (the Dependent DH) the error term can be defined as $(\varepsilon_i, \mu_i) \sim N(0, \theta)$ where $\theta = \begin{bmatrix} 1 & \rho\sigma \\ \rho\sigma & \sigma^2 \end{bmatrix}$. The model is said to be a dependent model if there is a relationship between the decision to participate and the level of participation. This relationship can be expressed as follows: $\rho = \frac{\text{cov}\,(\varepsilon_i, \mu_i)}{\sqrt{\text{var}\varepsilon_i \text{var}\,\mu_i}}$. If $\rho = 0$, then the model decomposes into a Probit for participation and a standard OLS for Q. By testing the correlation between the first and second stage regression residuals, we can then establish whether the participation and outcome decisions are made sequentially or simultaneously. In this paper, we assumed sequential, and following Smith (2003) we assume that the error terms ε_i and μ_i are independently and normally distributed, and thus we have the following expression: $\begin{pmatrix} \varepsilon_i \\ \mu_i \end{pmatrix} N \left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{matrix} 1 & 0 \\ 0 & \sigma^2 \end{matrix} \right]$ [45].

5.3. Materials and Methods

The materials and specific research methods applied in the study on farm household livestock market participation are discussed in this section. The section is organized two-part. Section 5.3.1 discusses the data source and sample size determination, while section 5.3.2 presents the procedure to estimation the probability of market participation and the degree of participation.

5.3.1. Data Source and Sample Size

The critical aspect of this study was to appropriately analyse the constraints limiting pastoral farm household to participate in livestock markets. To do so, we used a national

[45] Alternatively, if both decisions are assumed to be made jointly the error term can be defined as $(\varepsilon_i, \mu_i) \sim N(0, \theta)$ where $\theta = \begin{bmatrix} 1 & \rho\sigma \\ \rho\sigma & \sigma^2 \end{bmatrix}$

farm-level household dataset a dataset which was collected during September – October 2013. For this study, the dataset comprises a sample size of 1512 smallholder pastoral households who were randomly selected from ten counties that are found in southern rangelands of Kenya namely Kajiado, Makueni, Kitui, Machakos, Narok, Taita-Taveta, Tana-River, Lamu, Kwale and Garissa. The bases for selecting these counties was because livestock farming is the mainstay among the households and cattle grazing is generally carried out in association with goat and sheep production and, to a lesser degree, cropping. Additionally, these counties were deemed representative of many livestock production zones in Kenya and also of sub-Saharan African countries. Output and input data were extrapolated on the basis of the prevailing market values in the year 2013. In this study, it is also worth noting that household analysis was grouped into two classes based on the livestock production enterprises; cattle representing large ruminant and shoat – representing small ruminates that comprises of sheep and goat. The grouping of sheep and goat together was prudent because the two species of livestock share the same inputs and are marketed together and therefore the reason for their market participation among households are assumed to be the same. Details on the sampling and data collection procedures are as discussed in section 3.3.3 of chapter 3.

5.3.2. Procedure for Estimation Market Participation Model

Because of the stochastic nature of market participation and intensity effect model, we used the maximum likelihood estimation (MLE) procedure. Market participation models and the output supply functions were estimated using the double-hurdle model (Wooldridge 2010) involving a Probit model in the first stage and truncated normal regression in the second stage. The two stages or double hurdle are estimated separately based on the assumption that the respective error terms (ε and μ) are not correlated. The dependent variable in the Probit model (Equation 37) was whether or not a farmer participated in the market while in the truncated regression models (Equation 38) represent the quantities sold. Since the probability equation does not show by how much a particular variable increases or decreases, the likelihood of participating in the livestock product market will be considered by comparing probabilities of that result when dummy variables take their values (1 if participating in livestock product markets and zero otherwise) while holding others independent variables at their sample mean values (Wooldridge 2010).

Assume that we have a random sample of size N, the ML estimate of β is the particular vector $\hat{\beta}^{ML}$ that gives the greatest likelihood of observing the sample $\{q_1, q_2, .. q_N\}$ conditional on the explanatory variables x. By assumption, the probability of observing $\{q_1 = 1\}$ is $f(x\beta)$ while the probability of observing $\{q_1 = 0\}$ is $f(1 - x\beta)$. It follows that the probability of observing the entire sample is,

$$L(q|x;\beta) = \prod_{i\in l} f(x_i\beta) \prod_{i\epsilon m}[1 - f(x_i\beta)], \tag{39}$$

where l refers to the observations for which $q = 1$ and m to the observations for which $q = 0$. We can rewrite this as:

$$L(q|x;\beta) = \prod_{i=1}^{N} f(x_i\beta)\,[1 - f(x_i\beta)]^{(1-q_i)}, \tag{40}$$

because when $y = 1$ we get $f(x_i\beta)$ and when $y = 0$ we get $1 - f(x_i\beta)$, the log-likelihood for the sample is:

$$lnL(q|x;\beta) = \sum_{i=1}^{N}\{q_i ln\, f(x_i\beta) + (1 - q_i) ln\,[1 - f(x_i\beta)]\}, \tag{41}$$

The MLE of β maximizes this log-likelihood function. If $f(x_i\beta)$ is the standard normal cumulative distribution function (CDF) we get the Probit estimator as:

$$lnL(q|x;\beta) = \sum_{i=1}^{N}\{q_i ln\, \Phi(x_i\beta) + (1 - q_i) ln\,[1 - \Phi(x_i\beta)]\}, \tag{42}$$

In the second hurdle involves, for the truncated normal regression model (Equation 38), we followed the Wooldridge (2010) estimation procedure. The classical model assumptions of μ must not be independent of Z, but also normally distributed, $\mu|z{\sim}N(0,\sigma^2)$. To estimate γ_i (along with σ) we need the distribution of Q_i given that $Q_i \leq c_i$ and z_i. This can be expressed as:

$$g(Q|\boldsymbol{z_i}, c_i) = \frac{\mathrm{f}(Q|\boldsymbol{z_i}\gamma_i,\sigma^2)}{\mathrm{F}(c_i|\boldsymbol{z_i}\gamma_i,\sigma^2)}, Q_i \leq c_i, \tag{43}$$

where $f(Q|z_i\gamma_i, \sigma^2)$ denotes the normal density with mean $\gamma_0{+}Z_i'\gamma_i$ and variance σ^2 and $F(c_i|z_i\gamma_i, \sigma^2)$ is the normal CDF with the same mean and variance, evaluated at c_i. By taking the log of Equation 43, summed across all i, and maximize the result with respect to γ_i and σ^2, then we obtained the maximum likelihood estimators which lead to consistent approximately normal estimations

5.3.3. Contextual Variables

The dependent variable, market participation, is measured by both the probability of selling and the number of livestock sold in the market. Thus, there are two dependent variables for each household. The first variable indicates whether the household participates in the market. This is an indicator variable, which takes the value of one of the households participates, and zero otherwise. For those who participate, the second variable indicates the total number of TLUs marketed, which constitutes the intensity of participation. The independent variables included a set of standard variables theoretically expected to influence livestock market participation decision and quantities traded. Past studies such as Key et al. (2000) have categorised independents variables into fixed and variable transaction costs. Either case, transaction costs are the barriers of access to market participation by resource-poor smallholders and are typically defined as all costs of entering into contracts, exchange or agreement, searching for trading partners, screening potential candidates, obtaining and verifying information, bargaining, transferring the product, monitoring, controlling and enforcing the transaction (Randela et al. 2008). At best, these costs are partly observable. The definition of independent variables and their expected signs are summarised in Table 26 and are categorised as household characteristics, transaction costs (that include transport assets and information assets) and institutional assets. Besides, we also included production-enhancing assets variables presented as 'household endowment' as *control variables*.

The transaction costs associated with household characteristics include human capacity presented by gender, age and education level of the household head, as do the studies by Bellemare-Barrett (2006), Randela et al. (2008), Alene et al. (2008), Ouma et al. (2010), Olwande-Mathenge (2011) and Wickramasinghe et al. (2014). These household characteristics variables capture several possible concepts of household behaviour and therefore in market participation analysis, these variables may reflect the attitudes of farmers (that might affect search costs, negotiating skills, etc.) towards risks caused by price and quantity fluctuations. The variable for the gender of the household head has been included in Olwande-Mathenge (2011) study since it influences market participation and market volume as it is linked to financial and labour resources access. The study found a lower likelihood for female-headed households to participate in the market as sellers compared to male-headed households because most female-headed households lack access to productive assets (land, labour, capital) thereby limiting their production capabilities. However, in Alene et al. (2008) study, gender variable was found to have theoretically consistent differential effects on market participation and supply with an average male-headed household being 10% less likely to participate than a female-headed household. In our current study, gender variable (measured as a dummy) capture differences in market orientation between males and females, with males expected to have a higher propensity to participate in livestock markets than females; hence positive sign is expected. Age of household head is an indicator of experience in farming and is frequently measured in years. In most cases, years of farming experience has been found to be positively related to the probability of participating in the market as a seller. For instance, Gabre-Madhin (2001) and Bellemare-Barrett (2006) have shown that successfully repeated contacts, gained through long-term marketing relationships, enhances trust, an essential element in market exchange. In contrast, experience acquired by old age can also be expected to be negatively associated with market participation, as found in Ehui et al. (2009) study that older household heads (up to a certain maximum) tend to have more dependents and hence more subsistence production activities. Although age variable is said to have the unclear effect, in this study, we expect older producers to be more experienced, have established contacts, which may enhance mutual trust and allow trading opportunities to be undertaken at lower costs (Goetz 1992). The age variable is hypothesized to influence the fixed costs of market participation. Education is an important tool to escape poverty, but only if the education system reaches the right people with the right content (Heierli-Gass 2001). Human capital is represented by formal education of household head, and the variable was measured by the number of years the household head had taken in acquiring formal education. More years in school are assumed as a proxy to better educated hence better negotiation skills and better able to use available information leading to the reduction of search, screening and information costs and thus a positive effect on market participation (e.g. Alene et al. 2008, Olwande-Mathenge 2011, Wickramasinghe et al. 2014). However, the expectation may be reversed as observed by Lapar et al. (2003) especially when there are competing and more remunerative employment opportunities available in the area that require skills that are enhanced by more education. For instance, in Ouma et al. (2010) study, education variable was inversely related to the probability of market participants as a seller, a finding that suggests that advancement in education reduces time spent in on-farm compared to off-farm income generation activities.

Under livestock marketing participation studies, the analysis does not only include the transaction costs of the exchange itself but also encompasses other non-transaction costs associated with the reorganisation of household production-enhancing assets, which would influence the production of a marketable surplus. In this thesis, we referred to them as household endowments assets and were introduced as control parameters in the analysis. Household endowments provide households with the leverage to invest in productive activities, generate more output, and thereby increase their probability to participate in market transactions (Randela et al. 2008). Under this category, two variables were included. One of them was the number of livestock tropical units (TLUs) owned by the smallholder household. More in TLUs indicates more wealth and more surpluses for the market; hence a positive impact on both the likelihood that participants will occur and the amount of selling that will be undertaken once the decision to participate has been made is expected. This hypothesis is in line with Heierli-Gass (2001) who argue that acquisition and ownership of productive assets (e.g. livestock) can pave the way for a family to participate in economic activities. However, the multifunctional nature of livestock holding in pastoralist regions becomes evident when Bellemare-Barrett (2006) consider the estimated effect of livestock prices on net sales. The other production-enhancing asset variable included was the size of pastureland measured in hectares. Access to pastureland is thought as a necessary condition for market participation and the larger the size of pastureland a household uses, the higher the production levels are likely to be, and the higher the probability of market participation. Hence, the variable was hypothesized to have a positive relationship with the production of a marketable surplus. Ouma et al. (2010), found a freehold land tenure system to influence the sellers positively and negatively for buyers. In contrast, Randela et al. (2008) reveal the existence of an unexpected negative relationship between land size and level of market participation which is probably an indication that increased market participation is also a function of land productivity.

Transactions costs are important determinants of market participation, but they pose empirical challenges relating to their measurement (Alene et al. 2008). According to Barrett (2008), there are two distinct layers of transactions costs; one that is household-specific and another that is product-and-location-specific. Due to data limitation, we focus on the former that addresses household-specific transaction costs because the later concern local market participate in the broader, national or global market. Household specific transaction costs are the embodiment of access barriers to market participation by resource-poor smallholders. This study relied on the (observable) factors that explain (e.g., distance to input as well as output markets) or mitigate transactions costs (e.g., ownership of transport and communication assets). Key et al. (2000) have isolated high transaction costs resulting from remoteness with poor transport and market infrastructures to be one of the critical reasons for smallholder farmers' failure to participate in markets. In this regard, distance to market in kilometres is considered as a proxy to fixed transaction costs and, thus hypothesized to affect market participation negatively - it captures the role of travel costs in influencing market participation. Transportation to the market can be done partly by intermediaries and partly by the farmers themselves. For the part done by intermediaries such as motor vehicles, monetary costs are directly observable. When farmers transport their livestock themselves, they incur direct costs for transportation. As the latter is unobserved, we use ownership of motorised transport as a determinant of these costs. Related to ownership of transport assets such as car or motorcycle, While Randela et al. (2008) and Ouma et al. (2010) found a positive effect on participation and the intensity of participation by reducing the cost of transporting output to the market, Olwande-Mathenge (2011) observed, ownership of transport equipment is associated with the decision to sell not on the decision about how much to sell of any of the commodities. Given motorised transport bottlenecks in the region, variable transport cost may be exogenous to individual marketing decisions by increasing at those times when households most want to restock. In this case, a dummy variable for car or motorcycle ownership was added in the analysis to assess households' transportation ease to the market and, therefore, we expected to influence market participation positively. This lack of information arises due to households' remoteness from markets combined with undeveloped communications network with market towns. Ownership of information assets eases access to information on prices and other market incentives for smallholder agricultural households in Papua New Guinea (Wickramasinghe et al. 2014). Randela et al. (2008) found that access to market information not only significant influence market participation, but also the probability of commercial farming. Building on these two studies, access to a communication facility (such as mobile phones or TV/radio) can substantially mitigate the fixed costs of accessing information and is thus expected to facilitate market entry. The dummy variable representing whether the household head or the decision-maker had access to information through ownership of communication equipment such as telephone, radio and television was introduced and hypothesised to have a positive impact on the decision to participate in markets.

Institutional factors are said to be transaction cost minimising arrangements, and this category of the variables was measurable using proxies such average livestock product prices, access to credit and livestock market information, a common approach in empirical research.

Access to formal credit, indicate access to production-enhancing assets, which would influence the production of a marketable surplus. However, in Ouma et al. (2010) study, access to credit raises the probability of market participation for buyers which implies that credit acts as a consumption-enhancer rather than a production-enhancing input. Key, et al. 2000 introduced a dummy variable for access to formal credit and found the variable to be exogenous as a production shifter and, thus, positively significant to market participants as a seller. In Olwande et al. (2009) study, access to credit to poor households could also partly explain the low market participation because it may limit their ability to access inputs to improve their production. Recently, Rutto et al. (2013) found access to credit as a production-enhancing input which boosts productivity and consequently increases the level of surplus marketable output thus encouraging livestock keepers to sell small ruminants. Stephen-Barrett (2011) found that households with access to credit transact more in the products markets. Building on the above studies enabled us to conclude that unavailability of credit can inflate transaction costs in both input and output markets and, therefore, in this research, we hypothesized that its availability would impacts positively on farmers' ability to participate in markets.

Analogously to Randela et al. (2008), and tied to communication asset, access to livestock market information is hypothesised to play a significant decisive role in influencing market participation. Access to veterinary services was included based on authors' experiences in the sector studied and Balirwa1–Waholi (2019) finding where access to veterinary services significantly influenced the decision of a household to participate in the milk market in Uganda. Balirwa1–Waholi (2019) study observed that those who access veterinary services are more likely to receive technical knowledge for improved productive performance leading to higher yields and hence surplus which precipitates participation decision and market sales. Following these observations, it is expected that livestock farming households who have access to veterinary services have health sound animals and also widens the household's knowledge concerning the use of improved livestock production technologies and this is likely to influence market participation decision of a household positively. Additional, veterinary services and advisory services (either through extension or agricultural research) as observed in Manyeki-Kotosz (2019) study may lead to more technical inefficiency.

The other construct of transaction costs is off-farm income and per capita income. As Randela et al. (2008) and Ouma et al. (2010) stated, access to off-farm income may lead to risk reduction in household decision making and, with it, increased propensity to undertake higher-risk activities, notably livestock producing for the market. The off-farm income mostly consists of non-farm employment in the nearby major urban centre. Off-farm income is viewed as an alternative to livestock cash incomes and as Alene et al. (2008) noted, non-farm income contributes to more marketable output if invested in farm technology and other farm improvement activities, therefore we expected a reduction in entry barriers and, hence an increase in market access. Otherwise, marketed farm output drops if non-farm income triggers off-farm diversification. The other variable that was included based on authors' experiences in the sector studied was household per capita income. The variable is expected to have a controversial effect on market participation with high per capita income per day expected to reduce market entry barriers for smallholder producers resulting to a high level of sale or conversely, may limit the number of livestock offered for sale, hence negative effect.

Table 26: Definition of variables that will be used in market participation models

Variable Name	Unit	Market Participation	Intensity Effect	Expected Sign
Household characteristics				
Household head sex (1=male and 0=female)	%	Yes	Yes	+
Household head age	Number	Yes	Yes	+
Household head age squared	Number	Yes	Yes	-
Household size (adult aged 15–64))	Number	Yes	Yes	+
The education level of the household head	%	Yes	Yes	+
Household endowments				
Land asset (hectare)	Ha	Yes	Yes	+
Number of livestock unit owned	Number	No	Yes	+
Transaction costs				
Transport assets/distance				
Transportation technology (car/motorcycle) (1 = yes, 0 = no)	%	Yes	Yes	+
Average distance to the main market	Number	Yes	Yes	-
Information assets				
Household owns a television - TV (1 = yes, 0 = no)	%	Yes	Yes	+
Household owns cell phone (1 = yes, 0 = no)	%	Yes	Yes	+
Institutional factors				
Access to extension services (1 = yes, 0 = no)	%	Yes	Yes	+
Access to market information (1 = yes, 0 = no)	%	Yes	Yes	+
Access to financial information (1 = yes, 0 = no)	%	Yes	Yes	+
The average price of livestock	KES	No	Yes	+
Membership in groups –Market alliance/cooperative (1=yes, 0 = no)	%	Yes	Yes	+
Others				
Off-farm Income	KES	Yes	Yes	+
Per capita wealth per day	Number	No	Yes	±

Source: Author's own construction based on the literature

5.4. Empirical Results, Analysis, and Interpretation

This section presents the discussion of the results that entails descriptive statistics (section 5.4.1) and analysis of factors determining the probability and level of market participation (section 5.4.2).

5.4.1. Descriptive Statistics for Market Participation Model for livestock products

The dependent variable, market participation, is measured by both the probability of participation and the number of livestock (TLU[46]) sold in the market. The descriptive statistics in Table 27 revealed that on average market participation is about 35.9% and 45.3% for cattle and shoats respectively, and that of the level of participation is 1.488 and 3.651 for cattle and shoat respectively. This concurred with the ranges of 6-45% market participation among the smallholder rural farmer as reported by in Barrett (2008). The descriptions statistics of independent variables are also summarized in Table 27 classified as household characteristics, household endowment, transport assets, information asset, institutional asset.

The transaction costs associated with household characteristics include human capacity presented by gender, age and education level of the household head. Gender variable was categorical and descriptive statistic indicates that more than 85 per cent of the households are male-headed, which was slightly above the average of 0.74 found in Alene et al. (2008). This confirms the notion that despite rural women's significant contribution to agriculture and livestock, they face more challenges than men in exercising their decision-making power perhaps due to limited inability to access natural resources, extension services, marketing opportunities and financial services. The other variable in this category was the age of household head which was measured in years. The average age of the sampled household was 49 years which indicate that the majority of the sampled households are a relatively old adult, which is expected to have a positive influence on both livestock production and markets participation. This concurred with the average age of 48.80 years with a standard deviation of 14.70 reported by Bellemare-Barrett (2006) along the Kenyan and Ethiopian livestock farmers boarder. Next in the line was the number of years the household head had taken in acquiring formal education. For the sampled households, the average level of education was about 6.0 years with a high standard deviation of over 5.1 years indicating that a large proportion of the households do have a formal education of at least one year - a figure, which shows a significant rise in literate among pastoral communities. Similar education levels were found in Ouma et al. (2010) study where the average years of schooling were 4.3 years with a standard deviation of 3.3 among smallholder farmers' participation of Burundi.

[46] One TLUs refers to livestock tropical unit of a 250 kg live weight animal: 1 cattle (cow/bull) is equivalent to 1 TLUs while 1 small ruminant is equivalent to 0.12 TLUs (ILCA, 1990).

Regarding non-transaction costs presented as household endowments assets, number of TLUs owned averages 18.378 and 33.284 for cattle and shoats respectively. The same range (19.237 TLUs with a standard deviation of 29.29) was found among the smallholder pastoral communities along the border of Kenya by Ethiopia Bellemare-Barrett (2006). The other variable was the size of pastureland measured in hectares. On average, the sampled household operates on about 28.758 hectares of pastureland though the variation is quite large across households as is evident by a substantial standard deviation of more than 144.864; an indication that livestock farmer in the area sampled operate at different levels of production. In addition, the security of land tenure is a wealth indicator and also influences the production objective function and types of initiatives that a household would undertake.

Access to transport, information and institutional assets were captured as dummy and constitute proxies to transaction costs. The descriptive results show less than 1% indicated owning a transportation asset; perhaps due to harsh terrain found on the Kenyan rangelands. A similar result was reported by Ouma et al. (2010). This only readily available means of transport for livestock for smallholder farmers is by trekking the animals to the markets. With regards to ownership of information assets (that are said to ease access to information on prices and other market incentives), mobile cell phone penetration topped with over 75% of the sample population, followed by radio with over 65%. A similar result was observed by Wickramasinghe et al. (2014) on smallholder agricultural households in Papua New Guinea.

Institutional factors that are thought as transaction cost minimizing arrangements and this category of the variable was measurable using a proxy such as distance to markets, average livestock product prices, access to credit and market information, a common approach in empirical research. Smallholder pastoral farmers sampled are located in remote areas far (about 10 km) away from service providers, and major consumers of farm products and the distance to the market, together with the poor infrastructure, poor access to assets, supervision (e.g. access to extension services) and incentive (e.g. price, access to financial etc.) costs and imperfect information (e.g. poor market information access) is manifested in high exchange costs. For a better and efficient livestock market, prices are expected to act as an incentive to market participation, hence positive effect. However, with an average price ranges of KES 25,812.75 (USA dollars 256.27) and KES 3,378.45 (USA dollars 33.54) for cattle and shoats respectively, the TLUs sold was less than 2 and 4 for cattle and shoats respectively in a year. Access to credit and use of veterinary services is limited with later reached out to almost 36% of the farm households, while the credit facilities extended credit to a little less than 1%. Access to market and livestock information is hypothesized to play a significant positive role in influencing market participation. However, the result shows that an equivalent to 25% of all households rearing livestock had access to market information, while only 15% accessed information related to livestock production and marketing.

The other construct of transaction costs is off-farm income and per capita income, an indication of endowment and wealth. The descriptive statistic shows that farmers operate at different wealth index.

Table 27: Descriptive Statistics of the Variables used in Double-hurdle Estimation

	Cattle (N=1245)			Shoats (N=1512)		
Variable Name	**Mean**	**Min**	**Max**	**Mean**	**Min**	**Max**
Dependent variables						
Market participation	0.359 (0.480)	0	1	0.453 (0.498)	0	1
*Livestock sold**	1.488 (4.492)	0	80	3.651 (7.801)	0	105
Independent variables						
Household characteristics						
Gender	0.868 (0.338)	0	1	0.859 (0.349)	0	1
Age	48.818 (15.030)	15	102	49.281 (14.962)	15	102
Education level	6.160 (5.209)	0	19	6.006 (5.131)	0	19
Household endowments						
Land asset (ha)	33.388 (158.851)	0.13	3002	28.758 (144.864)	0.13	3002
Livestock produced	18.378 (49.463)	1	958	33.284 (72.003)	1	1,307
Transport assets						
Own Car	0.0305 (0.1721	0	1	0.0284 (0.1663)	0	1
Own Motorcycle	0.0996 (0.2996)	0	1	0.0893 (0.2853)	0	1
Information assets						
Own TV	0.13656 (0.3435)	0	1	0.1389 (0.3459)	0	1
Own Radio	0.68196 (0.4659)	0	1	0.6528 (0.4762)	0	1
Own cell phone	0.7575 (0.4288)	0	1	0.7579 (0.4285)	0	1
Institutional factors						
Distance to market	9.578 (14.273)	1	85	11.042 (15.51)	1	85
*Average selling price**	25,812 (11,941)	1700	80,000	3,378 (1,135)	250	9,500
Credit services	0.0129 (0.1127)	0	1	0.0099 (0.09914)	0	1
Veterinary services	0.36467 (0.4815)	0	1	0.3307 (0.4706)	0	1
Livestock information	0.15347 (0.3605)	0	1	0.1138 (0.3176)	0	1
Market information	0.25067 (0.4335)	0	1	0.2474 (0.4316)	0	1
Others						
Off-farm Income	76,940 (196,217)	0	3,420,000	76,388 (183,126)	0	3,420,000
Per capita wealth	84.35 (181.93)	0	2,417.71	78.75 (174.50)	0	2417.71

Note: * Cattle, N=447; Shoats, N=683; NA = not applicable; Parentheses is the standard deviation.
Source: Author's own construction based on National household data

5.4.2. Empirical Result for Household-Level Livestock Market participation

Markets and improved market access are critical for improving rural incomes and lifting rural households out of poverty trap, particularly in developing countries. However, agricultural households often face imperfect or incomplete markets for some goods and factors, which are then non-tradable, and this market failure is associated to costs resulting from distance to markets, poor infrastructure, imperfect information and supervision, and incentive costs among others. Under this sub-section, we consider livestock farmers' participation in the market, and this enable us to test the hypotheses that; H_5**:** ***s****ocioeconomic (e.g. household characteristics such as age, gender, education level, ownership of mobile phone, radio, television, vehicle etc.; endowments factors such as farm size and livestock numbers etc.) factors have promoted market participation of the smallholder pastoral farmers,* H_6**:** *institutions (such as financial, markets, farmer groups, extension service providers) have promoted market participation of the smallholder pastoral farmers* and lastly, H_7**:** *factors affecting livestock farmers' decision to participate in the market are not different with those affecting the extent of participation*. We estimated Equation 37 to determine the probability of market participation by smallholder pastoral farm households using variable presented in Table 28. As explained during the model specification of Equation 37, the dependent variable used in this analysis is market participation measured by the probability of participation in the livestock market. All variables mentioned in Table 28 were considered in model estimation. A step by step process of deletion of highly insignificant variables (obviously by a cross-check on p-value and standard deviation) reduced the number of variables included in the estimation of Equation 37 to eighteen as shown in Table 28. In addition, the test of multicollinearity through the computation of variance inflation factors (VIF) and conditional number for each of the variables was done (Appendix 4.2a). Since all the independent variables exhibited $VIF_i < 5$ (with an average VIF=1.20) and conditional index of about 16.6785 (< 30), it was concluded that there was no multicollinearity, and therefore all these variables were eligible for inclusion in the model estimation. To capture what effect of advancement in education would have to market participation, we included a control, variable namely 'education squared'.

The marginal effect shows the probability of market participation which was about 35.19% and 45.94% for cattle and shoats respectively. These results indicate below average market orientation of poor smallholders' pastoral households in the study area and confirmed the long puzzled by the limited use of livestock markets by east African pastoralists who hold most of their wealth in the form of livestock and who regularly confront climatic shocks that plunge them into massive herd die-offs and loss of scarce wealth (Bellemare–Barrett 2006, Barrett 2008). The estimate of Pseudo R2 that maximized the Probit function for Cattle and Shoat was 0.1271, and 0.0718 respectively was found to be significantly different from zero at the 1% level. This suggests that the random disturbances in the smallholder livestock market participation decisions are affected in the positive directions by random shocks. The sample value of the likelihood ratio is 205.98 and 149.05 for cattle and shoat respectively and with a critical value of $\chi^2_{18.0.01} = 20.09$ is highly statistically significant (P < 0.000), suggesting that the independent variables are taken together influence market participation decisions.

Equations (37) and (38) were estimated to identify the determinants of probability and extent of livestock market participation. As presented in Table 28, some of the transaction costs proxies influence the level of market participation significantly, and the signs of the estimated coefficients are consistent with *prior* expectations. This is particularly true for gender, squared education level, the size of pastureland asset, TLUs produced, ownership of motorcycle and radio, distance to the market, access to veterinary services and per capita income. On gender, the coefficient had the expected sign (although only significant for cattle case) suggesting that being a male-headed household increases the likelihood of market participation. This seems to suggest that male-headed households face less resource constraint for effective engagement in markets. A closely related result was found by Bellemare–Barrett (2006), where female-headed households among pastoralists were found to participate less by buying and selling fewer animals than their male counterpart.

One of the biggest challenges to the pastoral household involvement in livestock marketing in Kenya can be associated with the nature and quantity of household factor endowment such as size of pastureland and livestock tropical units at farmer disposal (Manyeki- Kotosz 2019). For instance, the size of the pastureland is important because transaction costs are primarily fixed costs that can be spread across more output on large farms. Results in Table 28 reveal the existence of the expected positive relationship between pastureland size and livestock market participation. This is probably an indication that increased market participation is also a function of land productivity. The number of tropical livestock units provides households with leverage to invest in market participation. This result concurs with Ouma et al. (2010) finding where smallholder farmers' markets participation in Central Africa is determined by the size of the land under banana plantation. The Probit results indicate that ownership of livestock has a positive relationship on the probability of market participation. This result is supported by Heierli–Gass (2001) who found that acquisition and ownership of productive assets (e.g. cattle) can pave the way for a family to participate in economic activities. Ownership of transport equipment such as, motorcycles have a positive impact on market participation by reducing the cost of transporting output from the farm to the market which concurs with the finding by Key et al. (2000) and Randela et al. (2008). This implies that households that own transport assets are more likely to participate more in livestock market than those without, perhaps owing to the long distance to the markets that is about 10kms (as shown in Table 27). On information assets, ownership of radio had the expected positive sign and statistically significant; the result that concurs with Ouma et al. (2010) findings. This is possible because communication assets are more useful in accessing market information and in facilitating transactions in the region. Thus, the more information the household has on livestock marketing, the lower transaction costs will be thus increasing market participation.

The other construct of transaction cost is the distance to the market, access to veterinary services and per capita income. Greater distance to the livestock markets increases transaction costs which are associated with institutional failures. The sign of the coefficient for distance to the market is negative and in line with *a priori* expectation. This implies that the farther away the smallholder household is from the livestock market, the more difficult and costly it would be to get involved. A similar sentiment was observed by Key et al. (2000), who isolated remoteness as the primary contributor to high transaction costs. Access to veterinary services had the expected positive sign and statistically significant. Veterinary activities make vital contributions to all stages of livestock production from 'farm to fork' by reducing animal diseases at the farm and market level and public health risks and attaining food quality and safety standards, a finding that concurred with Balirwa1-Waholi (2019) result. From market participation point of view as was the case from the production side, veterinary services and more advisory services on health issues might lead to more technical and market efficiency (Manyeki-Kotosz 2019). The coefficient for per capita income was positive and significant. This implies that high per capita income would reduce market entry barriers for smallholder producers resulting in a high level of sale.

Turning to significant transaction costs with unexpected *a priori* signs, the Probit analysis found lower education level to be inversely related to the probability of market participation but the propensity to participate increases with the advancement in education (variable Education level squared). High level of education gives an indication of the household ability to have better access to understanding and interpretation of information than others, which may lead to the reduction of search, screening and information costs. A similar finding was reported in Olwande-Mathenge (2011) study where secondary and post-secondary education was found to positively influence the level of market participation. The negative and significant coefficient of variable age contrary to the *a priori* expectation confirms the general observation that farming operations in the study areas are increasingly manned by the elderly. A possible explanation that can be advanced for this is that older farmers view farming as a way of life rather than as a business and have an intensely emotional or almost biological connection with farming and land. The result is also found to be consistent with Alene et al. (2008) argument that market participation declines with age since older people are perceived to be risk-averse and reluctant to adopt the technology. The coefficient for off-farm income was negative and significant, a result that did not conforms to expectations that households with access to off-farm income would result in an increase in market access and reduction in entry barriers. A similar result was found by Alene et al. (2008), where they observed theoretically consistent differential effects of off-farm income to market participation and supply. A possible explanation of this result could be that farmers may be involved in substitute high-value enterprises rather than livestock farming, thus motivating them to subsistence livestock production rather than producing surplus for sale.

The partial effects of a unit change in the continuous and discrete variables, computed at sample means, on the probability of livestock market participants were also estimated. The partial effects of the discrete variables are calculated taking the difference of the probabilities estimated when the value of the variable changes from 0 to 1. With regards to continuous variables, the magnitude of the partial effect of the significant variables computed at sample means, on the probability of household livestock market participation is positive but very small. However, the partial effect of the probability of livestock market participation portrayed by lower education level and off-farm income variables ranges from -0.0317 to -0.0672, respectively. This means that the probability of livestock market participation decreases by 0.0317 to 0.0672 (about 3-6.7%) for a one-unit increase in education level or off-farm income. When it comes to discrete variables, a positive and significant relationship was found between gender, owning a motorcycle and/or radio and access to veterinary services. According to Table 28, a shift from having no access to veterinary services, owning a motorcycle and a radio (X_i= 0) to access to veterinary services, owning a motorcycle and a radio (X_i = 1) increases the probability of market participation by 6.1%, 10.3% and 7.5% respectively. Similarly, being a female-headed household in the pastoral community decrease the probability of livestock market participation by 16.4% and 25% respectively.

Table 28: Determinants of Livestock Market Participation Decision

	Cattle		Shoats	
Variable Name	**Coef.**	**Partial effects**	**Coef.**	**Partial effects**
Constant	0.0256	-	0.317*	-
	(0.219)		(0.187)	
Household characteristics				
Gender	0.482***	0.164	0.0544	0.0216
	(0.125)	(0.0377)	(0.0989)	(0.0391)
Age	-0.0117***	-0.00436	-0.00918***	-0.00364
	(0.00273)	(0.00101)	(0.00238)	(0.00094)
Education level	-0.179***	-0.0666	-0.0799***	-0.0317
	(0.0269)	(0.00995)	(0.0231)	(0.00915)
Education level squared	0.00866***	0.00321	0.00238*	0.000944
	(0.00159)	(0.00059)	(0.00140)	(0.00056)
Household endowments				
Land asset (ha)	0.00115***	0.0004277	0.00194***	0.000772
	(0.00044)	(0.00016)	(0.00068)	(0.00027)
Livestock produced	0.00265***	0.000983	0.00313***	0.00124
	(0.00103)	(0.00038)	(0.00068)	(0.00027)
Transport assets				
Own Car	0.256	0.0984	0.190	0.0757
	(0.237)	(0.0934)	(0.219)	(0.0873)
Own Motorcycle	0.269**	0.103	0.304**	0.121
	(0.133)	(0.0522)	(0.124)	(0.0488)
Information assets				
Own Television - TV	0.194	0.0739	0.0238	0.00946
	(0.120)	(0.0466)	(0.107)	(0.0425)
Own Radio	0.206**	0.0752	0.0509	0.0202
	(0.0905)	(0.0324)	(0.0749)	(0.0297)
Own cell phone	-0.110	-0.0412	-0.0277	-0.0110
	(0.0959)	(0.03628)	(0.0816)	(0.0324)
Institutional factors				
Distance to the market	-0.0141***	-0.00525	0.00132	0.000526
	(0.00323)	(0.00119)	(0.00234)	(0.00093)
Credit services	0.296	0.115	0.175	0.0695
	(0.327)	(0.130)	(0.330)	(0.131)
Veterinary services	0.163*	0.0608	0.213***	0.0846
	(0.0846)	(0.0318)	(0.0733)	(0.0291)
Livestock information	-0.106	-0.0387	-0.0129	-0.00510
	(0.111)	(0.0401)	(0.108)	(0.0428)
Market information	-0.0621	-0.0229	0.0713	0.0283
	(0.0942)	(0.0345)	(0.0805)	(0.0320)
Others				
Off-farm Income	-0.181***	-0.0672	-0.0263	-0.0105
	(0.0668)	(0.0249)	(0.0496)	(0.0197)
Per capita wealth	0.00224***	0.000831	0.00008	0.0000324
	(0.00048)	(0.00018)	(0.00027)	(0.00011)
LR chi2(18)	205.98***	-	149.05***	-
Pseudo R2	0.127***	-	0.0718***	-
Marginal effects	0.3519		0.4594	

Note: *Significant at 10% level; **Significant at 5% level; ***Significant at 1%
Source: Author's own construction.

Having established the critical factors that influence the probability of smallholder market participation, the question remains as to why there exists such a low rate of participation (as indicated in Table 27 and 28). This question was addressed by determining the factors influencing the extent of market participation in livestock marketing. The truncated regression model was estimated with the livestock sale volumes being endogenous variable. Again, a step by step process of deletion of insignificant variables and a check of VIF ($VIF_i < 5$) and conditional index (< 30) (Appendix 4.2b) reduced the number of significant variables to thirteen, as shown in Table 29. Here, age, education, number of livestock produced, cell phone and shoats' and cattle price, distance to market, access to veterinary services and livestock information and per capital income emerged as the significant factors that influence the household behaviour toward livestock marketing. With the exception of access to the veterinary services that had the unexpected negative sign, all the other significant variables portrayed the a priori expected influence on the degree of market participation. The health of an animal is a critical determinant of the market price it can obtain. However, the negative influence on shoats marketing can perhaps mainly be due to inadequate recognition of the contributions shoats make to the livelihoods of the poor pastoralists, resulting in underutilization of professional health services following animal health services liberalization - an indicator to institution failure.

As was observed by Manyeki et al. (2016) study, price information is a vital instrument during marketing because it informs the farmers about marketing conditions. Farmers who have price information prior to marketing tend to sell more of their products than those without. However, the analysis produced varying results with regards to own livestock prices, both cases being insignificant. Cattle price was found to have a complementary effect to the extent of shoats market participation while shoats prices portray a substitution effect to cattle market participation. The Wald Chi-square value (Wald chi2(13)) showed that statistical tests are highly significant ($P < 0.000$), suggesting that the model had strong explanatory power.

Table 29: Determinants of the Intensity of Livestock Market Participation

	Cattle		Shoats	
Variable Name	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
Constant	2.383*	1.297	0.625	1.196
Household characteristics				
Gender	0.279	0.199	-0.0296	0.171
Age	-0.00781**	0.00375	-0.00471	0.00336
Education level	-0.0302***	-0.0108	-0.00556	0.00985
Household endowments				
Livestock produced	0.00447***	0.00089	0.00283***	0.00039
Transport assets				
Own Motorcycle	-0.0468	0.138	-0.217	0.137
Information assets				
Own cell phone	0.309***	0.115	0.121	0.105
Institutional factors				
Distance to market	-0.00250	0.00500	-0.0102*	0.00539
Credit services	0.391	0.49844	-0.984	0.619
Veterinary services	0.0339	0.10909	-0.198*	0.104
Livestock information	0.113	0.137	0.263*	0.136
Price of cattle	0.0356	0.0870	0.181**	0.0874
Price of shoats	-0.193*	0.103	-0.0463	0.0921
Others				
Per capita wealth	0.00036	0.00022	0.00042*	0.00022
/sigma	0.666***	0.0386	0.742***	0.0341
Wald chi2(13)	62.65***	-	112.98***	-

Note: **Significant at 10% level; **Significant at 5% level; ***Significant at 1%*
Source: Author own construction.

5.5. Summary of the chapter

This chapter provides empirical evidence of the significant transaction and non-transaction related factors influencing livestock market participation decision. Applying the Double-Hurdle estimation procedure reveals that market participation is governed by two independent decisions: the decision to participate in the market and the decision on the extent of participation. The empirical results show that smallholder pastoral households in the southern rangelands counties of Kenya make relatively little use of livestock markets with less than 50 per cent of the household sampled, indicating participating in the livestock market. Socioeconomic factors such as household characteristic (e.g. gender, education level, ownership of motorcycle and radio) and endowments factors (such as farm size and livestock numbers) had the expected sign across livestock enterprise considered and therefore seems to promote market participation of the smallholder pastoral farmers. Thus, we can accept the hypothesis H_5 that '*socioeconomic (e.g. household characteristics such as age, gender, education level,* *ownership of the mobile phone, radio, television, vehicle etc.; endowments factors such as farm size and livestock numbers etc.) factors have promoted market participation of the smallholder pastoral farmers'*.

The analysis also found evidence of institutional factors that seem to promote market participation. These were institutional proxies such as distance to market, livestock product prices, access to veterinary services, livestock and market information and factor and other factors such as off-farm income that influence decision to participate in livestock market and thus, we accept the hypothesis H_6 that '*institutions (such as financial, markets, farmer groups, extension service providers) have promoted market participation of the smallholder pastoral farmers*'. However, the significant factors that affect the decision to participate and the extent of participation in the livestock market are not the same which is sufficient evidence to reject the hypothesis H_7 that '*factors affecting livestock farmers' decision to participate in the market are not different with those affecting the extent of participation.'*

CHAPTER SIX

SUMMARY, CONCLUSION AND POLICY RECOMMENDATIONS

This chapter provides the summary, conclusion and policy recommendation of the research work. The overall objective of this study was to investigate the key factors that contribute to decision making of smallholder pastoral farmer in production, supply and factor input demand and market participation behaviour for the beef cattle, sheep and goat meat component of the livestock sector. This has generally been addressed by the findings from the analysis through the various hypotheses. Important conclusions based on the findings are presented in this section following the hypothesis of the study. Those relations to farmers' technical efficiency analysis are presented in section 6.1, while those related to product supply and factor demand responses presented in section 6.2. In section 6.3, we have those related to market participation. Subsequent to policy recommendation (section 6.4), the chapter ends with the recommendation for future study (section 6.5).

6.1. On Technical Efficiency Analysis in Smallholder Livestock Production

Under this topic, two hypotheses were tested. The first one (**H_1**) states, '*the size and access to agricultural factors of production (land, labour and livestock production supplies) positively influences livestock production of the smallholder pastoral farming and their impact is not homogenous in the farmer population*'. This was done by estimating a single stochastic and latent class frontier models in the SFA framework using a cross-sectional farm-level dataset collected from pastoral farm households residing in the ten counties that are found in the southern rangelands of Kenya. In the first instance, we applied a single stochastic frontier analysis to evaluate the role of distributions in estimating the technical efficiency in smallholder livestock production in the southern rangelands of Kenya. Stochastic production frontiers were parametrically estimated for both CD and Translog model types while also considering the widely applied distributions for the composite error term. The model performs well in estimating TE and inefficiency, and in explaining it in terms of farm-specific variables as identified in similar studies in other countries. We find significant variability in TEs, particularly among the different distributions with the normal-gamma CD and Translog functional forms resulting in higher overall efficiencies levels which means that normal-gamma generally "fits" the data better. Between the two functional forms, Translog seems to generally 'fit' the data better, allowing more observations to lie near the frontier. We also find that the mean TEs in most models were reasonably high in most models and are sensitive to the model choice. The estimated technical inefficiency ranges from 20-49%, suggesting that there is still room for improving livestock by ensuring efficiency in the use of the technologies available at farmer disposal.

The parametric estimates are found to be robust and of very close magnitudes for the majority of model, distributions considered. The results from CD and Translog production Frontier are different with elasticities estimate from CD generally being small, while those from the Translog model are larger mainly due to interaction effects of the variables. For the CD models, we verify that the greatest and statistically significant elasticity observed was that of labour input, followed by pasture land size and capital input in that order, confirming the importance of classical production factors (labour, capital and the size of agriculture pasture land) in executing livestock-related investments and thus accepting the hypothesis. Similarly, as expected, feed and minerals assumed a positive, although inferior elasticity in relation to the livestock production. When it comes to Translog technological form, the empirical results obtained in the estimation of livestock production frontier functions for the southern pastoral rangelands of Kenya indicate that the variance of asymmetric error in the model is a moderately highly significant component. Additionally, the most significant inputs that contributed for livestock productivity were labour factor, as well as the feed and mineral supplement and veterinary drugs. The interactions between labour and pastureland size and land and capital were positive and statistically significant at different levels indicating a compliment for one another in livestock production, thus accept the hypothesis. Based on the single stochastic frontier model that assume same production technologies for all farm; and considering the various distributions of inefficiency error terms, we can, therefore, conclude by **accepting the claim that the size and access to agricultural factors of production (land, labour and livestock production supplies) influences livestock production of the smallholder pastoral farming**.

With regards to the second part of this hypothesis, we targeted to explore the possibility of incorporation of unobserved heterogeneity that exists among pastoral livestock producer in the southern rangelands of Kenya, and also assess the implications of such heterogeneity for the estimation of inefficiency and the technical parameters. Again, our recent study (Manyeki– Kotosz 2019) where both functional forms were tested, the flexible Translog functional forms were found to be an adequate representation of the dataset and, therefore, we only estimated the same. Although inefficiency term can take many other forms of distributions, in the latent class stochastic frontier model, we restricted our analysis to half-normal and exponential since they are supported by latent class estimator in most of the statistical software. Apparent differences in the estimated TE, AIC and log-likelihood statistics tests were observed among the single frontier and latent class model. Applying both AIC and Likelihood Ratio test statistics leads to the conclusion that a model with 3 class stochastic frontier with inefficiency component of the composite error through a half-normal random variable is the preferred model for this data. Significant differences in TE estimates obtained in implementing both a single frontier and a three-class latent class model were observed, with TE scores being higher when farms are compared to their own frontier as the latent class model does, indicating that unless livestock farmers' heterogeneity is appropriately taken into account, estimated inefficiency is likely to be biased upward. This result implies that, if single production frontier function is used, technical inefficiency estimates tend to be overestimated if technology heterogeneity is present in the sample but not accounted for in the estimation process. Overall, the results point out the significance of correctly addressing technology heterogeneity in order to make correct policy recommendations regarding the improvement of farm economic performance, and also take into account farm differences in the design of the farm-level and other policy measures in Kenya. The results also suggest that, under the current state of environment, livestock producing can be said to be constrained by a variety of challenges ranging from low livestock production caused by low input use (e.g. lower TLUs per land area and differentiated capital per TLU), unsustainable and diminishing size of average landholding and low livestock supplies inputs, as such, the technologies smallholders use are challenging to depict only with data. This is because the coefficient of the stocking rate, capital unit per TLU and labour units per TLU affects prior probability, which proves our hypothesis that farm size, labour and capital assets play an essential role in the establishment of the three classes. Therefore, assuming heterogeneous technologies, again, we can **accept the hypothesis that the size and access to agricultural factors of production (land, labour and livestock production supplies) influence livestock production of the smallholder pastoral farming and their impact is not homogenous in the farmer population**.

The second hypothesis (**H_2**) stated that *'Human related attributes (e.g. gender, age, education level), access to socioeconomics factors (e.g. land ownership, off-farm income etc.), service providers (extension, agricultural institution etc.), market factors (e.g. input markets, market information etc.) and financial institutions (e.g. credit* *facilities etc.) influence efficiency in the livestock production for smallholder pastoral farmers'*. This hypothesis was tested based on the single and latent class stochastic frontier model. Based on single stochastic frontier model, the factor that significantly reduces technical inefficiency in livestock production were related to gender and high-level education of household head, number of technologies adopted, access to livestock market information, off-farm income and land ownership while at lower level of education, old age of household head in years and market access portray an opposite effect on technical inefficiency. Based on a single frontier, our suspicion is that the less efficient farms are those who are being maintained by families more reliant on off-farm income (which probably correlates with market access and high education), and which are being held for their asset and family security reasons rather than as income generators.

When we adopt a latent class stochastic frontier model, the determinants of inefficiency were found to be specific to the class structure of the livestock sector when we account for technological differences. This implies different policy measures needs to be formulated for different productive units based on the class structure in order to ensure efficiency. For instance, access to veterinary services and input markets seems to significantly reduce inefficiencies for capital-intensive farms than in the labour-intensive farms. Gender of household head, ownership for the land and access to input markets has the opposite effect on inefficiency, which implies that they would increase inefficiency; hence, their effects should be reduced to the bare minimum. The results allow us to conclude **that human-related attributes, access to socioeconomic factors, service providers and market factors influence the efficiency in livestock production differently for smallholder pastoral farmers** and, therefore, based on these mixed results **we can only partially accept the research hypothesis H_2.**

6.2. On Products supply and Factor Inputs Demand Responsiveness

The objective of products and input market responsiveness analysis was to investigate the hypothesis (**H_3**) that *'The supply of livestock products is not affected by price and non-price input incentives (e.g. such as size of pasture land, income and labour inventory)'* and (**H_4**) that *'factor demand for livestock production is not affected by price factors and non-price input incentives (e.g. such as size of pasture land, income and labour inventory)*'**.** A dual framework was adopted, and a profit maximization framework was selected given the multi-inputs, multi-outputs, and prices of the inputs. The livestock products supply and factor demand functions were derived analytically from a normalized profit maximization function from which output supply and input demand responsiveness were estimated. The results of the study show that all own-price elasticities of output supply for the three livestock product had the correct signs, which was positive. The own-price elasticity was elastic for cattle while for goat and sheep supply were inelastic with the most inelastic being sheep followed by the goat enterprise. The relatively elastic own-price elasticity cattle product concurred with the finding of Nyariki (2009) and Manyeki et al. (2016) in Kajiado District in Kenya. The possible explanation to this finding is perhaps producers respond to an increase in prices accompanied by diverting resources into increasing cattle herds in anticipation for a better price in future.

Cross-price elasticities were found to be in the inelastic range in all cases which indicate that a price change will result in a relatively small uptick in supply of livestock products. The cross-price elasticities result also shows that cattle can be a substitute for sheep and goat while there are some complement possibilities between sheep and goat for cattle. The possible explanation of this scenario can be associated by the observation made by Farmer–Mbwika, (2016) that goat meat prices at the consumption level are high and a slight increase in the price of goat prices would reduce the demand compressing the producer prices, and this would result into reduction in the supply. The high price would make the consumer shift to cattle meat, thereby increasing the demand for the cattle meat. Subsequently, the prices of cattle meat will increase, and that would result in an increase in the supply. The sheep quantity is more than thirteen-time as sensitive to the goat output prices than goat quantity is to sheep output prices. This finding, therefore, suggests that, in order to understand economic substitutability (or complementability) and the potential economic impacts of introducing livestock type-specific programs policy, it is informative to understand the relationships among the existing livestock product types. Outputs supply responsiveness was further measured to variable input such as cost of labour, the individual household income and the size of improved pastureland in hectares. Based on the magnitude of the elasticities, a slight change in labour price would have a more significant effect on output level than pastureland improvement price in all the livestock type. The unexpected negative elasticity with respect to household income can be associated with the data type, which was from survey sources and, thus, only the short-run response can be captured. However, in long-run, a sign switch is expected, and a policy incentive that would increase capital investment to the bottom of the income pyramid such as the poor farmers who, in the absence of formal insurance markets, tend to diversify including keeping livestock to achieve a balance between potential returns and the risks associated with climatic variability and market and institutional imperfections would improve livestock off-take. With regards to the livestock supply response to the fixed inputs, size of pastureland was found to be the most significant and positive as expected, which is consistent with theory. In relative terms for the three type of enterprises, cattle output supply is almost twice as sensitive to the size of the improved pastureland. The high magnitude on the pastureland variable for cattle output supply possibly may be associated with the fact that cattle being the primary beef producer in Kenya is pasture-based and hence dependent on land availability. Other factor inputs such as labour cost and household income were significant but had the unexpected sign. Overall, based on the above evaluation on the factors that influence livestock product supply responsiveness behaviour, there is sufficient evidence **to reject the hypothesis H_3 that the supply of livestock products is not affected by price and non-price input incentives (e.g. such as the size of pasture land, income and labour inventory).**

With respect to factor demand responsiveness, all variable considered were found to be in the inelastic range with exceptional to that of cattle output prices and labour cost which was elastic for land demand in cattle and goat production enterprises respectively. Of important was labour cost and its effect on labour demand was inelastic, having a positive own-price elasticity estimate that is not consistent with economic theory. The household income in both demand equations was positive in all cases with a relatively low negative effect on labour demand recorded in the cattle production enterprise. The household income effect can be observed under two scenarios: if a household aggregate level of income increases or if the relative cost of expanding pastureland or wage for labour decreases. Both situations increase the amount of discretionary income available, so does the quantity of pastureland and labour. Factor demands in sheep production enterprise were relatively more responsive to changes in household income. Generally, it is clear that most of the variables considered significantly affect factor inputs demand in all livestock enterprise considered and therefore we can conclude by **rejecting the hypothesis H_4 that factor demand for livestock production is not affected by price factors and non-price input incentives (e.g. such as size of pasture land, income and labour inventory).**

6.3. On Market Participation for Smallholder Livestock Farmers

This section provides empirical evidence of the significant transaction and non-transaction related factors influencing livestock market participation decision. Three hypotheses were tested. These were **H_5:** *Socioeconomic (e.g. household characteristics such as age, gender, education level, ownership of mobile phone, radio, television, vehicle etc.; endowments factors such as farm size and livestock numbers etc.) factors have promoted market participation of the smallholder pastoral farmers,* **H_6:** *Institutions (such as financial, markets, farmer groups, extension service providers, etc.) have promoted market participation of the smallholder pastoral farmers,* and **H_7:** *Factors affecting livestock farmers' decision to participate in the market are not different with those affecting the extent of participation*. To tests these three hypotheses, a Double-Hurdle estimation approach was applied since market participation comprises two distinct but sequential decision marking processes. Double-Hurdle estimation approach involved parametric generalization of the Tobit model where Probit model is used in the first stage to investigate the factors that determine the decision to participate, and in the second stage, for those that participate, a truncated regression model is fitted to examine the factors that influence the level of participation.

With regard to hypothesis **H_5,** it should be acknowledged that transaction costs are not easy to measure; and thus, proxy variables were used. The empirical result shows that these high transaction costs emanate from, among other factors, access to off-farm income and availability of means of transport represented by ownership of motorcycle or a radio. The empirical analysis revealed that smallholder households with less access to off-farm income are less likely to decide to participate in livestock market while those who have extensive pasturelands and tropical livestock units, access to motorcycle or radio are more likely to participate in the livestock market. However, a finding worth noting is the effect of land size on household livestock market participation. The positive direction of the impact of land size is probably an indication that increased market participation is also a function of land productivity. It, therefore, implies that any initiative in the livestock industry to increase land size must be preceded with efforts to increase the productivity of the land currently at farmers' disposal. The other transaction costs issues that may hamper the effective market participation of producers relate to smallholder households limited education and gender orientation. However, high education levels seem to promote market participation as it may enhance better negotiation skills and better able to use available information. Thus, there is **sufficient evidence to accept the hypothesis H_5 that socioeconomic (e.g. household characteristics such as age, gender, education level, ownership of the mobile phone, radio, television, vehicle etc.; endowments factors such as farm size and livestock**

numbers etc.) factors have promoted market participation of the smallholder pastoral farmers.

Regarding hypothesis **H_6**, market participation is said to depend on the status of institutions and institutions are transaction cost minimizing arrangements. Institutional assets were captured as dummy and constitute proxies to transaction costs. The type of transaction costs is hypothesized to impede market participation because they impose added cost burdens on the efficient conduct of market entry activities. The institutional factors that promote market participation include the ease in access to veterinary services, livestock products prices, access to credit facilities, livestock and market information. The other proxy to institution factors was associated with the long distances involved in trekking animals to the market. Greater distance to the livestock markets increases transaction costs which are associated with institutional failures. The sign of the coefficient for distance to the market is negative and in line with *a priori* expectation. This implies that the farther away the smallholder household is from the livestock market, the more difficult and costly it would be to get involved, and therefore the less the probability of participant. Thus, there is **also sufficient evidence to accept the hypothesis H_6 that institutions (such as financial, markets, farmer groups, extension service providers, etc.) have promoted market participation of the smallholder pastoral farmers**.

With regard to H_7, the empirical evidence shows that market participation is governed by two independent decisions: the decision to participate in the market and the decision on the intensity of participation. The estimation results show that these two separate decisions are determined by different sets of factors with about eighteen factors influencing the decision to participate and thirteen affecting the decision on the level of participation. Of the eighteen factors included in market participation model, seventeen seem to influence the probability of market participation, while only ten in the intensity effect models were significant at either 1%, 5% and 10% levels. Thus, we **reject the hypothesis H_7 that factors affecting livestock farmers' decision to participate in the market are not different from those affecting the extent of participation**.

6.4. Policy recommendation

Several interesting policy implications can be drawn from our empirical analysis of smallholder pastoral household. First of all, with reference to stochastic frontier analysis, from a methodological point of view in the, we have shown that the pooled model estimates a general technology which misrepresents the technology of different production systems. In particular, the study has demonstrated that there are clear differences in the production technologies, returns to scale and efficiency amongst the smallholder livestock farmers in the southern rangeland of Kenya. The differentiated livestock production technologies amongst the smallholder livestock farmers in southern rangeland of Kenya lends support to the importance of correctly accounting for heterogeneity in order to make correct policy recommendations regarding the livestock production and performance. The results of the study indicate that livestock production is positively related to the availability of labour, feed and mineral supplement, the size of pastureland, and capital. This, therefore, calls for policies that promote ownership of pastureland in which farmers can plant fodder and or crops residues to feed their livestock. More importantly, intentional adjudicate of economical land property rights, and exploration of other tenure reform arrangements would play a vital role in enhancing productivity in the livestock sector, hence increasing markable surplus. There is also a need for encouraging the farmers to consider livestock production as a promising business and liberal provision of better wages to attract and retain some young category of labour who are attracted to formal employment. Policies that would guarantee adequate access to credit facilities by the livestock farmers would ensure that the farmers have enough capital resources for expansion.

In addition, inefficiency in livestock production in Kenya could be reduced not only by better use of available resources, given the current state of technology, but also through policies that would encourage the livestock farmers to access to market information, off-farm income and ease in the adoption of technology. This can be achieved through formulation and judicious enforcement of policies on relevant aspects of enhance market information flow, injecting capital resources into the industry that can be used to strengthening linkages between the livestock farmers and the extension service provider or through innovative technology delivery approaches, such as mobile phone systems and radio-based training, coupled with tested approaches (pro-pastoral field schools), represent a significant opportunity for improving efficiency in both livestock production and extension. Finally, enhance support to institutions that can accelerate livestock productivity through research on new technologies so as to reduce the land area per unit livestock output.

Since livestock production, product supply and factor input demand are closely interlinked, policy option on livestock production and hence off-take are closely related.

However, to enhance livestock off-take, policy geared towards improving the institutional and environmental conditions that support livestock output prices and input marketing with an emphasis on specific livestock species seems to be a promising option. Priority areas of action appear to be an adequate and attractive option in order to increase aggregate output supply of livestock in Kenya without damage to the rangeland environment would, therefore, be a pro-pastoral support price policy. Equally, another appropriate option may be to encourage more intensive use of productivity-enhancing inputs such as land through investing on pasture improvement perhaps this way may increase its effect on the supply, encouraging investment among livestock farmers by improving their capital base through improved access to grant or loan.

With regards to market participation for smallholders farmers, the policy and programmatic implication of these results is not that, the ongoing public investments effort in market access in Kenya have no role to play in increasing market participation, but that, with current levels of production technology, increased private asset endowments (such as herd size and quality of land) appear necessary for households to be able to take advantage of the reasonably open access to livestock markets in Kenya and any associated public investments in improving market information flow or physical access to markets. Other transaction costs issues that hamper the effective participation of producers relate to limited education, gender orientation and ease in access to veterinary services. In the spirit of promoting literacy among smallholder, a properly targeted adult training program needs to be instituted. With gender variable, in Kenya pastoral setup, men generally have greater and easier access to property ownership (such as land, livestock, etc.) than women and youth, thus explaining why gender variable had a high partial effect. Prevailing gender inequalities may, therefore, constrain the net benefit for many women and policy that ensure intentional adjudication of land property rights to all gender would play a vital role in enhancing livestock market participation. Additionally, an innovative veterinary service delivery approaches, such as radio-based training represents a significant opportunity for improved market participation by smallholder pastoralists. In conclusion, to minimise remoteness of the smallholder farmers, building physical infrastructures such as roads, information and communications channels connecting small farms to markets, and institutions that reduce transaction costs and minimise risks, are essential to enhance the livestock farmer’s access to the market.

6.5. Recommendation for future study

In investigating the possibility of incorporating the effect of heterogeneity in measuring efficiency for the livestock sector, our analysis was based on the frequently used exponential and half-normal distributions. A promising avenue for further research would be to incorporate other types of distributions such as gamma and truncated-normal. It is also important to conduct a more detailed analysis of the sources of decreasing returns to some classical factors of production on livestock productivity in order to help semi-subsistence small-scale livestock households escape from poverty traps. Since livestock farming in Kenya is also carried in, diverge agroecological zones, overlooking the influence of agroecological conditions on productivity and efficiency may be biased. Therefore, the other possible research is to incorporate differences in agro-ecological zones which was not captured by the current modelling approach due to data limitation. Study such as Alvarez–del Corral 2010 controlled for different agro-climatic conditions, using sets of dummy variables and found that efficiency estimates to be sensitive to agro-climatic condition. The knowledge of how production efficiency varies across different agro-ecologies can assist policy in choosing technologies that are more adaptable to specific agro-ecologies and enhance sustainable development of the livestock sector in the face of climate change.

Another promising avenue for further research on efficiency estimation would be to look at the possibility of incorporating corruption cost in this type of model framework since according to the study by Anik et al. (2011), corruption costs might be efficiency-enhancing or reducing, depending on the specific situation and context. This is in line with the World Bank concession that in some cases, corruption might increase economic efficiency for individuals or groups if they enable firms to escape overly restrictive regulations or confiscatory tax rates, especially in the short run. Much of the current debate rages over the effects of current rampant corruption cost on the efficiency of economic agent and such research is lacking in Kenya livestock production literature.

On livestock product supply and input demands responsiveness, a promising suggestion for future research would be to use an integrative differential model that includes risk aversion of livestock producers since livestock producers' attitudes toward risk would affect the selection of livestock for sale. Regarding smallholder market participation, future research can also investigate whether there is a possibility that farmers' decisions to participate and the extent of participation are made simultaneously. Finally, it is, however, essential to note that the study uses cross-sectional data that do not capture changes over time. A longitudinal study is needed to capture changes over time regarding smallholder pastoral livestock farming.

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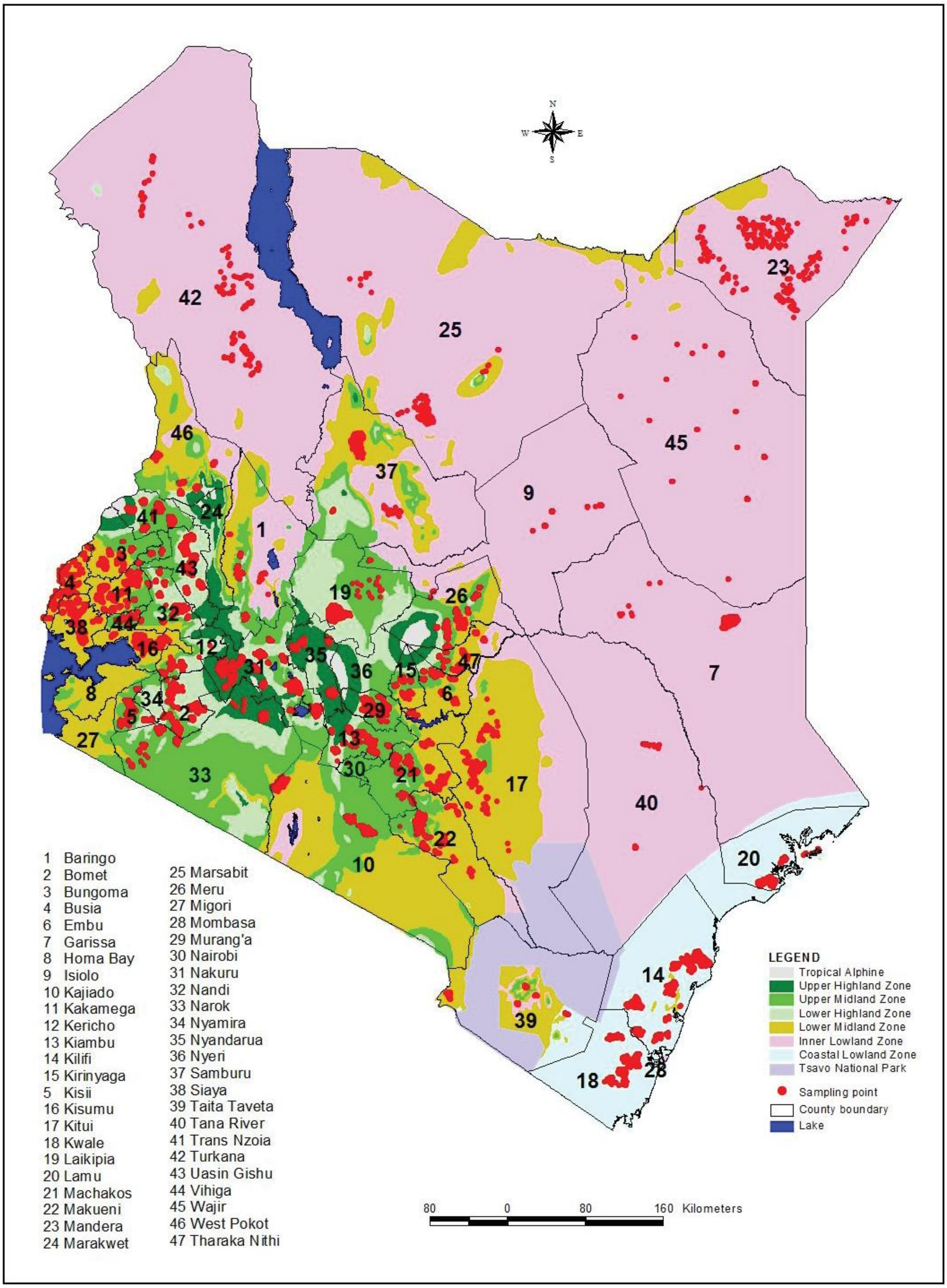
APPENDICES

Appendix 1. Trends in per capita production of ruminant livestock products in sub-Saharan Africa, 1989 to 1999

Region/country	Cow milk	Beef	Sheep meat	Goat meat
Central Africa				
Cameroon	-1.9	0.5	4.1	-0.2
Central African Republic	1.1	-0.4	-0.4	4.0
Dem. Republic of Congo	-7.2	-10.2	-2.8	-1.0
Congo, Republic of	-1.1	0.3	-1.8	0.0
Gabon	3.5	1.8	-0.7	-0.4
Subtotal	**0.1**	**-0.3**	**-0.5**	**1.6**
East Africa				
Burundi	-5.5	-4.8	3.3	-1.1
Djibouti	-2.4	-7.6	0.5	-1.8
Eritrea	-	-	-	-
Ethiopia	-	-	-	-
Kenya	-2.6	-1.6	-2.5	-0.3
Rwanda	0.0	2.2	-1.5	0.2
Somalia	-2.1	-1.4	-0.9	-6.0
Sudan	1.3	0.7	6.5	11.6
Tanzania	0.1	-1.4	-1.3	-1.0
Uganda	0.0	0.0	1.4	0.0
Subtotal	**-0.9**	**-2.8**	**1.4**	**-1.0**
Southern Africa				
Angola	-0.9	0.5	4.1	4.4
Botswana	-3.4	-2.9	-1.2	-0.9
Malawi	-2.3	-0.7	-4.0	2.1
Mozambique	-3.6	-3.8	-2.2	-2.6
Namibia	-1.3	-3.7	-2.8	-2.0
Zambia	-3.9	-3.8	5.2	5.4
Zimbabwe	-5.7	1.0	-5.4	0.9
Subtotal	**-3.1**	**-2.8**	**-2.7**	**-0.4**
West Africa				
Benin	1.5	1.7	-3.2	0.0
Burkina Faso	2.9	1.8	1.0	0.6
Côte d'Ivoire	0.8	1.1	0.3	0.4
Chad	0.0	-1.0	0.8	1.2
Gambia	-1.4	-3.0	0.0	-1.1
Ghana	1.2	-6.2	-1.9	-1.1
Guinea	1.2	1.1	0.0	2.6
Guinea-Bissau	-0.8	0.8	0.2	2.3
Liberia	-2.2	0.0	-0.9	-1.3
Mali	0.1	-0.5	-0.6	1.1
Mauritania	-2.1	-6.2	-1.5	-3.2
Niger	-0.8	1.0	-2.0	-1.7
Nigeria	-1.2	0.6	5.5	-0.1
Senegal	-1.7	-1.1	0.0	2.4
Sierra Leone	0.2	1.9	0.6	1.2
Togo	-3.2	2.1	-6.2	-4.6
Subtotal	**-0.6**	**-1.0**	**-0.8**	**-0.6**
Grand total	**-1.5**	**-2.2**	**-0.9**	**-0.4**

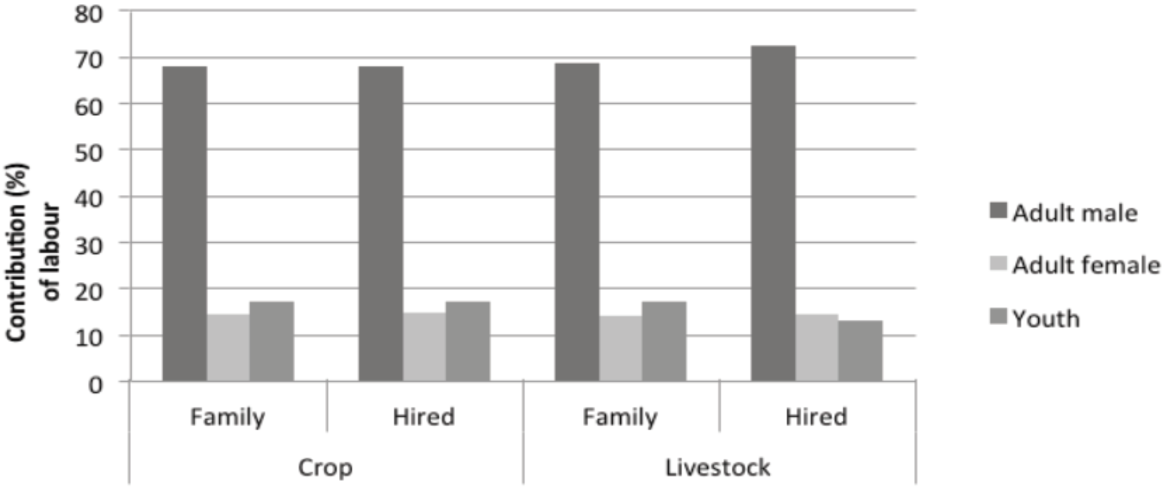
Source: Author own construction based on Otte–Chilonda (2002)

Appendix 2. Location of sampled households in the 1–47 of Counties in Kenyan



Source: Agricultural Sector Development Support Programme (ASDSP), *Volume 1: Household Baseline Survey Report – National Report* (GoK 2014).

Appendix 3. Distribution of labour used in crop and livestock production by gender of household head, 2014.



Source: GoK (2014) Agricultural Sector Development Support Programme (ASDSP), *Volume 1: Household Baseline Survey Report – National Report*

Appendix 4. Variance Inflation Factor (VIF) and conditional number for Collinearity test for variables

Appendix 4.1. Collinearity test for variables used for estimating inefficiency effect model

```
. collin agehhd gender educleve vetdrugs extacces agrirese agrictel marketac misacces imaccess ntechgy lownersh ofincome, c
> orr
(obs=1,283)
```

Collinearity Diagnostics

Variable	VIF	SQRT VIF	Tolerance	R-Squared
agehhd	1.07	1.04	0.9319	0.0681
gender	1.05	1.03	0.9513	0.0487
educleve	1.13	1.06	0.8823	0.1177
vetdrugs	1.04	1.02	0.9594	0.0406
extacces	1.11	1.05	0.9015	0.0985
agrirese	1.06	1.03	0.9399	0.0601
agrictel	1.05	1.02	0.9566	0.0434
marketac	5.73	2.39	0.1745	0.8255
misacces	2.43	1.56	0.4118	0.5882
imaccess	3.67	1.91	0.2727	0.7273
ntechgy	1.03	1.02	0.9677	0.0323
lownersh	1.02	1.01	0.9823	0.0177
ofincome	1.03	1.02	0.9667	0.0333
Mean VIF	1.73			

	Eigenval	Cond Index
1	2.2975	1.0000
2	1.4172	1.2732
3	1.2179	1.3735
4	1.1136	1.4363
5	1.0470	1.4814
6	0.9912	1.5225
7	0.8998	1.5979
8	0.8793	1.6164
9	0.8655	1.6293
10	0.7846	1.7112
11	0.7342	1.7689
12	0.6525	1.8765
13	0.0997	4.8010

Condition Number 4.8010

Eigenvalues & Cond Index computed from deviation sscp (no intercept)

Det(correlation matrix) 0.1176

Appendix 4.2. Collinearity test for variables used in market participation models

a. Independent variables used livestock market participation decision

```
. collin gender age educ tlsize tlstock owncar ownmotorcycle owntel ownradio ownmobil dist3 acaccess vsaccess liaccess mi
> ccess offfarm_nonfarm percapita_wealth_day
(obs=1,241)


  Collinearity Diagnostics

                          SQRT                   R-
  Variable       VIF      VIF    Tolerance    Squared
----------------------------------------------------
    gender      1.07     1.03     0.9358      0.0642
       age      1.10     1.05     0.9112      0.0888
      educ      1.32     1.15     0.7602      0.2398
    tlsize      1.09     1.04     0.9214      0.0786
   tlstock      1.27     1.13     0.7897      0.2103
    owncar      1.14     1.07     0.8740      0.1260
ownmotorcycle      1.11     1.05     0.9043      0.0957
    owntel      1.18     1.09     0.8463      0.1537
  ownradio      1.15     1.07     0.8672      0.1328
  ownmobil      1.12     1.06     0.8900      0.1100
     dist3      1.14     1.07     0.8754      0.1246
  acaccess      1.01     1.00     0.9926      0.0074
  vsaccess      1.09     1.04     0.9188      0.0812
  liaccess      1.08     1.04     0.9293      0.0707
 misaccess      1.09     1.04     0.9199      0.0801
offfarm_nonfarm      1.69     1.30     0.5900      0.4100
percapita_wealth_day      1.81     1.35     0.5521      0.4479
----------------------------------------------------
  Mean VIF      1.20

                           Cond
        Eigenval          Index
---------------------------------
    1     7.3752          1.0000
    2     1.5522          2.1797
    3     1.0912          2.5997
    4     0.9860          2.7349
    5     0.9673          2.7613
    6     0.9265          2.8214
    7     0.8047          3.0274
    8     0.7792          3.0766
    9     0.6840          3.2836
    10     0.6250          3.4351
    11     0.5816          3.5609
    12     0.4893          3.8822
    13     0.3028          4.9351
    14     0.2785          5.1457
    15     0.2370          5.5790
    16     0.1853          6.3091
    17     0.1076          8.2777
    18     0.0265         16.6785
---------------------------------
 Condition Number        16.6785
 Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)
 Det(correlation matrix)    0.2123

.
```

b. Independent variables used livestock market participation decision

```
. collin gender age educ tlstock ownmotorcycle ownmobil dist3 cpriceml sgpriceml acaccess vsaccess liaccess percapita_wea
> h_day
(obs=1,241)

  Collinearity Diagnostics

                        SQRT                   R-
  Variable      VIF     VIF    Tolerance    Squared
----------------------------------------------------
    gender      1.07    1.03    0.9378      0.0622
       age      1.11    1.05    0.9038      0.0962
      educ      1.29    1.14    0.7722      0.2278
   tlstock      1.21    1.10    0.8282      0.1718
ownmotorcycle      1.06    1.03    0.9395      0.0605
  ownmobil      1.05    1.03    0.9485      0.0515
     dist3      1.14    1.07    0.8766      0.1234
  cpriceml      1.26    1.12    0.7944      0.2056
 sgpriceml      1.16    1.08    0.8617      0.1383
  acaccess      1.01    1.00    0.9927      0.0073
  vsaccess      1.08    1.04    0.9268      0.0732
  liaccess      1.07    1.03    0.9388      0.0612
percapita_wealth_day      1.19    1.09    0.8422      0.1578
----------------------------------------------------
  Mean VIF      1.13

                           Cond
        Eigenval          Index
---------------------------------
    1     6.4243          1.0000
    2     1.2840          2.2368
    3     1.0137          2.5174
    4     0.9395          2.6150
    5     0.8310          2.7804
    6     0.7029          3.0233
    7     0.6658          3.1063
    8     0.5872          3.3075
    9     0.4919          3.6138
    10     0.4556          3.7549
    11     0.2785          4.8030
    12     0.1912          5.7961
    13     0.1083          7.7031
    14     0.0260         15.7046
---------------------------------
 Condition Number        15.7046
 Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)
 Det(correlation matrix)    0.4437

.
```