ENERGY EFFICIENCY AND SUBSTITUTION POSSIBILITIES IN KENYA'S MANUFACTURING SECTOR.

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DECLARATION

This thesis is my original work and has not been presented for the award of a degree in any other university.

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This thesis is dedicated to God and my family for all the support and prayers.

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LIST OF ABBREVIATIONS

AES	Allen Elasticity of Substitution
CEEC	Centre for Energy Efficiency and Conservation
CES	Constant Elasticity of Substitution
CLRM	Classical Linear Regression Model
DEA	Data Envelopment Analysis
DMU	Decision Making Unit
EPRA	Energy and Petroleum Regulatory Authority
EF	Energy Efficiency
EI	Energy Intensity
FE	Fixed Effects
GDP	Gross Domestic Product
GHG	Greenhouse Gases
GMM	Generalized Method of Moments
GWh	Giga watt-hour
IEA	International Energy Agency
IEO	International Energy Outlook
ILO	International Labour Organization
INDC	Intended Nationally Determined Contribution
IV	Instrumental Variable
KAM	Kenyan Association of Manufacturers
LAC	Latin American Caribbean
LP	Levinsohn and Petrin
LR	Likelihood Ratio
ME	Malmquist Index of Efficiency Change
MES	Morishima Elasticity of Substitution
MTC	Malmquist of Technical Change
MW	Megawatt
NEEC	National Energy Efficiency and Conversation Strategy

NRF	National Research Fund
OECD	Organization for Economic Co-operation and Development
OLS	Ordinary Least Squares
PED	Price Elasticity of Demand
PM	Pooled Model
POLS	Pooled Ordinary Least Squares
RE	Random Effects
REM	Random Effects Model
R&D	Research and Development
SDG	Sustainable Development Goals
SFA	Stochastic Frontier Analysis
SUR	Seemingly Unrelated Regression
TFEM	Total Fixed Effects Model
TFP	Total Factor Productivity
TOE	Tonne of Equivalent
TREM	Total Random Effects Model
UNFCCC	United Nations Framework Convention on Climate Change
UNDP	United Nations Development Programme
VECM	Vector Error Correction Model
VIF	Variance Inflation Factor
WEF	World Economic Forum
WDI	World Development Indicators

OPERATIONAL DEFINITION OF TERMS

Capital intensity: indicates the ratio of capital to labour.

Energy efficiency: the act of producing a given level of output using lesser amounts of energy or producing a higher level of output without an increase in energy use.

Energy intensity: indicates the amount of energy used to produce a unit of output.

Firm: an establishment involved in the production of goods through the use of factor inputs.

Labour productivity: refers to the ratio of output to labour input.

Manufacturing sector: a combination of various firms engaged in the production of goods through the employment of factors of production.

Productivity: indicates the ratio of output to inputs

Sub-sector: a combination of firms producing similar products.

ABSTRACT

Energy holds a pivotal role in an economy's social and economic transformation and it is a key ingredient driving the production of nearly entire goods and services. Consequently, energy demand has been increasing over years globally and locally owing to expanded population and economic activity. The manufacturing sector, a key engine of growth, is one of the largest energy end-user. While energy is a key input in the manufacturing processes, there is unease over its effects on the environmental quality, human health, and competitiveness of firms. This thesis sought to analyze energy efficiency, productivity, and energy and non-energy input substitution possibilities in Kenya's manufacturing sector. It was structured into three essays.

The first essay analyzed sub-sector energy efficiency differences, energy efficiency change as well as energy efficiency drivers in Kenya's manufacturing sector. Sub-sectors of concern were: chemicals, pharmaceuticals and plastics, food, textiles and garments, and paper and other manufacturing. Analysis was also conducted at the sectoral level for robustness check. The stochastic frontier analysis and more specifically translog input distance functions were estimated by adopting a pooled regression model covering the period 2007, 2013, and 2018 in the assessment of electricity efficiency and 2007 and 2013 in the assessment of fuel efficiency. The Malmquist index was applied to analyze energy efficiency change over the period under review. The World Bank Enterprise Surveys provided data used in this analysis. Study findings show considerable space to cut electricity and fuel wastage across the four sub-sectors and the overall sector. The Malmquist index showed an improvement in electricity efficiency in the chemicals, pharmaceuticals and plastics and textiles and garments sub-sectors. A decline in electricity efficiency was observed in the food and paper and other manufacturing sub-sectors and overall sector. Fuel efficiency improved in food and paper and other manufacturing sub-sectors and overall sector but declined in chemicals, pharmaceuticals and plastics and textiles and garments sub-sectors. Findings show that electricity and fuel efficiency could be enhanced by investing in research and development, exporting activities, female firm ownership, and highly experienced top management. The influence of these variables varied between the two energy forms and across sub-sectors. Firm age and size had no clear effect on electricity and fuel efficiency while labour productivity had a negative effect. These findings reveal the need to design policies that enhance technological innovations, uptake of new technologies, exporting and female firm ownership.

The second essay sought to explore the energy efficiency and productivity relation in the Kenyan manufacturing sector. Energy intensity was applied to indicate energy efficiency. Total factor productivity was analyzed using the Levinsohn-Petrin algorithm. A dynamic panel data model was employed to establish the energy efficiency and total factor productivity relation. An unbalanced panel data for the years 2007, 2013, and 2018 drawn from World Bank Enterprise Survey was also adopted in this essay. Study findings showed heterogeneity in energy intensity across sub-sectors. Heterogeneity in total factor productivity was also observed across sub-sectors, firm sizes, and firm age. Energy efficiency was found to positively influence total factor productivity. Study findings also showed that capital intensity, age and size of the firm, top manager's experience, foreign ownership, and exporting status positively influenced total factor productivity. The effect of these variables was found to be heterogeneous across sub-sectors and firm sizes. Study findings suggest that policies to improve energy efficiency should be matched with policies to enhance total factor productivity.

The third essay sought to assess energy and non-energy input substitution possibilities besides establishing whether these substitution possibilities varied with firm size in the Kenyan manufacturing sector. Iterated seemingly unrelated regression was applied on a pooled model and an unbalanced panel dataset for the years 2007, 2013, and 2018 drawn from World Bank Enterprise Survey and Energy and Petroleum Regulatory Authority. Analysis was performed in two steps. In the first step, there was a joint estimation of a translog cost function with cost-share equations. Elasticities were then worked out from parameter estimates of the translog cost function and cost shares in the second step. The Cross-price elasticities indicated that capital and labour were substitutes for energy across all sub-sectors and overall sector but capital was a weak substitute for energy in the chemicals, pharmaceuticals and plastics sub-sector. The Morishima elasticities affirmed that capital and labour were substitutes for energy across all sub-sectors and the overall sector. The cross-price elasticities at firm size level analysis showed that capital and labour were substitutes for energy across all firm sizes but capital was at best a weak substitute for energy in small firms. The Morishima elasticities further affirmed that capital and labour were substitutes for energy across firm sizes. Substitution of capital for energy was found to increase with firm size but no consistent pattern was observed in the substitution of labour for energy. Study findings suggest that energy price policies could reduce energy consumption and potentially boost capital intensiveness, employment, and environmental quality.

CHAPTER ONE: INTRODUCTION

1.1 Background

Energy holds a vital function in an economy's social and economic development and drives the production of nearly all goods and services. The World Economic Forum (WEF), observes that energy is an enabler of the growth of an economy and is helpful in two main avenues: directly generating jobs and implicitly expanding economic activity and citizens' well-being by stimulating growth in the rest of the sectors (WEF, 2012). The importance of energy makes it hold a central position in Sustainable Development Goal seven (SDG 7). Under this goal, nations commit to offer economical, reliable, sustainable and current energy to all citizens by the year 2030 (United Nations, 2015). The realization of this goal will create a world of openings for billions of people via emerging economic prospects and employment, empowered women, children, and youth, improved education and health, more reliable, equitable, and all-encompassing societies, and better safeguards from, and buoyancy to climate change (United Nations, 2015).

In Vision 2030 and the "Big Four" Agenda development plans, Kenya has recognized energy as a key ingredient in economic transformation. Subsequently, Kenya has set to lay down energy infrastructure to meet an anticipated increase in energy consumption. A huge share of energy investments has been channelled to more reliable renewable energy (Republic of Kenya, 2020a). However, non-renewable energy continues to dominate energy use in Kenya. Biomass consumption leads at 69 percent followed by petroleum at 22 percent and electricity at 9 percent in that order (Republic of Kenya, 2020a).

Energy demand has increased with time both worldwide and domestically as a result of increased economic activity, a rising populace and persistent improvement in the standard of life. For instance, the International Energy Outlook (IEO) anticipates worldwide energy consumption to grow by nearly 56 percent between 2010 and 2040 (IEO, 2014). Locally, an increase in electricity and fuel use has been witnessed with time. For instance, in the last decade, local demand for petroleum products rose from 3879.6 ('000 Tonnes) in 2011 to 4678.5 ('000 Tonnes) in 2020, representing a 21.11 percent increase. In the same period, local electricity demand rose from 6273.6 (Million KWh) to 8796.4 (Million KWh) representing a 40.21 percent increase (Republic of Kenya, 2014, 2021).

The manufacturing sector in Kenya is a major energy consumer. It dominates in electricity use and is the second-highest consumer of fuel behind the transport sector (Republic of Kenya, 2018). For example, during the period 2011-2020, electricity consumption in the manufacturing sector was consistently higher than that for domestic and small commercials and other consumers as shown in Figure 1 (Republic of Kenya, 2014, 2021). Figure 2 shows that the sector's consumption of petroleum was second after transport (road transport, marine, and aviation) (Republic of Kenya, 2014, 2021).

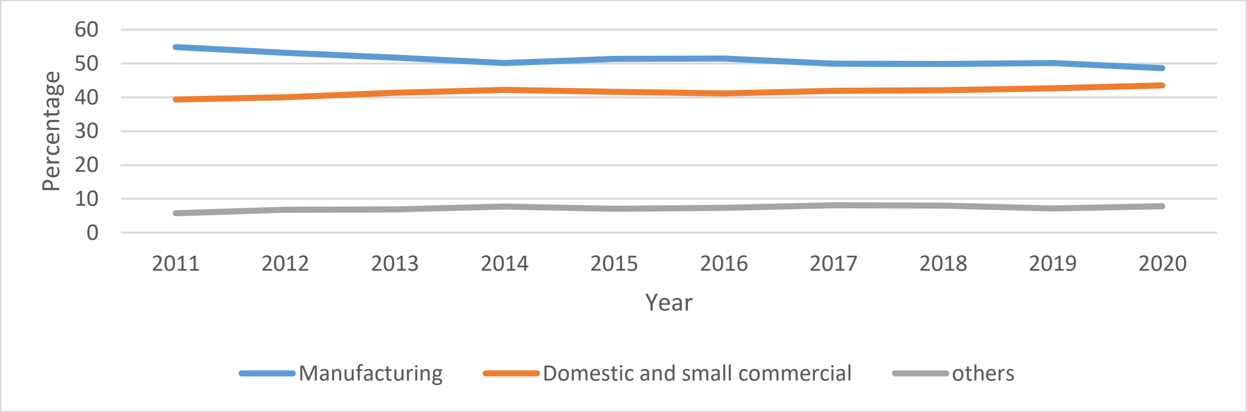

Figure 1.1:Electricity demand, 2011-2020
Source: Republic of Kenya (2014; 2021)

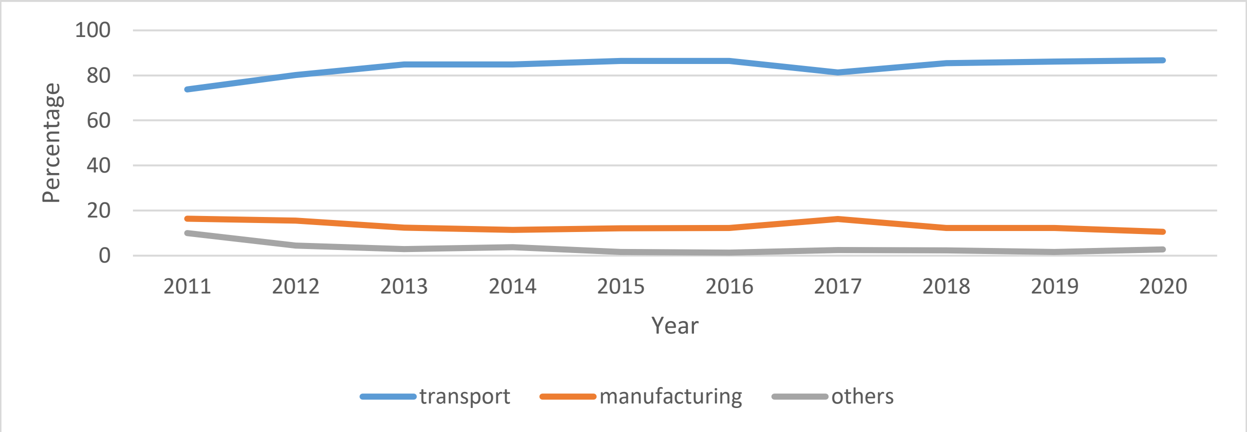

Figure 1.2:Petroleum consumption, 2011-2021
Source: Republic of Kenya (2014; 2021)

The manufacturing sector performs a sizeable role in propelling economic transformation given that it harbours highly productive commercial activities. Persistent growth of this sector promotes a country's competitiveness, creates employment, and improves efficiency in the employment of resources. Due to its solid links with the rest of the sectors, the manufacturing sector assumes a major role in the "Big Four" Agenda which aims to spur the economic growth of the Kenyan economy (Republic of Kenya, 2020c). The five-year plan running 2018-2022 seeks to enlarge the manufacturing sector's input to GDP from 8.4 to 15 percent. With this growth, the sector is expected to cut the existing trade deficit and generate employment by creating 1,000,000 additional jobs (Republic of Kenya, 2020c).

Over years, the manufacturing sector has remarkably supported the Kenyan economy through its contribution to GDP, employment, and export of goods. On average, the sector accounted for 9.31 percent of the overall GDP in the decade running 2011-2020. Figure 3 however, shows that the sector's contribution to GDP has been declining over time (Republic of Kenya, 2013; 2021). It plunged from 11.75 percent in 2011 to 7.61 percent in 2020. Nonetheless, the sector has on average been third in contributing to GDP after the service (55.78 percent) and agriculture, forestry and fishing (19.96) sectors (Republic of Kenya, 2014;2021).

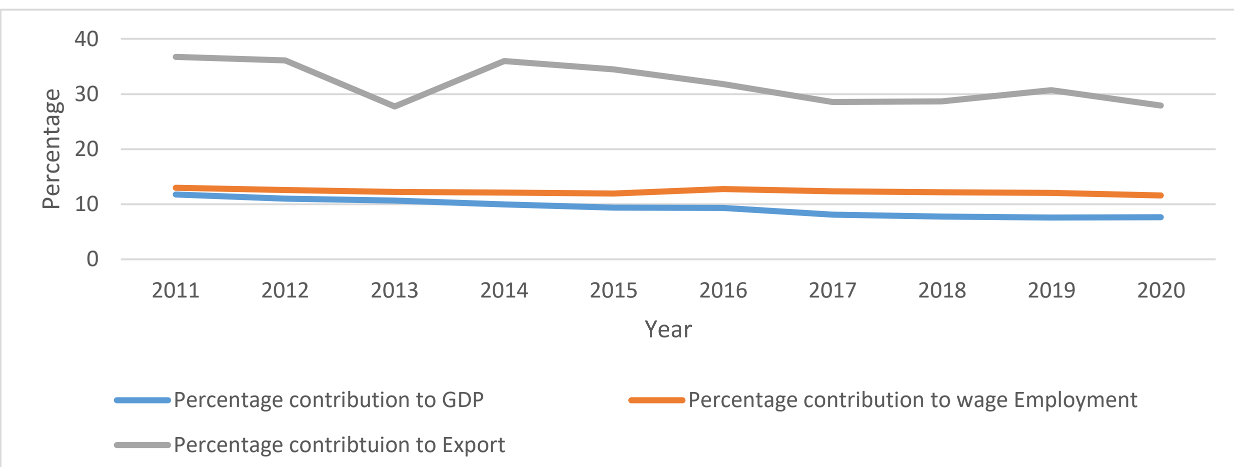

Figure 1.3:Performance of the manufacturing sector, 2011-2020.
Source: Author's computation from World Bank Development Indicators and Republic of Kenya (2014; 2021)

On employment, the World Development Indicators (WDI) show that the sector has historically been the third largest employer after the agriculture and service sectors in Kenya. Figure 1.3 shows that the contribution of the manufacturing sector's employment to total employment has been increasing over time. On average, the sector contributed 12.63 percent of the overall wage employment in the same decade (Republic of Kenya, 2014;2021). In addition, the sector is a significant source of informal employment, contributing an average of 20.05 percent in the period under review (Republic of Kenya, 2014, 2021). The sector's contribution to total employment is expected to be even higher due to its robust links and spill-over effects on other sectors in the economy. With regards to exports, Figure 1.3 shows that even though the sector's contribution to total exports was unstable over the period under review, this contribution was significant at an average of 31.87 percent of the total exports. (Republic of Kenya, 2014, 2021).

The sector uses energy as an input in the conversion of raw materials to intermediate and final capital and consumer goods and distribution and transport services (Onuonga et al., 2011; Boyd and Lee, 2019). Energy is also used to power machinery, heaters, ventilation and air condition equipment, lamps, material handlers, and office equipment while petroleum fuels are used in steam generators and heaters (Onut and Soner, 2006). Whereas energy is a vital ingredient in the manufacturing sector, there has been unease among researchers regarding its undesired implications on the environment, human health and financial performance of firms (Lin and Long, 2015; Campi et al., 2015; Wang and Yuan, 2019).

The negative effect of energy use on the environment and human health is caused by pollutant emissions stemming from the combustion of fossil fuels. Such emissions include Greenhouse Gases (GHG) associated with climate change and poisonous smoke linked to pneumonia, lung damage, and the risk of acute respiratory infection in children thereby resulting in premature deaths among children aged below 5 years (Basu et al, 2016). Fossil fuels are non-renewable implying that their continued use may lead to their depletion in the future and hence limiting the amount of resources available for use by future generations. In addition, with energy being an input in production, energy costs become a constraint for production thereby negatively impacting firms' competitiveness both in the domestic and foreign markets.

Given the concern over undesired implications of energy use, the necessity to promote energy efficiency is more pronounced. The International Energy Agency (IEA) (2014) opines that energy efficiency performs a fundamental function in containing energy-related shortcomings. The significance of energy efficiency has been reinforced by SDG 7, which has bestowed energy efficiency to play a pivotal role in containing climate change (United Nations, 2015). A production entity is said to be energy efficient if fewer amounts of energy can be used to produce a given amount of output. This infers that there is a reduction in energy wastage. Therefore, understanding the actual energy efficiency levels in the manufacturing sector would be useful in devising policies to cut energy consumption.

Secondly, while energy efficiency is highlighted to be a suitable approach to reducing energy use, its effect on economic performance cannot be ignored. This is more so in developing countries which are relatively more dependent on energy for their economic activities. An understanding of how energy efficiency affects manufacturing sector productivity is important in revealing whether policies to promote energy efficiency should incorporate productivity benefits. Thirdly, the substitution of non-energy inputs for energy is one of the key mechanisms to reduce energy use (Zha and Ding, 2014; Haller and Hyland, 2014). However, a prior understanding of the energy and non-energy inputs relation is useful in indicating whether energy price policies could lead to a decline or rise in energy consumption along with its implication on demand for non-energy inputs.

1.2 Statement of the Problem

Among economic sectors in Kenya, the manufacturing sector is a significant energy end-user. It is the second-highest consumer of petroleum fuels after the transport sector and is the highest consumer of electricity (Republic of Kenya, 2018). Energy is used as a key input in the manufacturing and transportation of produced goods and services. Although energy is a critical input to this sector, its uncontrolled use is associated with environmental degradation, ill health, and a high cost of production, particularly when energy prices are high. To avoid negativities linked to energy application in the manufacturing sector, the need for enhancing energy efficiency has received huge attraction. In spite of attempts to enhance energy efficiency in Kenya, energy application in the manufacturing sector has had a sustained increase with time. Contrastingly, the sector has exhibited an unsatisfactory performance that is typified by a declining growth rate and a drop in contribution to GDP over time.

The expansion in energy use that is not backed by the sector’s improvement in economic performance raises uncertainty regarding the sector’s energy efficiency level. The need to have an analytical assessment of the exact level of energy efficiency in Kenya’s manufacturing sector cannot be overemphasized. Although this assessment is critical, there is limited evidence for the Kenyan manufacturing sector. The limited existing linked research has not centred on this sector. For example, Ndichu et al. (2015) investigate the execution of energy efficiency techniques by maize milling firms whereas Zhang et al. (2011) estimate total factor energy efficiency in the overall economy. Besides providing an in-depth assessment of energy efficiency, the present study investigates energy efficiency change and explores energy efficiency drivers in Kenya's manufacturing sector.

Although energy efficiency is pivotal in dealing with issues emanating from energy use, a section of economists has raised concern over its implications on the productivity of firms. An understanding of the energy efficiency and manufacturing sector productivity relation is useful in informing whether productivity benefits should be incorporated in policies promoting energy efficiency. While various studies have assessed this relationship, there remains no consensus among researchers. Some studies have found energy efficiency to promote productivity while others have found energy efficiency to negatively influence manufacturing sector productivity. The failure to build consensus among studies could be signalling that the energy efficiency and manufacturing sector productivity relation could be country-specific thus calling for more country-specific studies. Further, the majority of existing studies have provided evidence for developed countries and evidence for developing countries is limited, yet these countries heavily depend on energy for their economic activities. This study, therefore, explores how energy efficiency influences productivity in Kenya's manufacturing sector.

The global discussion regarding energy and non-energy inputs substitution has been fueled by concerns about the implications of uncontrolled energy use on environmental quality and manufacturing sector competitiveness. An investigation of the energy and non-energy inputs substitution possibilities focuses on explaining how non-energy inputs demand responds to variations in energy prices. This has implications on investment and capital formation, employment and environmental quality. Whereas research on this subject has been extensively done, a mix of findings has been reported. The uncertainty in findings calls for more analysis on the subject, particularly in developing countries where evidence is scanty. In Kenya, Onuonga et al. (2011) find capital and labour to substitute energy. However, this study has applied time-series data at the macro level yet such data has been associated with results that suffer from aggregation bias (Solow, 1987). Further, the study does not provide recent elasticities, yet a shift in preferences or tastes and technological change is likely to adjust production relationships with time (Fiorito and van den Bergh, 2015). The present study offers an assessment of the energy and non-energy input substitution possibilities for Kenyan manufacturing using the most recent available micro-level data.

1.3 Research Questions

The thesis attended the following research questions:

a) What is the level of energy efficiency in Kenya's manufacturing sector?
b) What is the effect of energy efficiency on Kenya's manufacturing sector productivity?
c) What are the substitution possibilities between energy and non-energy inputs in Kenya's manufacturing sector?

1.4 Objectives of the Study

The overall objective of this study was to analyze energy efficiency, productivity, and energy and non-energy input substitution possibilities in Kenya's manufacturing sector. To attain this objective, the study sought to focus on the following specific objectives:

a) To investigate the level of energy efficiency in Kenya's manufacturing sector.
b) To analyze the effect of energy efficiency on productivity in Kenya's manufacturing sector.
c) To establish energy and non-energy input substitution possibilities in Kenya's manufacturing sector.

1.5 Contribution of the Study

This thesis furthers the extant literature regarding energy efficiency, productivity, and energy and non-energy input substitution possibilities in some avenues. First, the study provides empirical evidence for energy efficiency in Kenya's manufacturing sector. Previous research in Kenya has not addressed this subject. For instance, Ndichu et al. (2015) concentrate on exploring the execution of energy efficiency techniques while Zhang et al. (2011) focus on analysing economy-wide total factor energy efficiency. This research is important because the manufacturing sector is a significant energy end-user and the sector constitutes a key economic activity. The study provides evidence by analyzing the sub-sector differences in energy efficiency and by providing an examination of drivers of energy efficiency. This evidence is provided separately for electricity and fuel because the production process needs vary with energy form (Boyd and Lee, 2019). Estimating sub-sector energy efficiency differences is important because different sub-sectors are highly likely to have different technologies. Exploring drivers of energy efficiency is important in identifying factors responsible for sub-sector energy efficiency differences. The Ministry of Energy and Petroleum and manufacturing firms could find this useful in the development of policies to promote energy efficiency. Additionally, the study applies the Malmquist index to decompose energy efficiency change into efficiency change and technical change. Such a decomposition is useful in identifying factors that drive energy efficiency change.

Second, the study provides an empirical estimation of the manufacturing sector TFP using the most recent firm-level data. An investigation of the effect of energy efficiency on TFP is provided for the Kenyan manufacturing sector where evidence is limited despite a probable energy efficiency and productivity trade-off. To account for heterogeneity, the study provides analysis for different sub-sectors and firm size categories separately. In the process of this analysis, this research also furthers extant literature by providing an analysis of determinants of manufacturing sector TFP. The Ministry of Energy and Petroleum could find the results of this study important in indicating how energy efficiency policies should be designed. Manufacturing firms could also use the findings of the study to design policies to promote firm productivity. Some studies such as Sahu and Narayanan (2011a) in Indian manufacturing and Montalbano and Nenci (2019) in manufacturing firms in Latin American Caribbean (LAC) states fail to address reverse causality. This means that estimates of the effects of energy efficiency on manufacturing firm productivity are likely to be biased. This study addresses potential endogeneity resulting from reverse causality by estimating a dynamic panel data model.

Third, the study furthers the literature by presenting analytical evidence for energy and non-energy inputs substitution in Kenya's manufacturing sector. The Energy and Petroleum Regulatory Authority (EPRA) could apply the findings of this assessment in the design of energy price policies. A previous study by Onuonga et al. (2011) uses time-series data at the macro level. Estimates of elasticities provided by this study are therefore likely to suffer from aggregation bias. This is because estimates from such data capture more than technical substitution (Leon-Ledesma et al., 2010). In addition, it fails to provide recent elasticities. Research on this subject requires the use of recent data because production relations adjust over time as preferences or tastes and technological shifts over time. This study provides evidence on the subject using the most recent available firm-level data and analysis is done at the sub-sector and size category level. This is because production technology is likely to vary across sub-sectors and different manufacturing size categories resulting in different cost functions.

1.6 Structure of the Thesis

This thesis is structured into five chapters. The first chapter covers the introduction. Chapter two presents the analysis of energy efficiency in the Kenyan manufacturing sector. Chapter three explores the effect of energy efficiency on manufacturing sector productivity in Kenya. Chapter four provides an analysis of non-energy inputs and energy substitution possibilities in the Kenyan manufacturing sector. Chapter five provides the summary, conclusions, policy recommendations, and suggestions for further research.

CHAPTER TWO: ENERGY EFFICIENCY IN THE KENYAN MANUFACTURING SECTOR

ABSTRACT

Being a major energy end-user, the Kenyan manufacturing sector consumed 46.67 percent of the total electricity consumed in the country in 2020. It consumed 10.57 percent of total fuel which was the second-highest after that consumed by the transport sector. Providing an analytical assessment of sub-sector energy efficiency differences and drivers of energy efficiency besides exploring energy efficiency change in the sector is critical. Sub-sectors of concern were: chemicals, pharmaceuticals and plastics, food, textiles and garments, and paper and other manufacturing. Analysis was also conducted at the sectoral level for robustness check. The stochastic frontier analysis and more specifically translog input distance functions were estimated by adopting a pooled regression model covering the period 2007, 2013, and 2018 in the investigation of electricity efficiency and 2007 and 2013 in the investigation of fuel efficiency. The Malmquist index was applied to analyze energy efficiency change over the period under review. The World Bank Enterprise Surveys provided data used in this analysis. Study findings show considerable space to cut electricity and fuel wastage across the four sub-sectors and the overall sector. The Malmquist index reveals variations in electricity and fuel change across sub-sectors and time. Findings show that electricity and fuel efficiency could be enhanced by investing in research and development, exporting activities, female firm ownership, and highly experienced top management. The influence of these variables varied between the two energy forms and across sub-sectors. Firm age and size had no clear effect on electricity and fuel efficiency while labour productivity had a negative effect. These findings reveal the need to design policies that enhance technological innovations, uptake of new technologies, exporting and female firm ownership.

2.1 Introduction

Energy efficiency is one of the best methods by which the manufacturing sector can respond to energy use concerns (IEA, 2014). Such concerns include potential energy paucity, high energy prices, energy insecurity, and environmental degradation (Andrews-Speed, 2009). By definition, energy efficiency implies the use of less amount of energy for a given level of production or the use of the same amount of energy for more production (Mukherjee, 2008a). Therefore, it is the firm's ability to reduce energy wastage during production (Zhang, 2016). Manufacturing firms can achieve energy efficiency by employing more efficient machines, adopting modern systems, enhancing operation and maintenance activities, and substitution, especially energy for capital (Onut and Soner, 2006; Mukherjee, 2008a).

Improving energy efficiency comes with several benefits (Mukherjee, 2008a). First, energy efficiency promotes the conservation of energy, particularly that obtained from fossil fuels. Second, it helps in boosting a country's energy security. Third, by cutting greenhouse gas emissions, energy efficiency promotes environmental quality. Fourth, energy efficiency helps firms attain the objective of cost minimization, thus enhancing their competitiveness (Mukherjee, 2008a; Scheich, 2009). Fifth, energy efficiency relieves an economy from exchange rate pressure resulting from high energy import bills. Lastly, as the demand for energy among firms reduces, the overall demand for energy in the economy goes down resulting in less demand for energy-infrastructure investments at the national level. Savings from these investments can be reallocated to other sectors of the economy, which promotes the generation of jobs and value addition in the overall economy, thus helping in alleviating poverty.

Nevertheless, existing literature shows that running an effective energy efficiency policy often faces some obstacles. According to Scheich (2009), such obstacles include scant information on energy efficiency opportunities and energy efficiency measures, hidden costs associated with energy-efficient technologies, lack of access to capital to finance energy efficiency projects, and risk and uncertainty associated with energy-efficient technologies. Others are low level of technical education, especially at the management level, principal-agent barriers, ineffective regulation, split incentives, inefficient market structures, and rigidity to changes in the operating environment (Singh and Lalk, 2016; Worrell, 2011; Hassan et al., 2017). With the range of impediments to the implementation of an energy efficiency policy, it is important for governments to first direct their efforts to institutions where the greatest effect is likely to be realized and to use the most effective instruments (Energy Charter Secretariat, 2007).

In Kenya, given the pivotal position held by the manufacturing sector both in its effect on the economy and energy end-use, the objective of enhancing energy efficiency in this sector has occupied an even larger significance. The Ministry of Energy in collaboration with the Kenya Association of Manufacturers (KAM) created a Centre for Energy Efficiency and Conservation (CEEC) in the year 2006. The centre creates programmes to help firms enhance energy efficiency and conserve energy (Republic of Kenya, 2020d). The main objective of these initiatives is to cut costs and promote competitiveness and profitability as well as promote a clean and healthy environment. Among the programmes run by CEEC are energy audits which are expected to provide suggestions for firms to cut about 20 percent of energy costs. CEEC also provides a specialized training programme that equips firms with energy management skills which can help cut energy use and related costs significantly.

To coordinate energy efficiency measures in more sectors, the government recently established the Kenya National Energy Efficiency and Conservation Strategy (NEECS). NEECS provides a master plan for setting and realizing energy efficiency targets across various sectors (Republic of Kenya, 2020d). Under NEECS, CEEC is expected to increase energy audits in the manufacturing sector from 1800 to 4000 during 2019-2025. The sector is also expected to undertake recommended energy conservation actions to conserve 100 megawatts (MW) of electricity, 250 million litres of heavy fuel oil, and 9 million litres of industrial diesel oil from a baseline of 20MW of electricity, 51 million litres of heavy fuel oil and 1.8 million litres of industrial diesel oil in the same period (Republic of Kenya, 2020d). In addition, NEECS sets out to undertake resource mobilization in concerned government agencies to finance energy efficiency programs.

Despite concerted efforts to enhance energy efficiency in Kenya's manufacturing sector, consumption of energy in this sector has been rising over the years. For example, fuel use in the sector expanded from 414.6 thousand tonnes in 2010 to 635.5 thousand tonnes in 2019, representing a 38.57 percent increase. Nevertheless, the sector's fuel use reduced to 494.4 thousand tonnes in 2020 due to reduced economic activity occasioned by COVID-19 as shown in Figure 2.1 (Republic of Kenya, 2014;2021). Consumption of electricity soared from 3204.9 GWh in 2010 to

4441.0 GWh in 2019, representing a 38.57 percent increase. In 2020, electricity consumption reduced to 4281 GWh (Republic of Kenya, 2014;2021).

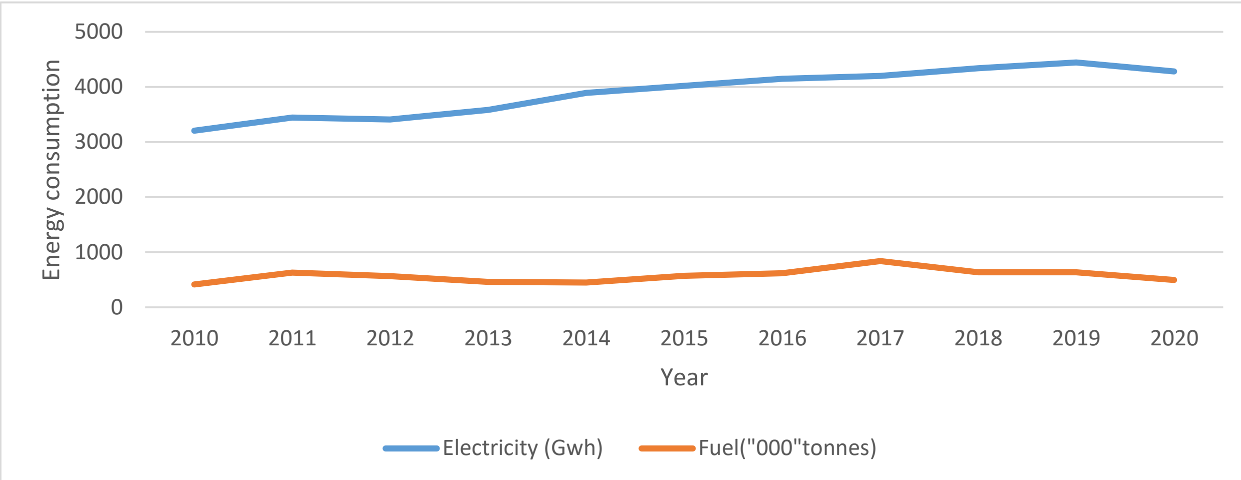

Figure 2.1:Energy consumption in the manufacturing sector in Kenya (2010-2020)
Source: Republic of Kenya (2014; 2021)

While researchers such as Essen and Bayrak (2017) and Tapsin (2017) have linked increased energy use to increased economic activity, the situation has been different in the context of Kenya's manufacturing sector performance. This is evidenced by the performance of the sector in the decade under review period as provided in Figure 2.2.

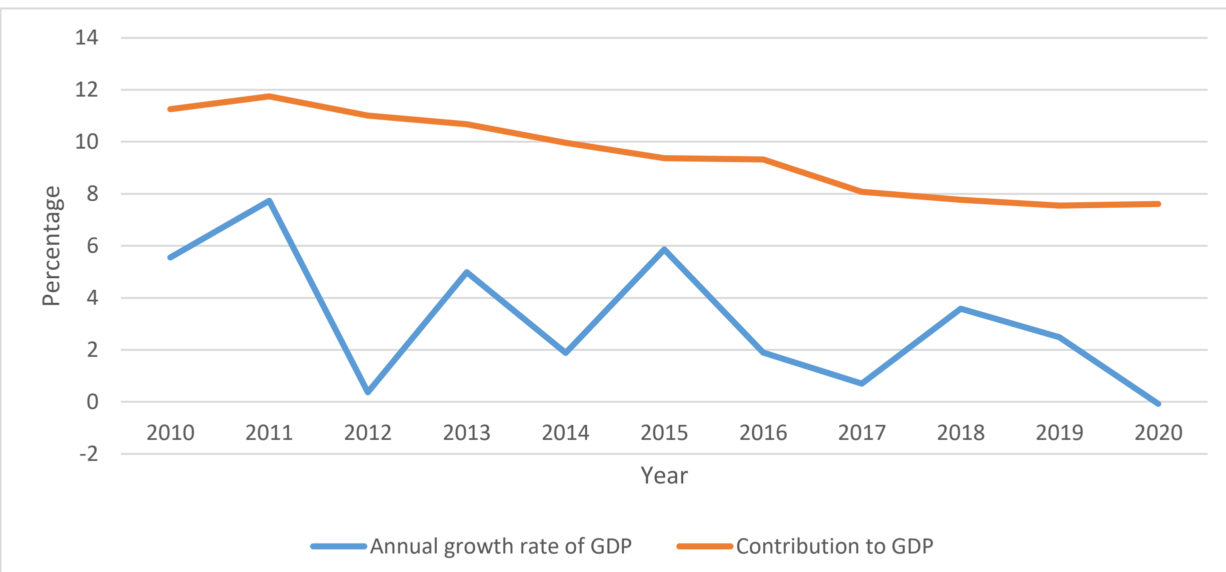

Figure 2.2:Performance of the manufacturing sector in Kenya (2010-2020)
Source: World Bank Indicators, 2021

Figure 2.2 illustrates that the manufacturing sector's growth rate remained unstable through the period 2010-2020. The sector's contribution to GDP displayed a declining trend over the same period. With the declining contribution to GDP, there is doubt if the manufacturing sector will achieve its set target of contributing 15 percent of the total GDP in 2022 as envisioned in the 'Big Four' Agenda (KAM, 2018a).

Failure of the manufacturing sector to match increased energy demand to improved performance could bring into question the sector's magnitude of energy efficiency. This calls for an analytical analysis of the sector's energy efficiency to ascertain the actual level of inefficiencies and potential ways to abate these inefficiencies. The ability to enhance energy efficiency nonetheless is expected to change across sub-sectors. This is because sub-sectors differ in terms of the structure of their capital, quality of labour force, and manufacturing output. This study, therefore, takes a sub-sector approach. The sub-sectors of concern were: chemicals, pharmaceuticals and plastics, food, textile and garments, and paper and other manufacturing sub-sectors.

The food sub-sector consists of alcoholic beverages and spirits, cocoa, chocolate, sugar and confectionery products, bakery and miller's products, dairy products, juices, water and other soft drinks, meat products, tobacco, and edible oils (KAM, 2018b). The sub-sector significantly adds to the total manufacturing sector's input to GDP. For example, in 2015, the sub-sector contributed 52 percent of the manufacturing sector's input to GDP (KAM, 2018a). The chemicals, pharmaceuticals and plastics sub-sector consists of paints and resins, agrochemicals, cosmetics and hygiene products, pharmaceutical and health care products, PVC pipes and fittings, packaging bags, plastics shoes, crates, bottles, floor tiles, household wares, and containers (KAM 2018b). In 2015, the sub-sector contributed around 13 percent of the manufacturing sector's input to GDP (KAM, 2018a). It is immensely reliant on imported raw materials.

The textiles and garments sub-sector is labour-intensive and consists of textile and apparel products for local and export markets. Regional markets consume most of the exports. The sub-sector contributed about 8 percent of the manufacturing sector's input to GDP in 2015(KAM, 2018a). Finally, paper and other manufacturing sub-sector contributed 27 percent of the overall manufacturing sector's input to GDP in the same year (KAM, 2018a). The sub-sector consists of other firms that are not included in the three major sub-sectors. It includes firms in paper products, basic metals, fabricated metals, print media, non-metallic minerals, wood and furniture, and transport equipment and machinery.

2.1.1 Statement of the Problem

Kenya's manufacturing sector is the biggest electricity end-user and second-largest fuel end-user after the transport sector (Republic of Kenya, 2018). This sector uses energy as an input in the manufacturing and transportation of goods and services. Even though energy is critical to this sector its use is linked to environmental degradation and high cost of production. In the wake of these shortcomings and intending to conserve energy, the intention to enhance energy efficiency in the manufacturing sector has received significant interest.

Various programmes have been initiated to help this sector enhance its energy efficiency. However, despite attempts to escalate energy efficiency, energy use in the sector has maintained an increasing trend over years. In the period 2010-2020, fuel use in the sector increased from 414.6 in thousand tonnes in 2010 to 635.5 thousand tonnes in 2019 but reduced to 494.4 thousand tonnes in 2020 due to a decrease in production resulting from COVID-19. Similarly, electricity use increased from 3204.9 GWh to 4441.0 GWh in the period 2010-2019 but reduced to 4281 GWh in 2020 (Republic of Kenya, 2014; 2021). Contrastingly, the sector's economic performance has remained unsatisfactory. The sector's growth rate was unsteady and dipped from 5.56 to 2.49 percent between 2010-2019. The growth rate dipped to -0.07 percent in 2020 due to COVID-19. Besides, the input to GDP by the sector dipped from 11.26 to 7.61 percent in the period under review. (Republic of Kenya, 2014; 2021).

The expansion in energy consumption that is not supported by an enhancement in the sector's economic performance raises uncertainty regarding the sector's energy efficiency level. The necessity to have an analytical assessment of the exact level of energy efficiency and practical actions to ease existing inefficiencies in Kenya's manufacturing sector need not be overstated. Whereas several studies such as Blomberg et al., (2012), Mandal and Madheswaran (2011), Li and Shi (2014), Filippini and Zhang (2016) and Moon and Min (2017) have estimated energy efficiency in the manufacturing sector in different countries, empirical evidence in Kenya's manufacturing sector is scant. The scarce associated research concentrates on the approaches of executing energy efficiency or focuses on energy efficiency at the economy-wide level. For example, Ndichu et al. (2015) investigate methods of implementing energy efficiency in maize milling firms whilst Zhang et al. (2011) analyze economy-wide total factor energy efficiency. This study aimed to fill the gap in research by presenting analytical evidence in Kenya's manufacturing sector. This objective was realized by providing an analysis of sub-sector energy efficiency differences and drivers of energy efficiency besides exploring energy efficiency change. An understanding of energy efficiency drivers in addition to energy efficiency change is useful in formulating policies to enhance energy efficiency.

2.1.2 Research Questions

The study addressed the following questions:

i. What are the sub-sector energy efficiency differences in Kenya's manufacturing sector?
ii. What is the extent of energy efficiency change over time in Kenya's manufacturing sector?
iii. What are the drivers of energy efficiency in Kenya's manufacturing sector?

2.1.3 Objectives of the Study

The general objective of the study was to analyze energy efficiency in Kenya's manufacturing sector. Specifically, this study sought to:

i. To analyze sub-sector energy efficiency differences in Kenya's manufacturing sector.
ii. To assess the extent of energy efficiency change over time in Kenya's manufacturing sector.
iii. To establish drivers of energy efficiency in Kenya's manufacturing sector.

2.1.4 Significance of the Study

Through several avenues, this research furthers extant literature on energy efficiency. First, the research gives empirical evidence on sub-sector energy efficiency differences in Kenya's manufacturing sector. This is provided separately for electricity and fuel. Analyzing electricity efficiency and fuel efficiency distinctly is important given that the production process's needs vary in energy form (Boyd and Lee, 2019). The less efficient manufacturing firms could use the results of this study in identifying well-performing peers from whom they can learn energy-efficient techniques. This analysis is important in revealing possible gains in terms of energy-saving and ultimately energy cost savings that may be realized by enhancing energy efficiency. Such information is useful to the manufacturing sector in devising policies to promote firm competitiveness. Second, information from this study will be useful in shaping policies to promote environmental quality. Third, understanding the drivers of energy efficiency and what causes energy efficiency change is fundamental in the design and execution of sound and effective energy efficiency policies by the Ministry of Energy and Petroleum and manufacturing firms.

2.2 Literature Review

2.2.1 Theoretical Literature

The central purpose of the broad application of efficiency analysis in economics is that contrasting the neoclassical theory, which assumes all firms to be perfectly efficient, firms are in practice never perfectly efficient. The neoclassical theory assumes that all economic actors have a maximizing behaviour with intentions to maximize profits and minimize costs and are in full knowledge of production possibilities. The theory further assumes that there exists a competitive environment where all inefficient entities are cleared from the market (Mefford, 2017). These assumptions have nevertheless been called into question following theoretical research on market failures. Owing to factors such as information asymmetry, agency problem and bargaining or contract costs, the assumptions may not hold (Abadi, 2014).

In reality, two alike firms never produce similar amounts of output. In addition, input usage, costs, and profits are never the same. Differences in output levels, input usage, costs, and profits can be described in the context of technical and allocative inefficiencies and some unpredicted exogenous disturbances. Technical efficiency is concerned with the quality in which firms transform inputs to outputs while allocative efficiency is concerned with how firms assign resources to production given their prices. A large part of research on efficiency assessment has nevertheless centred on assessing technical efficiency. This is because in most cases, data on input prices required for evaluating allocative efficiency is not available (Kumbhakar and Tsionas, 2006). Consequently, this study bases the measurement of energy efficiency on technical efficiency where the quality in which energy input is applied in the production process is evaluated.

The concept of technical efficiency is grounded in production theory. In this theory, production is defined as the process by which inputs are converted to output (Jehle and Reny, 2011). A production function describes the technology in a firm and the level of output that can be generated from a specified amount of inputs (Coelli et al., 2005). The state of technology describes the combinations of inputs and output that are technically feasible (Jehle and Reny, 2011). A firm’s production technology is specified through a behavioural objective function, such as cost minimization or profit maximization or a distance function expressed using input and output production technology (Coelli et al., 2005). According to Christensen and Greene (1976), a production function is preferred in empirical works whenever the output is endogenous.

Assessment of technical efficiency was initiated by seminal studies of Debreu (1951) and Farrell (1957). Previous attempts to estimate efficiency only produced unconvincing outcomes. One of the key causes of such outcomes is the failure to base measurement on theory. For instance, it was the norm to use a single-factor measure of efficiency. Under this measure, energy intensity is applied to indicate energy efficiency. It is expressed as the ratio of energy input to output and the inverse of this ratio indicates energy efficiency. A highly valued level of energy intensity suggests low energy efficiency while a low value of energy intensity suggests high energy efficiency. The weakness of the single-factor measure lies in its assumption that production involves the use of one input only, yet in reality, production involves the use of many inputs. Further, by assuming the use of one input only, it ignores the possibility of substitution among inputs. The seminal studies of Debreu (1951) and Farrell (1957) overcome such shortcomings by framing technical efficiency on production theory. This theory acknowledges that production involves the use of several inputs, primary among them being capital, labour, materials, and energy. It is the quality with which firms convert inputs to output that determines the level of technical efficiency.

The Jovanovic (1982) theory partly explains variations in technical efficiency in firms. The theory specifically describes how firm size and age affect technical efficiency. Regarding firm size and technical efficiency, the Jovanovic theory argues that large firms are more technically efficient compared to small firms. This is because firms self-select themselves. Firms with higher technical efficiency survive and grow whereas lowly technical efficient firms remain sluggish or exit the market. The self-selection process is also implicated in the firm age and technical efficiency relationship. Old firms are anticipated to be highly technically efficient compared to young firms. According to the Jovanovic theory, new entrants have limited knowledge of their potential and require time to realize this potential. Their older counterparts on the other hand capitalize on gains from learning by doing. Thus as time moves, the least technically efficient firms clear from the market leaving the more technically efficient firms in each age group.

The gender socialization and ethicality theories could partly explain variations in energy efficiency across firms. Women have been observed to be considerate and ethically caring (Atif et al., 2021). This consists of a considerable emphasis to cut off undesirable business habits, including those that lead to environmental degradation. According to the gender socialization and ethicality theories, there are two reasons why women might be more concerned about greater societal issues. First, to women, morality is about responsibilities which include the duty to care about others in addition to the duty to alleviate recognizable troubles of this world (Gilligan, 1977). Second, women have a helping conduct characterized by a caring and fostering character for the long term (Atief et al., 2021). Given that promoting environmental quality requires long-term strategies, women are expected to be more inclined to adopt such strategies. According to Atief et al. (2021), current research reveals that women leadership addresses global warming as indicated by shifts towards energy efficiency and green building in addition to the execution of climate change policies. Therefore, firms with female ownership are expected to be more energy efficient as energy efficiency measures are linked to promoting environmental quality.

2.2.2 Empirical Literature

This section focuses on various strands of literature relating to the estimation of energy efficiency. The first strand concentrates on the various energy efficiency measurement approaches. Literature provides two broad approaches to the measurement of energy efficiency: the one-factor measure and the total-factor measure. In the single-factor measure, energy intensity is traditionally used to indicate energy efficiency. This measure has been applied by several studies such as Sahu and Narayanan (2011b) in India's manufacturing sector, Montalbano and Nenci (2019) in Latin America's manufacturing firms and Bogoviz et al. (2018) in Russia's industrial sector.

While energy intensity is simple to compute and understand, it is not a suitable measure of energy efficiency (Lundgren, et al.,2016). This is because it is a single-factor measure that fails to recognize that production involves other inputs other than energy. This makes it impossible to indicate substitution possibilities between factor inputs.

The total factor measure acknowledges that the current production system is grounded on the application of many inputs. (Lin and Long, 2015). The measure, therefore, recognizes the substitution of factor inputs by firms. The non-parametric (DEA) and parametric (SFA) techniques dominate the total factor measure. Under DEA, efficiency is determined by the application of linear programming which entails the construction of a piecewise best linear frontier from observed data. Points deviating from the benchmark frontier are labelled as inefficiency measures. DMUs resting on the benchmark frontier are labelled efficient. Because DEA does not demand a prior description of a functional form, studies applying it are less likely to suffer from functional form misspecification errors. In addition, DEA is advantageous because it accommodates multiple inputs and outputs and does not suffer from statistical issues due to its non-parametric nature.

Examples of DEA employment are Mukherjee (2008a) in the estimation of energy efficiency in U. S's manufacturing sector in the period 1970-2001 and Mukherjee (2008b) in the estimation of India's manufacturing sector energy efficiency. In the Indian cement firms, Mandal and Madheswaran (2011) apply a micro panel during the period 1989-90 to 2006-07 to investigate energy efficiency. Al-Refaie et al. (2016) estimate energy efficiency in Jordan's industrial sector during the period 1999-2013. In Korea, Moon and Min (2017) assess pure energy efficiency and economic efficiency in energy-intensive firms using data for 63 firms running from 2012-2014. Li and Shi (2014) apply DEA to estimate China's industrial sector energy efficiency using data for the period 2001-2010. In India's paper industry, Haider et al. (2019) employ a panel of 67 firms during the period 2003-2004 to analyze energy efficiency. However, given that DEA presumes that entire departures from the best linear frontier are because of inefficiency, studies employing DEA could potentially overvalue or undervalue energy efficiency levels (Chirwa, 2001).

By using SFA, this problem is controlled. This is because SFA considers that both random variations and inefficiency could contribute to deviations from the linear best frontier. Examples of SFA applications include Lundgren et al. (2016) who analyze Sweden's manufacturing sector energy efficiency by applying an unbalanced panel of 4297 firms running from 2000-2008. In the Chinese chemical industry, Ling and Long (2015) analyze energy efficiency by utilizing a panel of 30 provinces during the period 2005-2011. With the employment of a firm-level panel during the period 1987-2012, Boyd and Lee (2019) analyze energy efficiency in U. S's metal-based durable manufacturing sectors. Other applications of SFA are Filippini and Hunt (2011) in the assessment of 29 OECD economies' energy demand and energy efficiency during the period 1978-2006 and Filippini and Zhang (2016) in the analysis of 29 Chinese provinces' energy efficiency using data running from 2003-2012.

The next part of the literature focuses on the objectives assumed during estimation. Examination of energy efficiency is founded on two main fundamental objectives; the energy conservation objective and the economic objective. The energy conservation objective is mainly pursued whenever the goal for a cut in energy use is to improve environmental quality. This is attained through a cut in emissions resulting from fossil fuel combustion (Mukherjee, 2008a). Under this objective, the level of energy efficiency is obtained through the technical efficiency approach. An essential benefit of this method is that it needs less information. Only information on the quantity of output and inputs is needed whereas the economic objective needs information on the input and output prices in addition to the quantity of output and inputs. Studies that have adopted this objective include Mukherjee (2008a) in the US manufacturing sector, Mukherjee (2008b) in India's manufacturing sector, and Lin and Long (2015) in China's chemical industry.

The economic objective is comprised of two sub-objectives; cost minimization and profit maximization. Under cost minimization, researchers analyze cost efficiency while profit efficiency is analyzed under profit maximization. Cost minimization however remains the most predominantly assumed sub-objective. Studies that have assumed this sub-objective are Mukherjee (2008a) in the U. S's manufacturing sector, Mukherjee (2008b) in the manufacturing sector in India, Lundgren et al. (2016) in Swedish manufacturing, and Boyd and Lee (2019) in the metal-based durable industry in the U.S. Under this sub-objective, energy efficiency is computed as the ratio of optimum energy use resulting from the cost minimization bundle to the exact energy consumed.

The attainment of cost efficiency requires firms to allocate inputs efficiently given the input prices. Input prices may however fail to change in the same proportion and hence a firm may be compelled to vary the input portions in response to the price changes. For example, during a period of high energy price, a change in input proportions may call for the substitution of the low-priced inputs for the relatively highly-priced energy (Mukherjee, 2008a). Substitution of the cheaper inputs for the relatively expensive energy may make energy reductions to be higher than those made under the energy conservation objective. For instance, in the U.S manufacturing sector, Mukherjee (2008b) finds energy efficiency scores from the cost minimization bundle to be lower than those from the energy conservation objective. The relatively lower efficiency scores imply that US manufacturing has a higher potential to reduce energy use under the cost minimization objective than under the energy conservation objective.

Nevertheless, the cost minimization objective may fail to guarantee a reduction in energy use. In occasions where the energy prices are relatively low, the cost minimization objective may advocate for use of more energy by substituting energy for the highly-priced factors of production. For instance, in the manufacturing sector in India, Mukherjee (2008a) find energy efficiency scores got from the cost minimization objective to be larger than those got from the energy conservation objective. This implies that fewer energy reductions should be made in the cost minimization objective than in the energy conservation objective. Mukherjee (2008a) and Ling and Long (2015) argue that this happens because the prices used in the computation of energy efficiency under the cost minimization approach do not account for social costs such as environmental and intergenerational costs. For instance, failure to account for externalities in energy prices may make energy appear relatively cheaper thus leading to more of its consumption.

In addition, the cost minimization objective fails to account for price regulation and imperfect market competition (Lin and Long, 2015). In many instances where the government is regulating energy prices, prices paid by users are often lower than those that would have been dictated by a competitive market and hence encouraging more consumption of energy.

The third strand of the literature concentrates on variations in findings by various studies. Researchers seem to agree that there exists sizable room to increase energy efficiency in the manufacturing sector. The room to enhance energy efficiency is found to vary across firms and localities. Considering differences across firms, Ohlan (2019) in India's iron and steel industry, finds bigger firms to be more energy-efficient than small and medium firms. In U. S's metal-based durable manufacturing sector, Boyd and Lee (2009) establish that new firms are better in energy efficiency compared to old firms. Mukherjee (2008a) establishes that in U.S manufacturing, the highest energy-using sub-sectors are more efficient compared to low energy-using sub-sectors. Lundgren et al. (2016) establish that in the Swedish manufacturing sector, the fabricated metal sub-sector performs best in fuel efficiency whilst the food sub-sector performs the least. The rubber/plastics sub-sector is observed to perform best in electricity efficiency as the stone/mineral sub-sector performs the least.

Concerning variation across localities, Mukherjee (2008b) observes that in the manufacturing sector in India, Goa, Haryana, and Maharashtra regions are the most energy-efficient whilst Andhra Pradesh, Madhya Pradesh, Orissa, and Rajasthan regions are the least energy efficient. In the chemical industry in China, Lin and Long (2015) find the Eastern region to be the most energy-efficient while the Western region is the least energy efficient. Bhat et al. (2018) find that in the Indian pulp industry, Bihar, Goa and Rajasthan states are on the efficient frontier while

Chhattisgarh, Andhra Pradesh and West Bengal, Gujarat and Karnataka states have a big room to enhance energy efficiency. In China's iron and steel industry, Lin and Wang (2014) find firms located in the North to be more energy-efficient compared to those situated in the West and Central parts.

To explain variations in results, several studies have shown effort in exploring drivers of energy efficiency. The first is ownership structure. In this case, firms are classified as local or foreign-owned. Sahu and Narayanan (2011b) in the manufacturing sector in India establish that foreign ownership promotes energy efficiency. The second is firm size. Lin and Long (2015) in the Chinese chemical industry, Lundgren et al. (2016) in Sweden's manufacturing, and Moon and Min (2017) in Korea's high energy-consuming firms find energy efficiency to increase with firm size. Contrasting small firms, large firms are characterized by better-skilled management, ample finance to procure superior technologies, and the potential to utilize economies of scale.

Some studies find a non-linear (Inverted-U shape) link between energy efficiency and firm size, indicating that very small and very large firms are potentially less energy efficient. As firms expand their scale of production, they become more energy efficient but after a certain scale of production, their internal structures get complicated making them consume more energy. This offsets gains made by firms in their relatively smaller scale of production. The studies include Mandal and Madheswaran (2011) in the cement industry in India, Sahu and Narayanan (2011b) in India's manufacturing industries, Li and Shi (2014) in the Chinese industry, and Haider et al. (2019) in the paper industry in India.

The third is exporting. Roy and Yasar (2015) on Indonesian firms and Campi et al. (2015) on Spanish firms find exporting to promote energy efficiency. By exporting, firms get exposed to technological innovations and their employees are introduced to better management practices. This outcome could also be due to firms adjusting to clean technologies as they comply with environmental standards set by importing countries (Roy and Yasar, 2015).

The fourth is firm age. Sahu and Narayanan (2011b) in the Indian manufacturing sector, Boyd and Lee (2019) in U. S's durable metal-based industry, and Haider et al. (2019) in India's paper industry establish that young firms have higher energy efficiency compared to older firms. Young firms operate under new technologies while old firms are characterized by old equipment which makes them less energy efficient. Nevertheless, in the Indian cement industry, Mandal and Madheswaran (2011) establish firm age to have an insignificant influence on energy efficiency.

The fifth is labour productivity. Lin et al. (2011) in China's steel industry, Mukherjee, (2008b) in the Indian manufacturing sector, and Mandal and Madheswaran, (2011) in India's cement industry find labour productivity to positively influence energy efficiency. According to Mandal and Madheswaran (2011), high labour productivity is characterized by the use of specialized energy-efficient technologies. However, in India's manufacturing sector, Sahu and Narayanan (2011b) establish that labour productivity has an insignificant influence on energy efficiency.

The sixth is R&D. Lutz et al. (2017) in the German manufacturing firms and Lin et al. (2011) in the Chinese steel industry establish that R&D promotes energy efficiency. By financing R&D activities, firms become more innovative and get to learn about specialized technologies that help them enhance energy efficiency. In contrast, Sahu and Narayanan (2011b) establish that R&D investments negatively affect energy efficiency. The study observes that firm-level data used does not classify whether R&D investments made are for product upgrading or coming up with energy-efficient technologies. Thus, the negative relationship between R&D and energy efficiency could imply that R&D investments were utilized on techniques to enhance products that could be energy-intensive and not in developing energy-efficient technologies. R&D's effect on energy efficiency is found to be insignificant by Li and Shi (2014) in China's industrial sectors and Haider et al. (2019) in India's paper industry. Li and Shi (2014) hold that this outcome could be due to the inability to peel off R&D expenditure on energy efficiency from total spending on R&D.

The fourth strand of literature looks at studies that have examined energy efficiency change. For U.S manufacturing, Boyd and Lee (2019) by employing SFA and using a panel for the period 1987-2012 examine energy efficiency change using the Malmquist index. The study finds modest advances in electricity efficiency while fuel efficiency has varying changes with both improvements and declines. In both instances, advances are a result of technological change. In addition, the inability to catch up, measured by efficiency change, erodes the improvement resulting from technical change leading to negative energy efficiency change in some sectors. By use of DEA, Wei et al. (2007) perform a similar estimation in china's iron and steel sector using a panel for the period 1994-2003. The study finds substantial improvement in energy efficiency both in state-owned and private-owned plants. This improvement is largely credited to technical change.

Still, in China, Wu et al. (2012) perform a non-parametric examination of energy efficiency for the industrial sector through the period 1997-2008. The study reveals that energy efficiency change improved over time. Efficiency change contributed negatively to this change while technological change had a positive contribution which overrun the negative effect of efficiency change giving an overall improvement in energy efficiency change. In Europe, Morfeldt and Silveira (2014) investigate energy efficiency trends in the iron and steel industry through the period 2000-2010 using DEA. While examining these trends, four-phase periods are identified where energy efficiency change is found to vary from improvements to declines. The decomposition of energy efficiency change reveals mixed contributions of catching up effect and technological change on energy efficiency change.

In a recent study for the European Union, Makridou et al. (2016) analyze energy efficiency trends of the high energy-using industries for the period 2000-2009. Findings show that there is a general improvement in energy efficiency across all sectors throughout the study period. A decomposition of the Malmquist Index reveals that most of the improvements in the majority of the sectors could be attributed to technical change. Contribution of efficiency change to overall energy efficiency improvement is at moderate levels.

2.2.3 Overview of Literature

Estimation of technical efficiency is centred on the seminal works of Debreu (1951) and Farrel (1957). These works were a departure from the neoclassical theory which presumed that all DMUs are perfectly efficient. The seminal works acknowledge the presence of inefficiency in the real world. Such inefficiencies are caused by several factors: information asymmetries, agency problem, bargaining, or contract costs among others.

Empirical studies provide two methods of measuring energy efficiency: the one-factor method and the total-factor method. Under the single-factor method, studies adopt energy intensity. This method is considered unsuitable for it is assumed that production involves the use of energy as the only factor of production, yet many factors are used. Further, it ignores substitution between factors of production.

The total factor method overcomes these shortcomings. Under this method are the non-parametric and parametric techniques. DEA dominates the non-parametric technique. This approach has several advantages. First, it accommodates numerous inputs and numerous outputs. Second, it is free from functional misspecification errors because it does not necessitate a prior description of the production function. Finally, it is immune from statistical issues due to its non-parametric nature. However, DEA may provide misleading efficiency scores given that it assumes all deviations from the benchmark frontier are a result of inefficiency. In reality, departures from the benchmark frontier are a consequence of both inefficiency and random shocks. The parametric approach dominated by SFA acknowledges the presence of random shocks and inefficiencies.

Reviewed literature shows that researchers assume two objectives when estimating energy efficiency: energy conservation objective and economic objective. Under the energy conservation objective, researchers' main goal is to achieve a cut in energy consumption to improve environmental quality. On the economic objective, researchers aim at cost minimization or profit maximization but cost maximization is predominantly assumed. This objective has however been put into question given that in nearly all cases, prices of energy do not account for social costs such as environmental and intergenerational costs, price regulation, and imperfect market competition.

Findings from reviewed studies indicate that there exists room to enhance energy efficiency in the manufacturing sector. This potential varies among sub-sectors as found by Mukherjee (2008a) and Lundgren et al. (2016) and regions as found by Mukherjee (2008b), Lin and Long (2015), Lin and Wang (2014). Reviewed literature indicates that several factors are liable to variations in energy efficiency: ownership structure (for example Sahu and Narayanan, 2011b), firm size (for instance Lin and Long, 2015; Lundgren et al., 2016; Moon and Min, 2017; Sahu and Narayanan, 2011b; Mandal and Madheswaran, 2011; Li and Shi, 2014; Haider et al., 2019), exporting (for example Roy and Yasar, 2015; Campi et al., 2015), firm age (For example Sahu and Narayanan, 2011b; Boyd and Lee, 2019; Haider et al., 2019), labour productivity (for example Mukherjee, 2008b; Lin et al., 2011; Mandal and Madheswaran, 2011) and R&D (for instance Lin et al., 2011; Lutz et al., 2017).

Finally, almost all studies reviewed report an improvement in energy efficiency over time. These include Boyd and Lee (2019), Wei at al. (2007), Wu et al. (2012), Morfeldt and Silveira (2014), and Makridou et al. (2016). A further decomposition of the efficiency change reveals that in almost all studies technical change positively influenced enhancements in energy efficiency while efficiency change contributed negatively.

Reviewed literature shows that there is scant empirical evidence on energy efficiency in the manufacturing sector in developing economies and in particular Kenya. The few existing related studies focus on analysing economy-wide energy efficiency or investigating the execution of energy efficiency strategies. For example, Zhang et al. (2011) investigate economy-wide total factor energy efficiency whilst Ndichu et al. (2015) investigate the extent of the application of energy efficiency methods in Kenya's maize milling firms. Further, evidence of energy efficiency change is scanty. This study sets out to analyze energy efficiency, its determinants and energy efficiency change in Kenya's manufacturing sector. Part of this thesis's novelty is the assessment of the effect of top manager's experience and female firm-ownership on energy efficiency. Because SFA recognizes the contribution of both random shocks and inefficiencies in explaining deviations from the best linear frontier, it is preferred in this study over DEA.

2.3 Methodology

2.3.1 Theoretical Framework

Debreu (1951) and Farrel (1957) provided groundbreaking studies in production efficiency. Debreu (1951) introduced the estimation of technical efficiency under the output-orientation approach while Farrel (1957) established the measurement of technical efficiency under the input-oriented approach. The output-oriented measure ascertains the quantity of output that can be proportionately raised with no change in input levels. The input-oriented measure determines the maximum proportionate cut in inputs without a change in output. According to Kumbharkar (2000), the two approaches are jointly referred to as Debreu-Farrel efficiency and they form the basis for analysis in the present research.

Assume a firm that produces output, Q, using Z inputs under the input vector $X \equiv x_1, \dots, x_z$. Following Aigner et al. (1977) its stochastic production frontier can be expressed as:

$$Q_i = \mathrm{g}(X_i, \alpha) + \varepsilon_i; \quad \varepsilon_i = \mu_i - \nu_i \tag{2.01}$$

Where *i* represents the observation of the *i*th firm (i = 1,…, N; N is the total number of firms), Q_i is the output of the *i*th firm, $g(.)$ is the production technology, X_i is a vector of factor input quantities for the *i*th firm, and α is a vector of parameters. $\varepsilon_i$is a composite error term comprised of the symmetric disturbance component (μ_i) and the technical inefficiency component ($-\,v_i$). Following Kumbhakar and Lovell (2000), it is presumed that the disturbance term has similar properties as the disturbance term in the classical linear regression model (CLRM). Thus it is independent and identically distributed with N(0, σ_μ^2). The technical inefficiency term has the same properties but its mean is truncated at zero to ensure that all the inefficiencies are non-negative. It is thus an independent and identically distributed truncated random variable with $N^+(\upsilon, \sigma_\nu^2), \upsilon > 0$.

Other often adopted models for the inefficiency term are the half-normal model ($N^+(0, \sigma_\nu^2)$, exponential model $N^+(\lambda, \sigma_\nu^2)$ and gamma model ($N^+(\lambda, m)$, where m is the degree of freedom (Coelli et al., 2005). The terms μ_i and ν_i are further presumed to be homoskedastic [E($\mu_i{}^2) = \sigma_\mu^2$ and E($\nu_i{}^2) = \sigma_\nu^2$] and distributed independently of each other [E($\mu_i \mu_j) = 0$ and E($\nu_i \nu_j) = 0$] and of explanatory variables. The random component (μ_i) accounts for aspects that cannot be managed by the firm. Examples of such are measurement errors in the dependent variable, omitted regressors, and machine performance (Aigner et al., 1977). This makes the deterministic component ($g(X_i, \alpha)$) to vary across firms. The technical inefficiency component (ν_i) on the flip side represents deviations from the stochastic production frontier ($g(X_i, \alpha) + \varepsilon_i$) that are within the control of the firm.

Considering energy conservation is the objective of the firm, the study follows Lin and Long (2015) in employing a stochastic input distance function form of the input-oriented model suggested by Shephard (1970). This equation is written as follows:

$$D(Q, X) = \max\{\gamma\colon X/\gamma \mid \gamma \in W^t(Q)\}, \qquad W^t(Q) = \{ X \epsilon\, R_+^Z\colon \text{X can produce Q}\} \qquad (2.02)$$

where X is an input vector and Q is an output vector. γ is a positive scaler “distance” by which the input vector can be deflated and $W^t(Q)$ is the technology set which encompasses a set of all input vectors, Xϵ R_+^Z, which can potentially generate output vector $Q \epsilon R_+^H$.

Equation (2.02), suggests that at time *t*, for an identified level of output vector Q and the existing technology, the input vector X is cut by the largest fraction and for any practical output, $D(Q, X) \geq 1$. If $D(Q, X) = 1$, point (X, Q) lies on the production frontier, an indication of full efficiency. If $D(Q, X) > 1$, point (X, Q) lies outside the frontier signalling that possibly, technical inefficiency exists in the production process (Lin and Wang, 2014). It is assumed that the input distance function is linearly homogeneous and non-declining in inputs, declining in output, concave in the input vector and quasi-concave in the output vector (Coelli, 2000; Lin and Long, 2015).

As provided by Boyd (2008) and Zhou et al. (2008), a sub-vector input distance function can be feasibly developed from equation (2.02) by scaling a subset of some inputs while letting others remain unchanged. Because this research aims at finding the maximum feasible proportionate reduction in energy consumption, energy is scaled as follows:

$$D_I(X_{z-1}, R, Q) = \max\{\ \gamma : (X_{z-1}, \frac{\mathrm{R}}{\gamma}, Q) \in W,\ W = \{\ (X,Q) : (X\ ) \text{ produces } Q\} \qquad (2.03)$$

Where X_{z-1} is a *Z-1* vector of fixed inputs, R is energy and Q is output.

The sub-vector input distance function can also be explained graphically as follows:

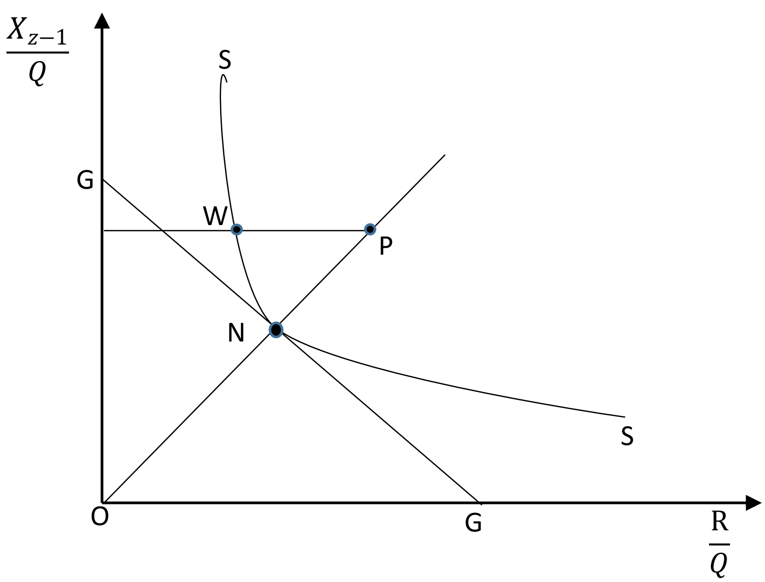

Figure 2.1: Shepard Input Distance Function
Source: Boyd and Lee (2019)

In Figure 2.1, SS signifies the full technical efficiency isoquant and GG denotes the isocost line. Points W and N represent technically efficient DMUs given that they sit on the efficient frontier. If a DMU produces a unit of output with the application of inputs outlined by point P, line NP signifies the input distance function. This is the amount by which all inputs could be proportionately scaled down with no drop in output level. The technical efficiency of this DMU is the ratio OP/ON. This study is however not interested in the whole vector of inputs, but the distance covered by energy. Thus, a sub-vector energy input distance is obtained by letting energy be a variable input while other inputs remain fixed. The energy sub-vector input distance is represented by the line WP, denoting the maximum amount possible to proportionately reduce energy use with no change in output level. In this case, the ratio OP/OW provides the energy efficiency of the DMU.

2.3.1.1 Malmquist Index Decomposition

The Malmquist Index is a measure of productivity change first proposed by Malmquist (1953). Caves et al. (1982) later developed it by extending its measurement to the application of distance functions. The index presumes that the majority of firms lie inside the production frontier. The best practice observations lie on the frontier's surface and any productivity change is a consequence of technological and efficiency changes. Technical change denotes a shift in the production frontier. The shift may be positive indicating technological improvement or negative indicating a decline in technology. Technological improvements may be achieved directly through innovations or indirectly by spillover effects. On the other hand, efficiency change indicates that non-best practice firms are moving nearer to or far away from the best frontier.

This study only focuses on energy efficiency, thus technical change and efficiency change refer to energy efficiency, not the whole production technology. To determine the Malmquist Index of energy efficiency change, the study follows Boyd and Lee (2019) and (Wei et al., 2007). Suppose there are two periods, *s* and *t* with *s* as the reference period. The Malmquist index of energy efficiency change between periods *s* and *t* is expressed as the geometric mean of the ratio of the input distance function in every period, estimated at the examined input-output mix (Boyd and Lee, 2019). This index estimates the total change in relative efficiency (that is, the total change in how far observed energy use is from the lowest possible energy use) from period *s* to *t* (Wei, et al., 2007). The index is expressed as

$$\mathrm{M_i}\ (q^t, x^t, q^s, x^s) = [\frac{D_i^s(q^s,x^s)D_i^t(q^s,x^s)}{D_i^s(q^t,x^t)D_i^t(q^t,x^t)}]^{\frac{1}{2}} \tag{2.04}$$

where $\mathrm{M_i}$ is the Malmquist index of the *i*th firm, D_i is the input distance function and q and *x* are output and input vectors respectively. The index is then decomposed into its two parts, efficiency change and technical change, first introduced by Fare et al. (1994). This decomposition helps to distinguish factors that drive energy efficiency change. Efficiency change is expressed as

$$\mathrm{ME_i}\ (q^t, x^t, q^s, x^s)= [\frac{D_i^s(q^s,x^s)}{D_i^t(q^t,x^t)}] \tag{2.05}$$

where ME_i is the Malmquist efficiency change index of the *i*th firm. Equation (2.05) shows that efficiency change is the ratio between two consecutive input distance functions. It evaluates the firm's ability to increase efficiency from period *s* to *t* and is often used to denote a catching-up effect (Coelli et al., 2005). The energy efficiency measurement framework adopted by this study constructs a benchmark frontier based on the data from all firms in the sample. Each firm is compared to the benchmark frontier. The extent to which a firm is closer to the benchmark frontier is what is referred to as "catching up" (Wei et al., 2007). Following the definition of efficiency change, technical change, MTC_i, is expressed as

$$MTC_i\ (q^t, x^t, q^s, x^s)=[\frac{D_i^t(q^t,x^t)D_i^t(q^s,x^s)}{D_i^s(q^t,x^t)D_i^s(q^s,x^s)}]^{\frac{1}{2}} \qquad (2.06)$$

Thus,

$$M_i=ME_i.\ MTC_i \qquad (2.07)$$

2.3.2 Analytical Model

A functional form specification needs to be made before empirical estimation of equation (2.03). With the availability of panel data, a translog production function is assumed in this study. Contrasting the Cobb-Douglas production function, the translog production function is flexible, gives room to the interaction of variables and fulfils the convexity condition (Lin and Wang, 2014). In addition, the translog production function fulfils the condition of linear homogeneity in inputs. This condition is imposed by normalizing data. According to Kumbhakar et al. (2015), data is normalized by deflating the distance measure and the *Z-1* inputs by the *Z-th* input variable. Because energy is the variable of concern, it is treated as the numeraire variable as follows:

$$D_{Ii}X_{zi}^{-1}= \text{g}(x_{\ i}, Q_i) \qquad \text{where } x = ({}^{X_1}/_{X_z}, \dots, {}^{X_{z-1}}/_{X_z}) \qquad (2.08)$$

Taking logs on both sides yields:

$$ln\ D_{Ii}\text{- ln } X_{zi}= \text{ln g}(x_{\ i}, Q_i) \qquad (2.09)$$

The translog input distance function for equation (2.09) is presented as follows:

$$\begin{aligned}\text{Ln}D_{Iit}\text{-ln } R_{it} &= \alpha_0+ \alpha_q\text{ln } Q_{it}+ \alpha_k\text{ln } k_{it}+ \alpha_l\text{ln } l_{it}+ \alpha_m\text{ln } m_{it}+\alpha_T\, T_{it} + \frac{1}{2}\,\alpha_{qq}(\text{ln } Q_{it})^2+ \\ &\frac{1}{2}\,\alpha_{kk}(\text{ln } k_{it})^2+\frac{1}{2}\,\alpha_{ll}(\text{ln } l_{it})^2+\frac{1}{2}\,\alpha_{mm}(\text{ln } m_{it})^2+\alpha_{kl}\text{ln}k_{it}\text{ln}l_{it}+\alpha_{km}\text{ln}k_{it}\text{ln}m_{it}+ \\ &\alpha_{kq}\text{ln}k_{it}\text{ln}Q_{it}+\alpha_{lm}\text{ln}l_{it}\text{ln}m_{it}+\alpha_{lq}\text{ln}l\text{ln}Q_{it}+\alpha_{mq}\text{ln}m_{it}LnQ_{it}+\frac{1}{2}\,\alpha_{TT}(\text{ln } T_{it})^2+ \\ &\alpha_{kT}\text{ln}k_{it}\text{ln}T_{it}+ \alpha_{mT}\text{ln}m_{it}\text{ln}T_{it} + \alpha_{lT}\text{ln}l_{it}\text{ln}T_{it} + \alpha_q\text{ln}Q_{it}LnT_{it}\end{aligned} \qquad (2.10)$$

where $k_{it} = K_{it}/R_{it}$ is capital, $l_{it} = L_{it}/R_{it}$ is labour, R_{it} is energy, $m_{it} = M_{it}/R_{it}$ is materials, Q_{it} is output, *i* is firm and *t* is time. α_0, α_z, α_T, α_{zj}, α_{zT} are parameters to be estimated. T is a time trend incorporated to represent technical change.

For $\text{Ln}D_{Iit} \geq 0$, the following symmetric conditions should be fulfilled by equation (2.10).

$$\sum_z \alpha_{zj} = \sum_z \alpha_{zy} = \sum_z \alpha_{zT} = 0, \quad \alpha_{zj} = \alpha_{jz}, \quad z \neq j \tag{2.11}$$

$\text{Ln}D_{it}$ in equation (2.10) is not observable, indicating that assessment of the model is not practical. Therefore, the equation is reorganized to yield:

$$-\text{Ln}\, R_{it} = \text{g}(k_{it}, l_{it}, m_{it}, Q_{it}, T) - \text{Ln}D_{it} \tag{2.12}$$

LnD_{it} is an inefficiency term. Therefore letting $\text{Ln}D_{it} = v_{it}$, $v_{it} > 0$ and introducing the error term μ_{it} gives:

$$-\text{Ln}\, R_{it} = \text{g}(k_{it}, l_{it}, m_{it}, Q_{it}, T) + \mu_{it} - v_{it} \tag{2.13}$$

Equation (2.13) presents a stochastic frontier model for energy input. Taking antilog on this equation generates:

$$R_{it} = g(k_{it}, l_{it}, m_{it}, Q_{it}, T)\exp(-v_{it} + \mu_{it}) \tag{2.14}$$

where R_{it} indicates the actual energy input, $\text{g}(k_{it}, l_{it}, m_{it}, Q_{it}, T)$ denotes the derived energy demand function and $\exp(-v_{it} + \mu_{it})$ is a composite error component.

By using the Debreu-Farrell efficiency framework as the basis for modelling, the study considers the derived energy demand function to be the best linear frontier (Lin and Long, 2015). Deviations of the actual energy input from the best linear frontier denote the excess energy consumption originating from technical inefficiency. Detaching the inefficient component from the composite error $(-v_{it} + \mu_{it})$ yields the level of energy efficiency:

$$EF_{it} = \frac{E(R_{it}|v_{it=0}, k_{it}, l_{it}, m_{it}, Q_{it}, T)}{E(R_{it}|v_{it} \neq 0, k_{it}, l_{it}, m_{it}, Q_{it}, T)} = \frac{{R_{it}}^F}{R_{it}} = \exp(-v_{it}) \tag{2.15}$$

where *E(·)* indicates conditional expectation and EF_t denotes energy input efficiency, ${R_{it}}^F$ is the benchmark or minimum energy demand and R_{it} is the actual energy input of the *i*th firm in time t

Various panel data model specifications can be employed in the evaluation of a stochastic frontier function. These include the pooled model (PM), the random effects model (REM), the true fixed effects model (TFEM) and the true random effects model (TREM) (Filippini and Zhang, 2016)[1].

[1] For more detailed information on these models, see Farsi and Filippini (2009).

Further, in recent studies by Filippini and Hunt (2012;2013) on the aggregate energy demand, a segment of the stochastic frontier models has been analysed by an adjustment proposed by Mundlak (1978). This adjustment allows for prospective unobserved heterogeneity bias and splits transient inefficiency from time-invariant unobserved heterogeneity. The highlighted models are characterized by both strengths and weaknesses and the task of selecting a suitable model is not clear-cut. Model selection is dependent on the research objectives, data type and existing covariates (Filippini and Hunt, 2013).

The PM is the SFA model in its initial state introduced by Aigner et al. (1977) and modified for panel data by Pitt and Lee (1981). This model fails to capitalize on panel data by allowing for time-invariant unobserved heterogeneity. Thus, the model is subject to suffering from unobserved heterogeneity bias. In contrast, the REM proposed by Pitt and Lee (1981) acknowledges the standard panel data individual random effects as inefficiencies instead of unobserved heterogeneity as is the case in conventional literature on panel data econometrics (Filippini and Hunt, 2013).

To address this drawback by applying panel data, Greene (2005a;2005b) suggested TFEM and TREM through which the SFA model in its initial form is broadened by including fixed and random individual effects respectively. In TFEM and TREM, the intercept is substituted with a series of firm-specific fixed or random effects that allow for time-invariant unobserved heterogeneity. The TFEM and TREM can separate time-invariant unobserved heterogeneity from the time-varying level of efficiency component. Nonetheless, in these models, any time-invariant or persistent component of inefficiency is completely absorbed in the firm-specific constant terms (Filippini and Hunt, 2013). Thus, because some energy inefficiency sources can induce time-invariant excess energy use, these models' estimates could generate relatively high and inaccurate energy efficiency levels (Filippini and Hunt, 2011).

Lastly, the PM, REM and TREM could all suffer from 'unobserved heterogeneity bias'; for instance, a case where the correlation between observable and unobservable variables could bias some coefficients of the explanatory covariates (Filippini and Hunt, 2013). To attend to this problem, Farsi et al. (2005a; 2005b) suggested the use of the Mundlak version of the REM. The Mundlak version is where the correlation of the firm-specific effects and the explanatory covariates are considered in an auxiliary equation which is included in the main equation and estimated using the REM (Filippini and Hunt, 2013). Given that correlation between the individual-specific effects and the explanatory variables is at least partially captured in the model, the heterogeneity bias is predicted to be fairly low.

This model would be appropriate for this study. However, despite its attractive nature and that of other random and fixed effects models, the models failed to converge. The panel data suffers from a large number of entries and exits by firms so that only a few firms are in the sample for all the years included in the analysis. Consequently, following Filippini and Hunt (2011) the PM model fit by maximum likelihood estimation (MLE) was adopted in this study.

2.3.2.1 Likelihood Ratio Test

The generalised likelihood ratio (LR) test statistic is applied in testing for restrictions on parameters of the stochastic frontier. It has a chi-square distribution with the degrees of freedom (j) defined by the number of restricted parameters. The restricted model is captured by the null hypothesis (H_0) while the unrestricted model is captured by the alternative hypothesis (H_1). Following Coelli et al. (2005), the LR test statistic is computed as follows:

$$\mathrm{LR} = -2[\ln(\mathrm{l}(\mathrm{H}_0)) - \ln(\mathrm{l}(\mathrm{H}_1))] \sim \chi^2_{\mathrm{j}} \qquad (2.16)$$

where $l(H_0)$ is the log-likelihood function value for the model with restricted parameters as identified by the null hypothesis and $l(H_1)$ is the log-likelihood function value for the model with unrestricted parameters as stated by the alternative hypothesis. At a level of significance, θ, the null hypothesis (H_0) is rejected if the computed LR overdoes the critical value $\chi^2_{1-\theta}$(j).

2.3.2.2 Malmquist Decomposition of Energy Efficiency Change

To evaluate and decompose the Malmquist index, this study uses the outcome of the translog input distance function obtained in the SFA first-stage estimation. On one hand, the efficiency change index for the *i*th firm is obtained as:

$$ME_i = \frac{EF_{it}}{EF_{is}} \qquad (2.17)$$

where EF_{it} is the energy efficiency for the *i*th firm in period *t* and EF_{is} is the energy efficiency for the *i*th firm in period *s*. On the other hand, the technical change index from period *s* to *t* is computed right from the estimated parameters of the translog input distance function. Following Coelli et al. (2005), the process involves first getting the partial derivatives of the translog production function provided in equation (2.10) with respect to time using firm data for the *i*th firm for periods *s* and *t*. For period s, technical change is provided as

$$\frac{\partial lnR_{is}}{\partial T} = \alpha_T + \alpha_{TT}T + \alpha_{qT}lnQ_{is} + \sum_{z=1}^{3} \alpha_{zT}lnX_{zis} \tag{2.18}$$

and period t technical change is provided as

$$\frac{\partial lnR_{it}}{\partial T} = \alpha_T + \alpha_{TT}T + \alpha_{qT}lnQ_{it} + \sum_{z=1}^{3} \alpha_{zT}lnX_{zit} \tag{2.19}$$

where R_{it} is energy, $Q_{it}$is output, X_{it} is a vector of *z-1*, *T* is the time trend, *i* is firm and s and *t* are time. The technical change index between the two neighbouring periods is then obtained by calculating the geometric mean of the two partial derivatives.

$$MTC_i=[(1 + \frac{\partial lnR_{is}}{\partial T}) \times (1 + \frac{\partial lnR_{it}}{\partial T})]^{1/2}$$

$$[(1 + \alpha_T + \alpha_{TT}T + \alpha_{qT}lnQ_{is} + \sum_{z=1}^{3} \alpha_{zT}lnX_{zis}) \times (1 + \alpha_T + \alpha_{TT}T + \alpha_{qT}lnQ_{it} + \sum_{z=1}^{3} \alpha_{zT}lnX_{zit})]^{1/2} \tag{2.20}$$

This index takes values of less than one, one or greater than one, which implies technical regress, no technical change and technical progress, respectively. Technical progress entails improvements in technology which are denoted by an upward shift in the production frontier while technical regress is denoted by a downward shift in the production frontier.

The measures of efficiency change and technical change provided in equations (2.18) and (2.19) are then multiplied to get the Malmquist index. The Malmquist index of energy efficiency also takes values of less than one, one and greater than one, implying a respective decline, no change and an improvement in energy efficiency change.

2.3.2.3 Determinants of Energy Efficiency

In the investigation of energy efficiency determinants, this study applies the one-stage estimation approach. In this approach, energy efficiency level and determinants of energy efficiency are estimated simultaneously. The approach entails regressing proposed determinants on the inefficiency term v_{it} conditional on the composite error term of the model (Battese and Coelli, 1995). A major strength of this approach is that it accounts for potential sources of heteroscedasticity available in the stochastic term. The resulting model is expressed as follows:

$$v_{it} = C_{it}\beta + \varepsilon_{it}, \qquad v_{it} > 0. \tag{2.21}$$

where C_{it} denotes a vector of explanatory variables, β represents a vector of parameters to be estimated and ε_{it} is an error term following a normal distribution with mean zero and variance $\delta^2_{\varepsilon_{it}}$ truncated at -$C_{it}\beta$. A positively signed coefficient of a regressor is taken to imply that the regressor has negatively affected energy efficiency and vice versa.

2.3.3 Definition and Measurement of Variables

Table 2.1:Definition and Measurement of Variables

Variable	Definition and measurement	Source of variable and data
Output	Finished goods produced by manufacturing firms. Measured as total annual sales (Ksh).	Lin and Long (2015), World Bank Enterprise Survey (WBES).
Capital	Physical machinery and equipment used in production. Measured as the total value of machinery and equipment (Ksh).	Lin and Long (2015), World Bank Enterprise Survey (WBES).
Labour	Physical and mental workforce provided for wages and salaries. Measured as total wages paid to permanent, full-time employees (Ksh).	Lin and Long (2015), World Bank Enterprise Survey (WBES).
Materials	Finished goods used in the final production of other goods. Measured as the cost of raw materials (Ksh).	Lin and Long (2015), World Bank Enterprise Survey (WBES).
Energy	Electricity and petroleum used in production. Measured as the total cost of electricity and fuel (Ksh).	Lin and Long (2015), World Bank Enterprise Survey (WBES).
Labour productivity	The ratio of output per unit of labour	Mandal and Madheswaran (2011) World Bank Enterprise Survey (WBES).
Firm age	Time in years an establishment has been in existence	Haider et al.,2019, World Bank Enterprise Survey (WBES).
Firm size	Number of permanent full-time workers in a firm	Mandal and Madheswaran, (2011), World Bank Enterprise Survey (WBES).
R&D	The activity of discovering new products or services or enhancing the quality or mode of production of existing goods and services. Measured as a dummy variable, 1 if a firm takes part in R&D and 0 if otherwise.	Lutz et al. (2017), World Bank Enterprise Survey (WBES).
Foreign ownership	Whether a firm is foreign-owned. Measured as a dummy variable with a value of 1 if foreign-owned and 0 if otherwise.	Sahu and Narayanan (2011b), World Bank Enterprise Survey (WBES).

Exporting status	Whether a firm exports or not. Measured as a dummy variable with a value of 1 if a firm exports and 0 if otherwise.	Roy and Yasar (2015), World Bank Enterprise Survey (WBES).
Top manager's experience	Skills gained by working. Measured as the time in years the top manager has been working	Lemi and Wright (2018), World Bank Enterprise Survey (WBES).
Female firm ownership	Whether a firm has female ownership or not. Measured as a dummy variable, 1 if there is a female member in firm ownership and 0 if there is none.	World Bank Enterprise Survey (WBES).

Source: Author's compilation

2.3.4 Data Type and Sources

An unbalanced panel got from the WBES was applied in this thesis. The World Bank collects information on enterprises to have an understanding of the business environment firms face in the private sector. This information is intended to help the World Bank in developing policies to improve the business environment, which is key to job creation and sustainable growth. The WBES provides data on manufacturing and service firms collected through stratified random sampling. The levels of stratification are regions, sub-sectors and firm size. The surveys present information on individual firm features, infrastructure and services, sales and supplies, competition, finance, performance and business environment relations, crime, labour and land. The surveys are available in different waves for 169,000 firms in 146 countries. This gives room for the comparison of enterprise performance across countries and across time. In addition, the WBES can be used to create a firm-level panel that makes it feasible to trail developments in the operating environment and evaluate the effect of reforms.

The surveys try as much as possible to match variables across waves. If required, matches are created by changing variable names in older waves to variable names in the most current wave. Panel data used in this study was for 2007, 2013 and 2018 where firms were followed over time. Natural occurrences such as the entry and exit of firms during the survey period make the panel unbalanced. In total, the panel had 2439 observations for both manufacturing and service firms from which a panel of 1265 observations for manufacturing firms was drawn. The electricity model applied data for the three waves which contain 1265 observations. Nevertheless, 2018 does not have data on fuel expenditure. Therefore, 810 observations for 2007 and 2013 were applied in the estimation of the fuel model. Given that some variables of interest had missing observations; the multiple imputation technique was applied to fill the missing gaps.

2.3.5 Justification for Inclusion of the Various Determinants of Energy Efficiency

Following recent literature, the study uses firm size, firm age, labour productivity, foreign ownership, exporting status and R&D status to analyze determinants of energy efficiency (Mandal and Madheswaran, 2011; Lin and Long, 2015; Roy and Yasar 2015; Haider et al., 2019). Moreover, top manager's experience and female ownership status are included as determinants of energy efficiency.

Firm size was included to assess whether energy efficiency increased with firm size. It was anticipated to have an unclear effect on energy efficiency. On one hand, large firms were expected to be more energy-efficient relative to small firms. This is because, in contrast to small firms, large firms are characterized by skilled leadership, better access to financial resources, particularly from third parties and the potential to leverage on economies of scale (Lin and Long 2015; Lundgren et al., 2016; Moon and Min, 2017). On the other hand, studies (Sahu and Narayanan, 2011b; Mandal and Madheswaran, 2011; Li and Shi, 2014) observe that firm size could negatively affect energy efficiency. This is because as firms expand in size, bottlenecks in management develop, rendering it difficult for them to detect inefficiencies.

Firm age was included to establish whether energy efficiency increased with firm age. Firm age was anticipated to have an unclear effect on energy efficiency. On the one hand, the effect could be positive because of the benefits associated with learning-by-doing. Moreover, this effect could be observed because older firms could potentially have more R&D activities compared to younger firms. Contrastingly, firm age could have a negative effect on energy efficiency because old firms are likely to be characterized by energy-intensive vintage capital while young firms employ recent energy-efficient technology (Sahu and Narayanan, 2011b; Haider et al.,2019).

R&D was included to investigate whether firms that invested in R&D activities were more energy-efficient than those with no R&D investments. R&D was anticipated to have a positive effect on energy efficiency. This is because R&D activities increase innovations in firms and make them learn of recent technologies that may enhance energy efficiency. Such an outcome has been found by Lin et al. (2011) and Lutz et al. (2017).

Top manager's level of experience was added to investigate whether firms with highly experienced top managers were more energy-efficient than those with low experienced top managers. This variable was anticipated to positively affect energy efficiency. This is because experienced top managers could potentially have assimilated the expertise and techniques required to enhance energy efficiency. Such a finding has been reported by Chaffai et al. (2012) and Lemi and Wright (2018).

Female firm-ownership was included to test whether female firm-ownership was linked to higher energy efficiency. This variable was anticipated to positively affect energy efficiency. This according to ILO (2019) is because female members are observed to inject teamwork, skills to provide solutions to problems, ingenuity and innovation and honesty. These traits are essential to promoting energy efficiency. This could also be explained by the moral responsibility and care for the environment by women as outlined by the gender socialization and ethicality theories (Atif et al., 2021).

Labour productivity was added to investigate whether high labour productivity was linked to higher energy efficiency. The influence of this variable on energy efficiency was expected to be positive. According to Mandal and Madheswaran (2011), high labour productivity is likely to be associated with the application of energy-efficient technologies. This outcome has been found by Mukherjee (2008b), Lin et al. (2011) and Mandal and Madheswaran (2011).

Exporting status was included to establish whether there were energy efficiency benefits in exporting activities. The influence of exporting status on energy efficiency was anticipated to be positive. This is because exporting firms get exposed to efficient technologies and their workers get to learn better management skills from foreign countries (Campi et al., 2015). This process is referred to as learning-by-exporting (Bigsten and Soderbom, 2006). Moreover, some destination countries may impose a condition requiring exporting nations to satisfy some environmental quality standards for them to gain entry to their markets (Roy and Yasar, 2015). This outcome has been found by Roy and Yasar (2015) and Campi et al. (2015).

Foreign ownership status was included to investigate whether foreign-owned firms had higher energy efficiency than firms with no foreign ownership. The effect of this variable on energy efficiency was anticipated to be positive. This is because foreign-owned firms are exposed to advanced technologies and their workers get specialized training. Such an outcome has been reported by Sahu and Narayanan (2011b).

2.4. Results and Discussions

This section contains descriptive statistics, empirical results of the stochastic frontier analysis for electricity and fuel, results of electricity and fuel change as well as the determinants of electricity and fuel efficiencies.

2.4.1 Descriptive Statistics

Table 2.2 Descriptive statistics for variables included in the energy stochastic frontier production function

Statistics	Output	Capital	Labour	Materials	Electricity	Fuel	Firm size	Firm Age	TME	LP	FO	FM	Ex	R&D
Chemicals, Pharmaceuticals and Plastics sub-sector														
2007(N=28)														
Mean	167949.7	29008.61	9441.424	78625.78	11076.71	2997.11	113.0	7.25	13.64	2.271	0.1742	0.5955	0.4494	0.2921
SD	292492.2	53246.83	15882.48	198591.6	35517.55	6226.11	306.0	4.02	10.08	3.413	0.3803	0.4922	0.4988	0.4560
Minimum	500	500	180	16.8	6	12	1	1	1	0.054	0	0	0	0
Maximum	1000000	250000	70000	1000000	180000	3000	1500	15	40	17.96	1	1	1	1
2013(N=52)														
Mean	497064.1	362654.8	57713.78	180879.6	25993.75	18316.6	123.08	25.13	21.27	2.407	0.1154	0.5769	0.4038	0.25
SD	1210990	2072631	125627.7	464971.9	67702.13	84686.51	244.08	8.07	12.25	7.528	0.8846	0.4989	0.4955	0.4372
Minimum	1000	500	300	100	12	10	5	1	1	0.089	0	0	0	0
Maximum	8000000	15000000	650000	3000000	400000	600000	1500	35	60	54.90	1	1	1	1
2018(N=98)														
Mean	2025636	156492	161476.6	228133.6	16995.65		132.18	50.82	21.63	11.09	0.2041	0.5918	0.5204	0.3469
SD	9799724	393919	644912.8	695357.1	44352.45		293.30	22.68	13.60	73.35	0.4051	0.4940	0.5022	0.4784
Minimum	300	10.607	132	1	12		4	1	1	0.003	0	0	0	0
Maximum	80000000	3000000	5000000	5000000	250000		2000	103	65	718.6	1	1	1	1
Food sub-sector														
2007(N=110)														
Mean	359916.4	74901.92	34232.41	91473.01	7674.282	8440.883	65.35	10.56	13.24	2.966	0.1634	0.6636	0.3000	0.2455
SD	1333275	262780.3	104294	260128.7	26699.44	52958.64	157.33	4.35	9.13	15.95	0.3348	0.4746	0.4604	0.4323
Minimum	150	20	80	24	2.5	10	2	2	2	0.005	0	0	0	0
Maximum	12000000	2500000	750000	1400000	192000	536000	1200	18	40	165.8	1	1	1	1
2013(N=154)														
Mean	537768.5	109050.1	23826.06	129432.3	33460.68	7786.428	104.65	21.66	19.38	25.44	0.1883	0.6364	0.3896	0.3117
SD	2767741	417816.4	64907.24	600339.4	285252.2	51265.79	235.14	7.58	10.07	242.4	0.3922	0.4826	0.4893	0.4647
Minimum	300	100	150	30	7.5	10	4	3	1	0.008	0	0	0	0
Maximum	33000000	4670000	434000	7000000	170000	600000	1600	36	40	2964	1	1	1	1
2018(N=140)														
Mean	1771102	454789.8	111342.3	490036.7	49362.87		200.70	36.93	23.60	5.061	0.1643	0.6286	0.4929	0.3357
SD	3785358	2096753	438871.8	2174520	309010.4		747.94	11.75	13.28	17.30	0.3719	0.4849	0.5017	0.4739
Minimum	800	45.5	55	3	3.5		2	3	3	0.009	0	0	0	0
Maximum	84000000	15000000	4200000	17000000	3500000		8000	65	50	141.1	1	1	1	1
Paper and other manufacturing sub-sector														
2007(N=147)														
Mean	1369850	216360.1	76659.47	391678.3	14997.8	8839.272	127.33	10.03	12.34	2.432	0.1905	0.6327	0.3469	0.2109
SD	10100000	1118047	308708	2994413	85096.11	51390.43	494.98	4.545	9.077	5.063	0.3940	0.4837	0.4776	0.4093
Minimum	600	10.607	20	60	5	10	1	2	2	0.0001	0	0	0	0

Maximum	120000000	12300000	2000000	36000000	900000	600000	5500	18	48	45.60	1	1	1	1
2013(N=157)														
Mean	907697.8	280953.8	38938.56	479187.9	16046.66	13131.02	121.20	24.42	19.36	3.546	0.1274	0.6815	0.4650	0.2994
SD	4385846	1579738	116268.5	3052786	58450.31	50071.05	219.64	9.151	10.11	16.82	0.3345	0.4674	0.5004	0.4954
Minimum	100	45	45	20	5	10	2	2	0	0.051	0	0	0	0
Maximum	50000000	15000000	1200000	36000000	488000	500000	1700	35	50	207.3	1	1	1	1
2018(N=167)														
Mean	4527257	185035.8	81698.41	374821	19443.34		130.44	39.14	20.59	4.693	0.2096	0.5928	0.5449	0.3533
SD	34500000	547615.4	228291	1307864	47097.87		280.44	17.09	11.01	14.68	0.4082	0.4928	0.4995	0.4794
Minimum	500	100	132	100	0.5		3	2	2	0.009	0	0	0	0
Maximum	42500000	4670000	2500000	10000000	300000		2700	93	50	142.3	1	1	1	1
Textiles, and Garments sub-sector														
2007(N=111)														
Mean	626460.8	73253.59	20387.85	203415.5	4668.687	39694.74	91.31	10.06	13.15	2.462	0.1171	0.6937	0.3063	0.2432
SD	2611685	220592.6	58583.8	1019236	13283.63	264215.5	230.09	4.106	7.765	5.502	0.3230	0.4630	0.4630	0.4310
Minimum	450	10.607	50	20.3	3.6	28	2	2	2	0.008	0	0	0	0
Maximum	18000000	1500000	360000	8000000	85000	1980000	1700	18	30	34.49	1	1	1	1
2013(N=51)														
Mean	174226.7	41886.06	16647.21	73370.74	1606.079	3496.362	111.75	21.24	16.90	2.117	0.1373	0.6078	0.2941	0.2941
SD	501042	58092.79	31486.39	204512.3	2962.064	10442.44	349.16	9.026	9.729	3.300	0.3475	0.4930	0.4602	0.4602
Minimum	1500	200	50.8	25	8	12	2	2	3	0.060	0	0	0	0
Maximum	3500000	270000	176000	1300000	15700	72000	2500	33	40	17.97	1	1	1	1
2018(N=50)														
Mean	645406.6	395709.8	116167.7	770953.6	49397.47		175.18	45.04	17.26	2.235	0.2400	0.6000	0.3800	0.400
SD	1187350	1752118	372756.2	4086824	253933.5		243.88	22.06	10.61	4.521	0.4314	0.4949	0.4903	0.5014
Minimum	610	48	95	70	3.6		5	2	1	0.158	0	0	0	
Maximum	6500000	12300000	2500000	29000000	1800000		1000	107	40	26.95	1	1	1	

Note: The values of the variables output, capital, labour, intermediate materials, electricity and fuel are expressed in thousands of Kenya shillings. SD, TME, LP, FO, FM and Ex denote standard deviation, top manager experience, labour productivity, foreign ownership, female ownership and exporting respectively.

Source: Own computations from the WBES panel data

Table 2.2 presents summary statistics of various covariates based on wave year and sub-sectors. The summary statistics obtained are mean, standard deviation, minimum and maximum. Variables for which the summary statistics are obtained are output, capital, labour, intermediate materials, electricity and fuel. Others include firm age, firm size, top manager's level of experience, labour productivity, foreign ownership, female firm ownership, exporting and R&D. The sample comprised a broad size limit as demonstrated by the large disparities between the minimum and maximum values. This was pronounced in output, capital, labour, intermediate materials, electricity, fuel, firm size and firm age, labour productivity and top manager's years of experience variables. The variability in these variables resulted in many of them exhibiting standard deviations that are greater than the mean.

The averages for the different variables varied not only across sub-sectors but also through time. In general, the mean values for output increased through the three years under review. Firms in the paper and other manufacturing sub-sector recorded the highest output while those in the textiles and garments sub-sector recorded the least, especially in 2013 and 2018. Spending on electricity was higher than that on fuel across all the sub-sectors except in the textiles and garments sub-sector. This indicates that firms in the textiles and garments sub-sector relied more on fuel-powered equipment than on electricity-powered equipment. Labour productivity was found to increase with time in the chemicals, pharmaceuticals and plastics and the paper and other manufacturing sectors. However, no consistent pattern was observed in the food and textile and garments sub-sectors. On average, the food sub-sector had the highest labour productivity while the textiles and garments sub-sector had the least. The relatively low labour productivity in the textiles and garments sub-sector could in part have explained the relatively low output recorded in this sub-sector. The proportion of manufacturing firms with foreign ownership was significantly low with the majority of the sub-sectors recording less than 20 percent ownership. This implies that the Kenyan manufacturing sector was not optimally benefiting from the flow of foreign knowledge, technical progress and foreign capital that come with foreign investments.

Less than half of the firms across all the sub-sectors were found to engage in research and development. This probably shows that the Kenyan manufacturing sector placed less emphasis on this activity, yet it holds a central role in the creation of new products, upgrading existing products and developing efficient technologies. A notable reason for this could be because of the character of R&D. Blomberg et al. (2012) observe that R&D has a public good nature thereby reducing incentives for a single firm to undertake the activity. The proportion of firms that engaged in exporting was generally below 50 percent for most of the sub-sectors through the period under review apart from the chemicals, pharmaceuticals and plastics and paper and other manufacturing sub-sectors in 2018. The two sub-sectors had on average the highest proportion of exporting firms while the textiles and garments sub-sector had the least. These statistics indicated that there was room for firms to benefit from learning-by-exporting if export-promoting policies were to be implemented in-depth.

Some of the very old firms were found to be in the chemicals, pharmaceuticals and plastics and textiles and garments sub-sectors. The two sub-sectors also had some of the most experienced top managers. Regarding firm size which was indicated by the number of permanent employees, statistics show that the food sub-sector had the largest firm size. More than 50 percent of firms across all the sub-sectors had female members among the owners. Interestingly, the food sub-sector had the highest proportion of female firm ownership across the three periods while the chemicals, pharmaceuticals and plastics sub-sector had the least. This as provided by the World Bank Group (2019) indicated that women entrepreneurs in Kenya were still domiciled in the hospitality industry. Nevertheless, the more than 50 percent ownership in the chemicals, pharmaceuticals and plastics sub-sector signalled that female entrepreneurs were gaining entry into male-dominated sub-sectors.

2.4.2 Tests

Table 2.3 provides log-likelihood findings for tests of the production function, equality of parameters, technical change and inefficiency effects. Inferences were made based on a comparison of log-likelihood statistics with Kodde and Palm (1986) critical values at 5 percent level of significance.

Table 2.3:Log-likelihood test results for the stochastic frontier production function

Null Hypothesis H_0	**Model**	**χ^2- statistics (electricity model)**	**χ^2- statistics(fuel model)**	**Critical Value**
Cobb-Douglas				
	Chemicals, pharmaceuticals and plastics	90.76^{***}	97.91^{***}	24.384
	Food	70.32^{***}	55.21^{***}	24.384
	Textiles and garments	78.20^{***}	46.66^{***}	24.384
	Paper and other manufacturing	79.17^{***}	58.28^{***}	24.384
	Overall sector	260.58^{***}	84.31^{***}	24.384
Equality of parameters				
	Overall sector model *vs* Sub-sector based model	63.43^{***}	344.91^{***}	55.190
No technical change				
	Chemicals, pharmaceuticals and plastics	43.51^{***}	84.35^{***}	11.911
	Food	18.47^{***}	57.83^{***}	11.911
	Textiles and garments	19.15^{***}	25.80^{***}	11.911
	Paper and other manufacturing	30.54^{***}	45.41^{***}	11.911
	Overall sector	91.14^{***}	134.63^{***}	11.911
No efficiency effects				
	Chemicals, pharmaceuticals and plastics	60.23^{***}	66.84^{**}	16.274
	Food	22.63^{***}	75.51^{**}	16.274
	Textiles and garments	61.86^{***}	60.07^{**}	16.274
	Paper and other manufacturing	123.02^{***}	44.31^{**}	16.274
	Overall sector	308.09^{***}	114.41^{**}	16.274

χ^2 indicates the log-likelihood test results, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Source: Author's estimates from WBES data

A translog production function was evaluated against a Cobb-Douglas production function to select the functional form that best suited the available data. Results in Table 2.3 show that the null hypothesis for a Cobb-Douglas production function against a translog production function was rejected in both electricity and fuel models across all the sub-sectors and the overall sector at 5 percent level of significance. Therefore, the translog production specification was well suited for the available data. A translog production function is also adopted by Lin and Long (2015) and Lin and Wang (2014).

The null hypothesis that each of the four sub-sectors had similar slope parameters in both the electricity and fuel models was rejected at 5 percent level of significance. This signals that every sub-sector had distinct slope parameters and therefore pooling of the four sub-sectors could not be done. The results corroborate the findings of Chapelle and Plane (2005) and Ngui and Muniu (2012). The null hypothesis for no technological change in both electricity and fuel models was rejected across all the sub-sectors and in the overall sector. This means that in each of the sub-sectors and the overall sector, the production functions adjusted with time. This signals that probably, the macroeconomic environment significantly influenced electricity and fuel efficiency over the period under review. Time trend variables were thus incorporated in the models to capture technological change.

The null hypothesis for the absence of inefficiency effects in both the electricity and fuel models was rejected at 5 percent level of significance across all sub-sectors and in the overall sector. This implies that both random shocks and inefficiencies were responsible for deviations from the best linear frontier. Subsequently, regressors were incorporated in the first stage simultaneous estimation in the four sub-sector and overall sector models to identify determinants of energy efficiency. This outcome corroborates the findings of Chapelle and Plane (2005) and Ngui and Muniu (2012).

The models are also assessed for multicollinearity using the variance inflation factor (VIF). When inputs applied in a translog production function are highly correlated, SFA estimates become imprecise. Nevertheless, multicollinearity in these functions is minimized through centering variables around their sample means before computing their interaction terms. A VIF of 1 signals no collinearity between any two regressors while a VIF greater than 10 indicates severe multicollinearity. Table 2.4 provides results for the multicollinearity test.

Table 2.4:Multicollinearity test results

Sub-sector	**Electricity model**	**Fuel model**
Translog production function		
Chemicals, pharmaceuticals and plastics	2.89	4.53
Food	3.17	3.13
Textiles and garments	3.32	3.52
Paper and other manufacturing	2.99	3.33

Overall sector	3.56	4.01
Determinants of energy efficiency		
Chemicals, pharmaceuticals and plastics	3.96	5.07
Food	4.60	4.55
Textiles and garments	3.12	4.77
Paper and other manufacturing	2.78	4.15
Overall sector	2.89	4.23

Source: Author's computation using data from WBES

The VIF estimates show minimal collinearity among regressors in all the sub-sectors with values ranging between 2.89 and 3.32 in the electricity model and 3.13 to 4.53 in the fuel model. In the overall sector model, VIF estimates in the electricity and fuel models were 3.56 and 4.01 respectively. The results in Table 2.4 also showed minimal collinearity among determinants of energy efficiency. The VIF estimates ranged from 2.78 to 4.60 in the electricity model, and 4.15 to 5.07 in the fuel model.

2.4.3 Elasticities

The estimation by maximum log-likelihood process involves finding the estimate of an unidentified parameter that maximizes the likelihood of extracting a certain sample of observations randomly. Maximization is done by computing the first derivative of the log-likelihood function and equating it to zero. Solving the first-order condition yields the parameter that maximizes the likelihood function. Providing analytical solutions of such parameters may however not be straightforward in the case of non–linear first derivatives such as those of the translog production function. An iterative optimization process that entails analytically assessing the log-likelihood function for various values of the parameters until one that maximizes the log-likelihood function is obtained, solves for maximum log-likelihood estimators in the case of non-linear first derivatives (Coelli et al.,2005). The iterative optimization process may however not yield global maximum values but local maximum values. Various starting values are therefore set to confirm that the optimization process converges to a global maximum. In this study, different starting values were found to yield the same maximum likelihood estimates, a validation that the iterative process estimated converged to a global maximum. This was further reaffirmed by slope coefficients that were largely close to zero[2]. Robust standard errors were utilized to control for possible

[2] Coelli et al. (2005) provide that convergence of the optimization process can be confirmed by gradients that are adjacent to zero.

heteroscedasticity. Tables 2.5 and 2.6 provide the maximum log-likelihood findings of the stochastic frontier model for electricity and fuel, respectively.

Table 2.5:Stochastic frontier model estimation results of electricity for the Kenyan manufacturing sector.

	Models				
Variables	C, P and P sub-sector	Food sub-sector	T and G sub-sector	P and O M sub-sector	Overall Sector
Frontier					
ln$Q$	-0.983***	-0.789***	-0.815***	-0.643***	-0.757***
	(0.0951)	(0.137)	(0.0906)	(0.0717)	(0.0511)
ln$m$	0.483***	0.380**	0.159*	0.242**	0.267***
	(0.103)	(0.154)	(0.0905)	(0.106)	(0.0584)
ln$l$	0.341*	0.518***	0.725***	0.513***	0.562***
	(0.176)	(0.133)	(0.101)	(0.145)	(0.0768)
ln$k$	0.0877	0.0875	0.103*	-0.0178	0.0287
	(0.130)	(0.134)	(0.0605)	(0.0626)	(0.0435)
T	-0.0511	0.0308	-0.00225	0.0350	0.0150
	(0.0548)	(0.0350)	(0.0390)	(0.0282)	(0.0164)
ln$Q$ln$Q$	-0.00739	0.0305	0.0735***	0.0460**	0.0435***
	(0.0184)	(0.0416)	(0.0236)	(0.0182)	(0.0124)
ln$l$ln$l$	0.0394	-0.101**	-0.124***	0.0180	-0.0125
	(0.0516)	(0.0397)	(0.0472)	(0.0528)	(0.0329)
ln$m$ln$m$	-0.136***	-0.115***	-0.101***	-0.0402	-0.0843***
	(0.0329)	(0.0244)	(0.0358)	(0.0271)	(0.0146)
ln$k$ln$k$	-0.0384	-0.0336	-0.0458***	-0.0189	-0.0253**
	(0.0270)	(0.0332)	(0.0169)	(0.0140)	(0.00985)
ln$k$ln$l$	-0.0128	0.0260	0.0537**	0.0103	0.0165
	(0.0349)	(0.0286)	(0.0209)	(0.0254)	(0.0146)
ln$k$ln$m$	0.0140	-0.0112	-0.0232	-0.0197	-0.0133
	(0.0172)	(0.0345)	(0.0176)	(0.0173)	(0.0105)
ln$k$ln$Q$	-0.0397**	0.00853	0.00941	0.0259**	0.0108
	(0.0178)	(0.0308)	(0.0164)	(0.0121)	(0.00931)
ln$l$ln$m$	0.0504**	0.112***	0.0910**	0.0523**	0.0674***
	(0.0233)	(0.0278)	(0.0367)	(0.0248)	(0.0113)
ln$l$ln$Q$	0.00383	0.0166	0.0486*	-0.0209	0.00345
	(0.0233)	(0.0355)	(0.0252)	(0.0183)	(0.0150)
ln$m$ln$Q$	0.00734	-0.00571	-0.0495***	0.00543	-0.0139
	(0.0162)	(0.0341)	(0.0171)	(0.0185)	(0.0102)
TT	-0.00447	-0.000411	0.00123	0.00756	0.00370
	(0.00840)	(0.00667)	(0.00912)	(0.00505)	(0.00329)
Tln$Q$	-0.0108	-0.00391	0.00654	-0.00477	-0.00305
	(0.00990)	(0.00767)	(0.00585)	(0.00605)	(0.00351)
Tln$l$	-0.0251	-0.00349	0.00792	-0.0101	-0.00494
	(0.0177)	(0.00982)	(0.0106)	(0.00709)	(0.00523)
Tln$m$	0.00817	-0.00729	-0.00221	-0.00292	-0.00552
	(0.0136)	(0.00942)	(0.00889)	(0.00842)	(0.00434)
Tln$k$	0.0121	-0.00243	-0.00552	-0.00579	-0.000865
	(0.00932)	(0.00705)	(0.00523)	(0.00503)	(0.00307)
_cons	0.678**	0.679*	0.451***	0.708***	0.700***

	(0.339)	(0.353)	(0.174)	(0.160)	(0.115)
Determinants of electricity efficiency					
Labour	41.37***	-0.00219	3.507**	69.73***	5.404***
Productivity	(3.451)	(0.00511)	(1.618)	(6.035)	(0.427)
Firm age	-0.700**	1.349***	-0.373**	-0.0794	0.00130
	(0.344)	(0.477)	(0.187)	(0.575)	(0.0506)
Firm age squared	-0.00838	-0.0180**	-0.0388***	0.0115	0.000149
	(0.0212)	(0.00844)	(0.0102)	(0.0391)	(0.00163)
R and D	-105.8***	0.617	-1.155	-6.146	0.656
	(32.39)	(2.753)	(1.673)	(24.96)	(1.266)
Firm size	23.91***	0.00231***	-0.00168	-0.260***	0.00171***
	(3.943)	(0.000703)	(0.00152)	(0.0118)	(0.000497)
Foreign	-45.60	-2.566	2.913	38.43	3.301
ownership	(31.64)	(2.940)	(2.109)	(26.70)	(2.108)
Top manager's	42.39	-0.309***	-0.0224	-51.87**	-0.0195
experience	(31.75)	(0.117)	(0.159)	(21.00)	(0.0561)
Female	7.572	-6.350**	0.981	-23.11	-4.026**
ownership	(25.85)	(2.596)	(1.645)	(20.68)	(1.587)
Exporting	-62.33**	-6.875*	-2.821**	21.08	-2.808*
	(28.67)	(3.754)	(1.384)	(16.98)	(1.660)
_cons	-84.12	-8.416	-6.078	-198.6***	-18.58***
	(59.89)	(16.67)	(7.513)	(65.92)	(4.516)
Usigma_cons	3.384***	2.376***	0.391	4.774***	2.465***
	(0.426)	(0.692)	(0.652)	(0.164)	(0.0706)
Vsigma_cons	-0.477*	-0.766*	-0.958***	-0.771***	-0.683***
	(0.278)	(0.410)	(0.166)	(0.161)	(0.113)
sigma_u	5.430***	3.821***	10.88***	2.821***	3.430***
	(1.157)	(1.135)	(0.894)	(0.817)	(0.121)
sigma_v	0.788***	0.682***	0.680***	0.748***	0.711***
	(0.109)	(0.140)	(0.055)	(0.068)	(0.040)
lambda	6.893***	4.813***	16.00***	3.774***	4.825***
	(1.191)	(1.261)	(0.903)	(0.855)	(0.116)
Log-likelihood	-221.8394	-521.5466	-213.8522	-568.5541	-1557.5051
Returns to scale	1.017	1.267	1.227	1.555	1.321

Dependent variable for the translog production function: $-\ln R_{\mathrm{it}}$. Dependent variable for determinants of fuel efficiency: v_{it}

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C, P and P is chemicals, pharmaceuticals and plastics, T and G is textiles and garments and P and O M is paper and other manufacturing. All variables and coefficients are defined in section 2.1.

Source: Author's estimates from WBES data

Table 2.5 provides estimated electricity stochastic frontier in the upper rows, determinants of electricity efficiency in the middle rows and variance parameters, log-likelihood statistics and returns to scale in the lower rows. Results of the overall sector were also included for robustness check. Not all parameters have significant coefficients in all the models. However, according to Greene (1993), the statistical characteristics of the estimates of the coefficients are of less importance in efficiency estimation. The highest existing estimator is applied for coefficients of the inputs. Greene (1993) adds that for technical efficiency estimation, what should be longed for is consistency. Comparing this result with other similar studies, Lin and Long (2015) and Lin and Wang (2014) find that even though their estimation have insignificant input and output coefficients, the SFA models are still suitable for explaining energy efficiency. This is because the null hypotheses for no stochastic inefficiencies have been rejected implying that stochastic inefficiencies are present in the models. In the present study, at 5 percent level of significance, the p-value of lambda shows that the null hypothesis of the absence of inefficiency in the models was rejected, implying the presence of inefficiency hence validating the use of SFA. These findings were supported by the generalised log-likelihood test for inefficiency effects in Table 2.3.

The input and output variables were provided in their natural logarithm forms and they were mean-corrected by dividing each variable by its geometric mean before estimation. Because of these, the first-order coefficients of the translog production function were inferred as elasticities evaluated at their geometric means (Kumbhakar et al., 2007). The parameter estimates of output and all inputs had economically plausible signs at their geometric means apart from capital in the paper and other manufacturing sub-sector. Nevertheless, this variable's coefficient was not statistically significant at 5 percent level of significance.

The output elasticities were statistically significant and had negative signs which was in agreement with the property that output decreases with input distance functions. The input elasticities were positively signed and this conformed with the non-reducing in inputs property of input distance functions. All input covariates were significant at 5 percent level of significance, except capital which was only statistically significant in the textiles and garments sub-sector.

Elasticities of labour were higher than those of materials and capital in all the sub-sectors and overall sector except capital in the chemicals, pharmaceuticals and plastics sub-sectors. The elasticity of materials was found to be higher than the elasticity of labour in this sub-sector. It could be inferred that firms did not have the same space to scheme for each factor of production. However, labour, materials and capital elasticities had no direct comparability because capital is a stock variable while labour and materials are flow variables (Ngui and Muniu, 2012).

Output elasticities did not differ substantially across sub-sectors except in the chemicals, pharmaceuticals and plastics and paper and other manufacturing sub-sectors. Materials elasticities varied significantly across sub-sectors. Labour elasticities differed slightly in the paper and other manufacturing sub-sectors but differed considerably in the chemicals, pharmaceuticals and plastics and textiles and garments sub-sectors. Capital elasticities varied slightly in the chemicals, pharmaceuticals and plastics and food sub-sectors but varied significantly in the textiles and garments and paper and other manufacturing sub-sectors. This in turn reflected significant technological idiosyncrasies. The result raised a question on the methodological accuracy of the regular practice of estimating production functions on groups of firms functioning in different sub-sectors (Bottaso and Sembenelli, 2004).

Time elasticities were statistically insignificant across all sub-sectors and the overall sector. Insignificant time elasticities denoted no shift of the input distance function, implying that there was no technical change over the period under review hence no change in electricity efficiency. This finding contracted generalised likelihood results of technical change in Table 2.3. The idea of Returns to scale applies to the technical property of production functions regarding the link between changes in output following changes in inputs. In input distance functions, returns to scale are obtained by computing the absolute inverse of the output elasticities. In this study, increasing returns to scale were observed because all output elasticities were higher than one. Thus a proportionate growth in output in all models could result in a less than proportionate increase in electricity consumption.

Table 2.6:Stochastic frontier model estimation results of fuel for the Kenyan manufacturing sector.

	Models				
Variables	C, P and P sub-sector	Food sub-sector	T and G sub-sector	P and O M sub-sector	Overall Sector
Frontier					
ln$Q$	-0.855***	-0.682***	-0.458***	-0.757***	-0.646***
	(0.128)	(0.167)	(0.133)	(0.119)	(0.0833)
ln$m$	0.572***	-0.168	0.276**	0.424**	0.207***
	(0.144)	(0.166)	(0.113)	(0.207)	(0.0715)
ln$l$	0.204	0.568***	0.331	0.472*	0.586***
	(0.188)	(0.127)	(0.223)	(0.230)	(0.138)
ln$k$	-0.0306	-0.165	-0.0337	0.121	-0.0194
	(0.249)	(0.101)	(0.0899)	(0.113)	(0.0568)
T	0.204**	-0.0272	-0.0428	0.0694	-0.00298
	(0.0882)	(0.0630)	(0.0639)	(0.0617)	(0.0314)
ln$Q$ln$Q$	-0.0171	0.0690	0.0893**	0.108**	0.0487***
	(0.0283)	(0.0485)	(0.0387)	(0.0447)	(0.0179)
ln$l$ln$l$	0.238**	-0.0699	0.0195	-0.104*	-0.0472
	(0.0930)	(0.0647)	(0.0741)	(0.0551)	(0.0429)
ln$m$ln$m$	-0.0830	-0.0818**	-0.0569	-0.0848	-0.0818***
	(0.0620)	(0.0362)	(0.0483)	(0.0525)	(0.0231)
ln$k$ln$k$	-0.0309	0.0304	-0.0171	-0.0515**	-0.0198

	(0.0505)	(0.0233)	(0.0229)	(0.0260)	(0.0125)
ln*k*ln*l*	-0.0606	0.0203	-0.00936	-0.00864	0.0293
	(0.0480)	(0.0283)	(0.0395)	(0.0415)	(0.0250)
ln*k*ln*m*	0.0702***	-0.0418	-0.0163	0.0309	-0.0174
	(0.0224)	(0.0304)	(0.0228)	(0.0386)	(0.0134)
ln*k*ln*Q*	-0.00193	0.0254	0.0561**	0.00656	0.0172
	(0.0215)	(0.0345)	(0.0251)	(0.0209)	(0.0146)
ln*l*ln*m*	-0.0521	0.103***	0.0539+	0.114***	0.0776***
	(0.0665)	(0.0278)	(0.0288)	(0.0413)	(0.0178)
ln*l*ln*Q*	-0.124***	-0.0458	-0.0564	0.0188	-0.0423*
	(0.0414)	(0.0472)	(0.0344)	(0.0324)	(0.0250)
ln*m*ln*Q*	0.114***	-0.0153	-0.0167	-0.0932***	-0.00168
	(0.0434)	(0.0363)	(0.0280)	(0.0299)	(0.0184)
TT	0.00219	0.00406	0.00329	0.00197	0.00220
	(0.0153)	(0.0807)	(0.0162)	(0.0578)	(0.0335)
*T*ln*Q*	0.0352	-0.0105	0.0129	0.000301	0.00440
	(0.0302)	(0.0186)	(0.0124)	(0.0131)	(0.00677)
*T*ln*l*	-0.00674	-0.00956	-0.0300**	-0.0131	-0.00854
	(0.0363)	(0.0161)	(0.0150)	(0.0175)	(0.00896)
*T*ln*m*	0.0296	0.00979	0.00859	0.0380**	0.00441
	(0.0252)	(0.0158)	(0.0115)	(0.0187)	(0.00808)
*T*ln*k*	-0.0155	0.00285	0.00494	-0.0187	-0.000531
	(0.0168)	(0.0129)	(0.00962)	(0.0115)	(0.00573)
_cons	1.048*	0.824***	0.881***	0.513*	0.825***
	(0.607)	(0.254)	(0.290)	(0.264)	(0.137)
Determinants of fuel efficiency					
Labour productivity	0.852***	6.532*	22.44***	8.043**	17.02***
	(0.110)	(3.795)	(2.524)	(2.655)	(2.686)
Firm age	0.0320**	-0.0332	0.225	0.396	-0.309
	(0.0134)	(0.484)	(0.310)	(0.367)	(0.403)
Firm age squared	0.000268	-0.0534	0.0947**	-0.0637*	-0.106*
	(0.00217)	(0.0494)	(0.0417)	(0.0349)	(0.0623)
R and D	-0.379**	9.797	34.72***	0.779	36.36***
	(0.179)	(6.907)	(10.32)	(1.792)	(11.75)
Firm size	0.224	-0.279	-0.251***	-0.795	-0.0508***
	(0.154)	(0.261)	(0.0407)	(1.133)	(0.00711)
Foreign ownership	-0.537*	10.19	13.28	1.038	17.16
	(0.301)	(13.95)	(12.55)	(2.352)	(12.90)
Top manager's experience	0.251	-1.115	-5.028	-0.0528	3.459
	(0.319)	(3.657)	(7.075)	(0.425)	(4.276)
Female ownership	-0.303**	-5.922*	-8.151	2.586	12.94
	(0.131)	(3.414)	(6.537)	(2.345)	(10.57)
Exporting	-0.387**	-1.525	-1.978	-7.620*	8.409
	(0.189)	(10.19)	(9.954)	(4.011)	(7.125)
_cons	0.0217	-31.79	-124.7***	-8.023	-194.2***
	(0.977)	(26.52)	(25.98)	(6.431)	(55.65)
Usigma_cons	-4.479***	2.336**	3.593***	1.724***	3.560***
	(1.089)	(0.739)	(0.458)	(0.509)	(0.195)
Vsigma_cons	-1.674***	-1.149***	-1.014***	-1.296***	-0.745***
	(0.374)	(0.233)	(0.250)	(0.245)	(0.122)
sigma_u	0.107*	3.216***	6.028***	2.368***	5.929***

	(0.058)	(1.188)	(1.380)	(0.603)	(0.694)
sigma_v	0.433***	0.563***	0.602***	0.523***	0.689***
	(0.081)	(0.066)	(0.075)	(0.064)	(0.042)
lambda	0.246***	5.711***	10.01***	4.526***	8.607***
	(0.130)	(1.911)	(1.433)	(0.592)	(0.578)
Log-likelihood	-46.7522	-272.0141	-348.0967	-162.7753	-959.9403
Returns to scale	1.170	1.466	2.183	1.321	1.548

Dependent variable for the translog production function: -lnR_{it}. Dependent variable for determinants of fuel efficiency: v_{it}

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C, P and P is chemicals, pharmaceuticals and plastics, T and G is textiles and garments and P and O M is paper and other manufacturing. All variables and coefficients are defined in section 2.1.

Source: Author's estimates from WBES data

Table 2.6 provides estimated fuel stochastic frontier in the upper rows, determinants of fuel efficiency in the middle rows and variance parameters, log-likelihood statistics, and returns to scale in the lower rows. Results of the overall sector were also included for robustness check. Some parameters had insignificant coefficients in all the models. However, as noted earlier, Green (1993) argues that in studies evaluating efficiency, the statistical features of the estimates of the coefficients are not of great significance. The highest existing efficient estimator is applied for coefficients of the inputs and what should matter in the estimation of technical efficiency is consistency. The null hypothesis for no stochastic inefficiencies indicated by the p-value of lambda was rejected at 5 percent level of significance across all the models, denoting that the SFA model was suitable for the present data. This finding is in line with Lin and Wang (2014) and Lin and Long (2015).

The input and output variables were presented in their natural logarithm forms and they were similarly corrected for their geometric means before analysis. This means that first-order coefficients of the translog production function input were inferred as elasticities at their geometric means. Estimates of output and inputs had economically plausible signs at their geometric means apart from materials in the food sub-sector and capital in the chemicals, pharmaceuticals and plastics, paper and other manufacturing and textile and garments sub-sectors and the overall sector. However, the exceptional variables were insignificant. Output elasticities were negative and statistically insignificant at 5 percent level of significance. This was in agreement with the decreasing in output property of input distance functions. Input elasticities that were statistically different from zero at 5 percent level of significance had positive signs. This finding supported the non-decreasing in inputs property of input distance functions.

Labour elasticities were higher than material elasticities across all the sub-sectors and in the overall sector apart from materials in the chemicals, pharmaceuticals and plastics sub-sector. Labour elasticities were also higher than capital elasticities across all the sub-sectors and in the overall sector. This demonstrated that manufacturing firms have different spaces to plan for each factor input. Nevertheless, given that capital is a stock variable and labour and materials are flow variables, these inputs have no direct comparability (Ngui and Muniu, 2012).

Output elasticities differed significantly across all the sub-sectors. Materials and labour elasticities also differed considerably across all the sub-sectors. Capital elasticities differed slightly between the chemicals, pharmaceuticals and plastics and textiles and garments sub-sectors but varied significantly in the food and paper and other manufacturing sub-sectors. This implies that these sub-sectors operated on different technologies. The result confirmed that the four sub-sector models should not be pooled during analysis.

Time elasticities across the sub-sectors were statistically insignificant except in the chemicals, pharmaceuticals and plastics sub-sector where the coefficient was positive and statistically significant at 5 percent level of significance. The positive sign on this coefficient revealed that there could have been a downward move in the input distance function which might have led to an improvement in fuel efficiency with time. The prevailing macroeconomic surrounding could be responsible for this outcome. The finding for the chemicals, pharmaceuticals and plastics sub-sector was in line with the outcome of the generalised log-likelihood test presented in Table 2.3. Returns to scale across the sub-sectors and in the overall sector were greater than one. This implies that expanding output resulted in a less than proportionate increase in energy consumption.

2.4.4 Electricity Efficiency Point Estimates

Table 2.7 presents empirical findings of electricity efficiency point estimates. Average electricity efficiency levels varied across sub-sectors indicating varying space to promote electricity efficiency across the four sub-sectors.

Table 2.7:Summary statistics for electricity efficiency point estimates

Model	Mean	Standard Deviation	Skewness	Minimum	Maximum
Chemicals, Pharmaceuticals and plastics	0.805	0. 169	-2.784	0. 005	0.960
Food	0.648	0. 173	-1.904	0. 013	0.905
Textiles and Garments	0.786	0. 191	-1.966	0. 010	0.982
Paper and other Manufacturing	0.678	0. 186	-1.679	0. 012	0.935
Overall sector	0.645	0. 181	-1.589	0. 004	0.936

Source: Author's estimates from WBES data.

The average electricity efficiency levels in the chemicals, pharmaceuticals and plastics, food, textiles and garments and paper and other manufacturing sub-sectors were 80.5, 64.8, 78.6 and 67.8 percent, respectively. They revealed that respective sub-sectors could potentially cut energy use by 19.5, 35.2, 21.4 and 32.2 percent without altering their output levels. In the overall sector, a mean electricity efficiency score of 64.5 percent showed that the overall manufacturing sector could continue producing the same output but consume 35.5 percent less electricity. These findings conform to other similar studies that have found significant room to enhance electricity efficiency.

For instance, in Sweden's 12 manufacturing sub-sectors, Lundgren et al. (2016) establish that electricity efficiency lies between 70 percent in the stone/mineral sub-sector and 98.2 percent in the rubber and printing sub-sector. Still, in Sweden, Blomberg et al. (2012) establish that electricity efficiency levels in the pulp and mills industry range from 81.3 percent to 97.7 percent. In the U.S manufacturing sector, Boyd and Lee (2019) establish that electricity efficiency ranges from 69 percent to 81 percent. The electricity efficiency scores in different countries are, however, not directly comparable to those of the current study because of differences in data samples, models, and estimation methods. According to Ngui and Muniu (2012), efficiency scores are sensitive to the method of analysis, assumptions imposed on the distribution of error terms, and sample applied.

The maximum electricity efficiency values were high and varied across sub-sectors revealing the existence of very electricity efficient firms across sub-sectors. The minimum electricity efficiency values were low and varied across sub-sectors signalling the presence of some very electricity inefficient firms across the sub-sectors. Lundgren et al. (2016) also find high maximum and low minimum electricity efficiency scores across sub-sectors in the Swedish manufacturing sector. Exploring the Kernel densities of electricity efficiency scores presented in Figure A1, the distribution showed that electricity efficiency across all the sub-sectors tended to be skewed towards the right. This implied that most firms had electricity efficiency scores that were above the average efficiency level.

The Kruskal-Wallis test result for the null hypothesis of equality of electricity efficiency values in the four sub-sectors was 290.339 with three degrees of freedom and greater than the Kodde and palm critical value of 7.81 resulting in the rejection of the null hypothesis. This means that there were substantial differences in electricity efficiency values in the four sub-sectors. However, as argued by O'Donell et al. (2008), efficiency scores cannot be compared directly across the four sub-sectors regarding whether one sub-sector has higher electricity efficiency compared to other sub-sectors. This is because efficiency analysis is founded on distinct sub-sector best linear frontiers. The comparison would be useful only in the case where different groups of firms have similar frontiers. O'Donell et al. (2008) provide that "as a general rule efficiency levels measured relative to one frontier cannot be compared with efficiency levels measured relative to another frontier." Caution should therefore be observed when interpreting differences in electricity efficiency across sub-sectors. As such, interpretation should only be done grounded only on the underlying sample (Lissita and Odening, 2005).

2.4.5 Distribution of Electricity Efficiency Point Estimates by Firm Size

Table 2.8 presents the results of electricity efficiency distribution by firm size. Manufacturing firms were classified into three sizes following the WBES classification. The classes are small (5-19 employees), medium (20-99 employees), and large (over 100 employees) sizes. This assessment is useful in singling firms with the greatest ability to achieve electricity efficiency goals.

Table 2.8:Mean electricity efficiency point estimates by size and sub-sector

Sub-sector	Mean	Minimum	Maximum	Kruskal-Wallis test statistic
C, P and P				
Small	0.840	0.628	0.938	
Medium	0.817	0.180	0.960	7.349
Large	0.763	0.005	0.935	
Food				
Small	0.651	0.013	0.893	
Medium	0.642	0.037	0.905	6.172
Large	0.651	0.034	0.877	
T and G				
Small	0.744	0.020	0.979	
Medium	0.801	0.010	0.965	6.102
Large	0.814	0.170	0.982	
P and OM				
Small	0.665	0.014	0.923	
Medium	0.688	0.012	0.922	8.022
Large	0.675	0.013	0.935	
Overall				
Small	0.644	0.008	0.918	
Medium	0.650	0.009	0.936	7.232
Large	0.638	0.004	0.921	

Source: Author's estimates from WBES data.

Results in Table 2.8 reveal the presence of heterogeneity in electricity efficiency levels across firms of different sizes in each of the four sub-sectors and the overall sector. The Kruskal-Wallis test statistic was greater than the critical value of 5.991 at 2 degrees of freedom in each sub-sector. Therefore, the null hypothesis that the average electricity efficiency scores were equal in all firm sizes in each of the sub-sectors and the overall sector was rejected at 5 percent level of significance. The mean electricity efficiency was significantly different across the three firm sizes in each sub-sector and the overall sector.

Results also show that evidence of common patterns in electricity efficiency across firm sizes was limited. It was difficult to tell whether small or large firms had the highest level of electricity efficiency. Electricity efficiency rose monotonically with declines in firm size in the chemicals, pharmaceuticals and plastics sub-sector. Small and large firms had equal levels of electricity efficiency and this was higher than that of medium firms. Electricity efficiency rose monotonically with the growth of firms in the textiles and garments sub-sector. Mediums firms had the highest electricity efficiency levels compared to small and large firms in the paper and other manufacturing sub-sector. Large firms performed better than small firms. Medium firms were the most electricity efficient in the overall sector followed by large and small firms in that order.

2.4.6 Fuel Efficiency Point Estimates

Table 2.9 presents empirical findings of average fuel efficiency point estimates. The average fuel efficiency levels varied across sub-sectors indicating varying room for expanding fuel efficiency across the sub-sectors.

Table 2.9:Summary statistics for fuel-efficiency point estimates

Model	Mean	Standard Deviation	Skewness	Minimum	Maximum
Chemicals, Pharmaceuticals and plastics	0.739	0. 308	-0.800	0. 019	0.996
Food	0.723	0. 205	-1.840	0. 023	0.978
Textiles and Garments	0.715	0. 200	-1.698	0. 004	0.955
Paper and other Manufacturing	0.688	0. 187	-1.541	0. 007	0.975
Overall sector	0.694	0. 162	-1.873	0. 023	0.942

Source: Author's estimates from WBES data.

The average fuel efficiency levels were 73.9, 72.3, 71.5 and 68.8 percent in the chemicals, pharmaceuticals and plastics, food, textile and garments and paper and other manufacturing sub-sectors, respectively. These scores implied that respective sub-sectors could potentially cut fuel consumption by 26.1, 27.7, 20.5 and 31.2 percent. The mean fuel efficiency score in the overall sector was 69.4 percent, which implied that the sector could potentially cut fuel consumption by

30.4 percent. The results of the current study corroborate similar studies that have established significant room to enhance fuel efficiency. Lundgren et al. (2016) find fuel efficiency in the 12 manufacturing sub-sectors in Sweden to range from 63.4 percent in the food sub-sector to 94.3 percent in the fabricated metals sub-sector. Nevertheless, a direct comparison of fuel efficiency results in the present study with those of Swedish manufacturing cannot be made because of differences in data and model employed.

Very high maximum and low minimum values of fuel efficiency were found across sub-sectors signalling the presence of some very fuel-efficient and inefficient firms in each sub-sector. Lundgren et al. (2016) also find very high maximum and minimum values of fuel efficiency in Swedish manufacturing sub-sectors. Exploring Kernel densities of fuel efficiency scores presented in Figure A2, the distributions showed that fuel efficiency for each sub-sector tended to be skewed towards the right. This implied that the majority of the firms had fuel efficiency scores that were above average fuel efficiency.

The Kruskal-Wallis test result for the null hypothesis of equality of fuel efficiency values in the four sub-sectors was 77.466 with three degrees of freedom and greater than the Kodde and palm (1986) critical value of 7.81 resulting in the rejection of the null hypothesis. This indicates that there were sizeable differences in fuel efficiency values in the four sub-sectors. Similarly, fuel efficiency values in the four sub-sectors could not be directly compared with regards to whether one sub-sector had a higher efficiency score than another sub-sector was less useful since efficiency scores for each sub-sector were established on a unique benchmark frontier.

2.4.7 Distribution of Fuel Efficiency Point Estimates by Firm Size

Table 2.10 presents sub-sector fuel efficiency distribution by firm size.

Table 2.10:Mean fuel efficiency point estimates by size and sub-sector

Sub-sector	Mean	Minimum	Maximum	Kruskal-Wallis test Statistic
C, P and P				
Small	0.770	0.285	0.996	
Medium	0.763	0.086	0.995	7.072
Large	0.682	0.019	0.992	
Food				
Small	0.743	0.026	0.978	
Medium	0.712	0.038	0.973	8.330
Large	0.712	0.023	0.953	
T and G				
Small	0.680	0.011	0.939	

Medium	0.742	0.004	0.955	8.741
Large	0.725	0.252	0.936	
P and OM				
Small	0.664	0.094	0.933	
Medium	0.702	0.709	0.935	8.171
Large	0.690	0.007	0.976	
Overall				
Small	0.687	0.035	0.920	
Medium	0.701	0.031	0.942	7.015
Large	0.694	0.023	0.916	

Source: Author's estimates from WBES data.

The results show heterogeneity in fuel efficiency levels across different firm sizes in each sub-sector. The Kruskal-Wallis test statistic was greater than the critical value of 5.991 at 2 degrees of freedom in each sub-sector and the overall sector. Therefore, the null hypothesis that the average fuel efficiency scores were equal in firms of all sizes in each sub-sector and the overall sector was rejected at 5 percent level of significance. The mean fuel efficiency scores differed significantly across the three firm sizes in each sub-sector and the overall sector.

Evidence for common patterns in fuel efficiency levels across firm sizes was scarce. Thus, there was difficulty in asserting whether large or small firms were best performing in fuel efficiency. Fuel efficiency rose monotonically with declining firm size in the chemicals, plastics and pharmaceuticals sub-sector. Small firms had the highest fuel efficiency in the food sub-sector. Large and medium firms had equal levels of fuel efficiency. Medium firms were the most fuel-efficient in the paper and other manufacturing sub-sector and in the overall sector followed by large firms and small firms in that order.

2.4.8 Malmquist Decomposition of the Total Change in Electricity Performance

Table 2.11 provides results of Malmquist decomposition of electricity efficiency change.

Table 2.11:Electricity efficiency change in the manufacturing sector in Kenya

Year	2007-2013			2013-2018		
Sub-sector	ME	MTC	M	ME	MTC	M
C, P and P	0.998	1.088	1.085	0.988	1.080	1.067
Food	0.905	0.988	0.895	0.962	0.986	0.948
T and G	1.058	0.975	1.032	1.177	0.994	1.170
P and O M	1.024	0.976	0.999	0.946	0.977	0.925
Overall	0.986	1.000	0.986	0.968	0.990	0.967

Source: Author's estimates from WBES data. Notes: ME is Malmquist index of efficiency change, MTC is Malmquist index of technical change and M is Malmquist index of electricity efficiency change.

The results in Table 2.11 reveal that electricity efficiency change was above 1 in the period 2007-2013 in the chemicals, pharmaceuticals and plastics and textiles and garments sub-sectors but below 1 in the food and paper and other manufacturing sub-sectors. This was indicative of an improvement in electricity efficiency in the chemicals, pharmaceuticals and plastics and textiles and garments sub-sectors and a regress in electricity efficiency in the food and paper and other manufacturing sub-sectors during the period under review. The improvement was by 8.5 and 3.2 percent respectively in the chemicals, pharmaceuticals and plastics and textiles and garments sub-sectors and the decrease was by 10.5 and 0.001 percent respectively in the food and paper and other manufacturing sub-sectors.

In the period 2013-2018, there was an improvement in electricity efficiency in the chemicals, pharmaceuticals and plastics and textiles and garments sub-sectors and a continued decline in electricity efficiency in food and paper and other manufacturing sub-sectors. The improvement in electricity efficiency was by 6.7 and 17 percent in the chemicals, pharmaceuticals and plastics and textiles and garments sub-sectors respectively. A decrease of 5.2 and 7.5 percent in electricity efficiency was observed in the food and paper other manufacturing sub-sectors respectively. In the overall sector, electricity efficiency performance was below 1 in both periods, implying a sustained decline in electricity efficiency of 1.4 percent in the period 2007-2013 and 3.3 percent in 2013-2018. Findings of improvement and decline in electricity efficiency over time among sub-sectors in this study corroborate the results of Boyd and Lee (2019).

Following the decomposition of the Malmquist index, results show that the effect of efficiency change and technical change on electricity efficiency change varied across sub-sectors. This outcome corroborates the findings of Wei et al. (2007), Makridou et al. (2015), and Boyd and Lee (2019). In the period 2007-2013, technical progress was only registered in the chemicals, pharmaceuticals and plastics sub-sector. This implies that this sub-sector had successfully invested in innovations and processes to enhance electricity efficiency. The other sub-sectors registered technical regress, implying that they were not successful in investing in electricity efficiency-enhancing innovations. The overall sector recorded no change, which implies that firms remained in their production frontier during the reference period.

With regards to efficiency change, the textiles and garments and paper and other manufacturing sub-sectors recorded an improvement, implying that these sub-sectors had successful investments in catching up with the benchmark frontier. Nevertheless, the chemicals, pharmaceuticals and plastics and food sub-sectors, and the overall sector recorded a reduction in efficiency change, implying that respective sub-sectors and the overall sector did not make successful efforts in catching up with the benchmark frontier. The efficiency improvement in the textiles and garments sub-sector overran the technical regress, implying that the catching-up effect was responsible for the improvement in electricity efficiency. Contrastingly, the enhancement in efficiency change in the food sub-sector was overpowered by technical regress. Hence the negative shift in the production frontier was responsible for the slight decline in electricity efficiency in this sub-sector.

Technical progress was large enough to overpower the slight decline in efficiency change in the chemicals, pharmaceuticals and plastics sub-sector. This implies that the positive shift in the production frontier was responsible for the improvement in electricity efficiency. In the food sub-sector, technical regress was reinforced by a decline in efficiency. Thus, both technical regress and failure to catch up with the benchmark frontier were responsible for the decline in electricity efficiency. In the overall sector, the decline in electricity efficiency was because of the reduction in efficiency change.

In the period 2013-2018, technical progress was only reported in the chemicals, pharmaceuticals and plastics sub-sector. The other sub-sectors recorded technical regress. Improvement in efficiency change was only recorded in the textiles and garments sub-sector. In the chemicals, pharmaceuticals and plastics sub-sector, technical progress was large enough to overpower the decline in efficiency change. Therefore, the positive shift in the production frontier was responsible for the improvement in electricity efficiency. In the textiles and garments sub-sector, the improvement in efficiency change was large enough to overpower the technical regress. Thus, the catching-up effect with the benchmark frontier was responsible for the improvement in electricity efficiency. In the food and paper and other manufacturing sub-sectors and the overall sector, technical regress was reinforced by a decline in efficiency change. This implies that both a negative shift in the production frontier and failure to catch up with the benchmark frontier were responsible for the decline in electricity efficiency.

2.4.9 Malmquist Decomposition of Total Change in Fuel Performance

Table 2.12 provides results of Malmquist decomposition of fuel efficiency change.

Table 2.12:Fuel efficiency change in the manufacturing sector in Kenya

Year		2007-2013	
Sub-sector	ME	MTC	M
C, P and P	0.854	0.904	0.772
Food	1.004	1.013	1.017

T and G	1.038	0.897	0.931
P and O M	0.993	1.032	1.025
Overall	1.010	0.999	1.009

Source: Author’s estimates from WBES data. Notes: ME is Malmquist index of efficiency change, MTC is Malmquist index of technical change and M is Malmquist index of electricity efficiency change.

Results in Table 2.12 show that unlike in the electricity model where improvements in electricity efficiency were recorded in the chemicals, pharmaceuticals and plastics and textiles and garments sub-sectors only, fuel efficiency was found to have declined in these sub-sectors. The food and paper and other manufacturing sub-sectors and the overall sector, which recorded declines in electricity efficiency, recorded improvements in fuel efficiency. Fuel efficiency declined by 22.8 and 6.9 percent in the chemicals, pharmaceuticals and plastics and textiles and garments sub-sectors respectively. The improvement in fuel efficiency was by 1.7 percent and 2.5 percent in the food and paper and other manufacturing sub-sectors respectively and by 0.9 percent in the overall sector. Improvement in fuel efficiency in these sub-sectors could partly explain why these sub-sectors performed better in fuel efficiency than in electricity efficiency. Findings of improvement and decline in fuel efficiency over time among sub-sectors corroborate Boyd and Lee (2019).

Then decomposition of the Malmquist index shows that the impact of efficiency change and technical change varied across sub-sectors. These results corroborate the findings of Wei et al. (2007), Makridou et al. (2015) and Boyd and Lee (2019). Technical progress was reported in the food and paper and other manufacturing sub-sectors, denoting successful investment in fuel efficiency-enhancing innovations. The other sub-sectors reported technical regress, implying that investments in fuel efficiency innovations were not successful in these sub-sectors. Improvement in efficiency change was reported in the food, textiles and garments sub-sectors as well as in the overall sector. This means that firms in these sub-sectors and the overall sector were successful in making investments to help them catch up with the benchmark frontier. A decline in efficiency change was recorded in the chemicals, pharmaceuticals and plastics and paper and other manufacturing sub-sectors, which means that efforts to catch up with the benchmark frontier were not fruitful.

Technical progress in the food sub-sector was reinforced by an improvement in efficiency change resulting in an improvement in fuel efficiency. In the paper and other manufacturing sub-sector, technical progress overran the decline in efficiency change resulting in an improvement in fuel efficiency. In the textiles and garments sub-sector, technical regress overpowered the improvement in efficiency change which led to a decline in fuel efficiency change. In the chemicals, pharmaceuticals and plastics sub-sector, the decline in efficiency change was bolstered by technical regress resulting in a decline in fuel efficiency change. In the overall sector, the improvement in efficiency change overpowered technical regress which led to an improvement in fuel efficiency.

2.4.10 Determinants of Electricity Efficiency

The determinants of electricity efficiency are provided in Table 2.5. The coefficient of labour productivity was positive and significant across the four sub-sectors, except in the food sub-sector, and the overall sector. This implies that high labour productivity influenced electricity efficiency negatively across all sub-sectors except in the food sub-sector. The results conflicted with the anticipation of the study. It appears that measures to improve labour productivity do not give additional emphasis to ensure a considerable level of skill advancement required to improve electricity efficiency. The finding contradicts Lin et al. (2011), Mandal and Madheswaran (2011) and Ohlan (2019).

Firm age had an ambiguous effect on electricity efficiency. Its effect on electricity efficiency in the food sub-sector was negative. This finding implies that young firms had higher electricity efficiency scores compared to older firms. Probably, recent electricity efficient technologies were being applied in young firms, while older firms used old technologies because of the huge sunk costs. The use of old technologies by older firms could also be attributed to inertia and rigidity in adapting to changing economic environments. The finding contrasts the Jovanovic (1982) theory but is, however, in line with Sahu and Narayanan, (2011b) and Haider et al. (2019).

Firm age had a positive and significant effect on electricity efficiency in the chemicals, pharmaceuticals and plastics and textiles and garments sub-sectors. This means that old firms had higher electricity efficiency levels compared to younger firms. Probably, old firms had learnt ways to improve electricity efficiency in their many years of production. The finding supports the Jovanovic (1982) theory and Mandal and Madheswaran (2011).

Firm age squared positively affected electricity efficiency in the food and textiles and garments sub-sectors. This means that electricity efficiency in these sub-sectors increased as the firms grew older. In the food sub-sector, firm age and electricity efficiency had an inverted U relation. A probable explanation for the outcome of this study is that the process of creating and successfully deploying efficient technologies is an active learning process, thus firms enhance their electricity efficiency levels as they advance in age. A second explanation could be that as firms grow older, their technologies become obsolete or break down, necessitating firms to replace them with new efficient technologies.

The coefficient of top manager's experience was negative and significant in the paper and other manufacturing and food sub-sectors. This implies that top managers with high experience led firms to achieve high energy efficiency levels compared to top managers with low experience. Experienced managers are likely to transform processes using skills and abilities accumulated over time. The finding confirms those of Chaffai et al. (2012) and Lemi and Wright (2018).

Firm size had an ambiguous effect on electricity efficiency. It positively affected electricity efficiency in the paper and other manufacturing sub-sector. This means that electricity efficiency in this sub-sector was greater in large-sized firms than in small-sized firms. This could be because large firms are characterized by a skilled workforce, enough resources to acquire new and efficient technology, high specialization and the ability to capitalize on economies of scale. In addition, this outcome could be due to self-selection, a case where only electricity efficient firms persist and expand in size while electricity inefficient firms remain sluggish or exit the market. This finding supports the Jovanovic (1982) theory, Lin and Long (2015) and Li and Shi (2014). Firm size negatively affected electricity efficiency in the chemicals, pharmaceuticals and plastics and food sub-sectors. This means that electricity efficiency was high in small firms in respective sub-sectors compared to large firms. Firm size was also found to negatively influence electricity efficiency in the overall sector. This outcome could be explained by complexities in large firms that result in more electricity consumption.

The effect of foreign ownership on electricity efficiency across all the sub-sectors and the overall sector was found to be insignificant. This was contrary to the predictions of the study. Foreign ownership patterns could have made it difficult to discern the effect of this variable on electricity efficiency. Table 2.1 shows that on average, only less than 20 percent of sampled firms were foreign-owned. This implies that spillovers from foreign world linkages accrued to only a few firms. The few foreign-owned firms were likely to keep the knowledge to themselves because of the limited number of firms aware of the existence of electricity efficient technologies. Limited foreign ownership means that the Kenyan manufacturing sector is denied the technological, productivity and efficiency externalities that come with this form of ownership (Ngui and Muniu, 2012).

The coefficient of female ownership was negative in the food sub-sector and the overall sector. This means that electricity efficiency in female-owned firms was higher than in firms with no female ownership. Interestingly, the food sub-sector had on average the highest proportion of female-owned firms. Women could be better at coordination and in skills to solve operational challenges, besides their ingenuity, novelty and openness (ILO, 2019). The moral responsibility to care for societal issues including environmental quality through energy efficiency enhancement as captured in the gender socialization and ethicality theories could also explain this finding (Atif et al., 2021).

Exporting had a positive effect on electricity efficiency across all the sub-sectors except the paper and other manufacturing sub-sector. This implies that exporting positively influenced electricity efficiency. The effect of exporting on electricity efficiency in the overall sector was also positive. Through learning by exporting, firms can enhance efficiency. Further, some buyers believe in environmentally friendly goods which makes exporting firms adhere to environmental quality standards (Roy and Yasar, 2015). The finding of this study corroborates Roy and Yasar (2015) and Campi et al. (2015).

Lastly, R&D’s influence on electricity efficiency in the chemicals, pharmaceuticals and plastics sub-sector was found to be positive. This means that electricity efficiency was higher in firms with R&D investments than in those with no R&D spending. By investing in R&D, firms are exposed to inventions in recent production equipment which improve electricity efficiency. This result corroborates Lin et al. (2011) and Lutz et al. (2017).

2.4.11 Determinants of Fuel Efficiency

The drivers of fuel efficiency are provided in Table 2.6. Labour productivity negatively influenced fuel efficiency across all sub-sectors and the overall sector, a finding that was contrary to the expected outcome. It seems that measures to enhance labour productivity fail to provide additional weight to ensure a significant level of skill improvement needed to improve fuel efficiency. The finding contradicts the outcome of Lin et al. (2011) and Mandal and Madheswaran (2011). It was expected that labour productivity could help enhance fuel efficiency.

Firm age had a negative effect on fuel efficiency in the chemicals, pharmaceuticals and plastics sub-sector. This means that fuel efficiency was higher in young firms compared to old firms. Probably, young firms produced using recent technologies while older firms employed old technologies due to the huge sunk costs. Additionally, inertia and the inability to adapt to changing economic environments by old firms could have resulted in the application of old technologies. The finding contradicts the Jovanovic (1982) theory but is, however in line with Mandal and Madheswaran (2011).

Firm age positively influenced fuel efficiency in the food sub-sector and the overall sector. This implies that as firms advanced in age, they became fuel-efficient. The process of creating and successfully deploying efficient technologies is an active learning process, thus firms could enhance their fuel efficiency levels as they advance in age. In addition, as firms advance in age, their technologies become obsolete or break down, necessitating them to replace these technologies with new efficient technologies. On the other hand, the coefficient of firm age squared was positive and significant in the textiles and garments sub-sector. This means that firm age squared negatively affected fuel efficiency. Probably, as firms in this sub-sector advanced in age, it became difficult to replace old technologies with new and efficient technologies due to huge sunk costs.

Firm size positively influenced fuel efficiency in the textiles and garments sub-sector and the overall sector. This means that fuel efficiency was greater in large-sized firms than in small-sized firms. Unlike small firms, large-sized firms are well endowed with highly skilled management and finances to acquire efficient technologies. They also can utilize economies of scale. Moreover, this outcome could be due to self-selection, a case where only fuel-efficient firms survive and grow in size while fuel-inefficient firms remain sluggish or leave the market. This result corroborates the findings of Lin and Long (2015), Lundgren et al. (2016) and Moon and Min (2017).

Foreign ownership had a positive effect on fuel efficiency in the chemicals, pharmaceuticals and plastics sub-sector. This means that foreign-owned firms had greater fuel efficiency compared to local-owned firms. Being foreign-owned, firms in the chemicals, pharmaceuticals and plastics sub-sector are potentially exposed to better technologies from abroad. Additionally, foreign-owned firms have links within which knowledge and technological progress streams from foreign nations. This outcome corroborates the results of Sahu and Narayanan (2011b).

Female ownership had a positive effect on fuel efficiency in the chemicals, pharmaceuticals and plastics and food sub-sectors. This means that fuel efficiency was higher in female-owned firms compared to those with no female ownership. Women could be better in organization and abilities to solve operational challenges, in addition to their ingenuity, innovation and openness (ILO, 2019). The finding could also be explained by the moral responsibility to care for societal concerns including environmental quality by improvements in energy efficiency as highlighted in the gender socialization and ethicality theories (Atif et al., 2021).

Exporting status had a positive effect on fuel efficiency in the chemicals, pharmaceuticals and plastics and the paper and other manufacturing sub-sectors. This means that fuel efficiency was higher in exporting firms compared to non-exporting firms. The finding is in line with Roy and Yasar (2015) and Campi et al. (2015). Several explanations are probable for this outcome. First, by participating in exporting, particularly to industrialized countries, firms get exposed to fuel-efficient technologies and their management gets introduced to good management practices. Second, importing countries may impose conditions on the nature of the production processes of the exporting countries. For instance, importing countries, especially in the European Union, may demand that some environmental quality standards be fulfilled by exporting nations for them to gain entry into foreign markets. Such conditions prompt exporting countries to initiate measures to protect the environment as they produce. Third, it's probable that fuel-efficient firms in these sub-sectors self-select themselves to exporting.

The influence of R&D on fuel efficiency in the chemicals, pharmaceuticals and plastics sub-sector was positive. This means that fuel efficiency was higher in firms with R&D investments compared to those without R&D spending. Probably, investing in R&D exposed firms to innovations in recent and efficient technologies which helped improve fuel efficiency. This finding supports the results of Lutz et al. (2017).

Contrastingly, the influence of R&D on fuel efficiency in the paper and other manufacturing sub-sector and the overall sector was negative. This implies that firms involved in R&D activities were less efficient than those with no R&D activities. This contradicted the expectation of the study. A possible explanation for this outcome could be due to the failure to distinguish R&D activities on fuel efficiency from those of developing new products and those of upgrading existing products. In addition, firms could be giving more emphasis on new product development and product upgrading at the expense of research and development on fuel-efficient technological innovations. Failure to decouple R&D activities on fuel efficiency from overall R&D activities could as well be the reason for this outcome. This outcome corroborates the results of Sahu and Narayanan (2011b).

2.5 Summary, Conclusion, Policy Implication and Areas for Further Research

Summary and Conclusion

Energy plays a pertinent function in a country's social and economic transformation. The WEF (2012), points out that energy enables the growth of an economy in two major ways: directly through job creation and indirectly through stimulation of other sections of the economy. Nevertheless, the use of energy has been linked to environmental pollution, ill human health and reduced competitiveness. Consequently, it has been argued that energy efficiency is the best cost-effective approach to attend to negativities associated with energy application. Because the manufacturing sector is a major energy consumer and a great player in the economy, understanding the state of energy efficiency in this sector is useful in developing suitable policies to deal with any inefficiencies that may be present.

While some studies such as Sahu and Narayanan (2011b), Blomberg et al. (2012), Mandal and Madheswaran (2011), Li and Shi (2014), Filippini and Zhang (2016) and Moon and Min (2017) have estimated energy efficiency in the manufacturing sector in different countries, empirical evidence in Kenya's manufacturing sector is scant. The scarce associated research concentrates on the approaches of executing energy efficiency or focuses on energy efficiency at the economy-wide level. For example, Ndichu et al. (2015) investigate methods of implementing energy efficiency in maize milling firms whilst Zhang et al. (2011) analyze the overall economy's total factor energy efficiency. This research aimed at filling the existing gap in research by presenting analytical evidence in Kenya's manufacturing sector. This objective was realized by providing an analysis of sub-sector energy efficiency differences and drivers of energy efficiency besides exploring energy efficiency change.

The stochastic frontier analysis technique was applied in the assessment of energy efficiency. Specifically, an input distance function with the assumption of a translog production function was estimated in a pooled regression model covering the years 2007, 2013 and 2018 in the analysis of electricity efficiency and 2007 and 2013 in the analysis of fuel efficiency. Data was sourced from the World Bank Enterprise Surveys (WBES). The findings revealed the existence of considerable room to enhance electricity and fuel efficiency in the Kenyan manufacturing sector. Energy efficiency point estimates were found to be varying across sub-sectors and between the two forms of energy. In general, energy efficiency point estimates showed that about 19.5, 35.2, 21.4, 32.2 and 35.5 percent of electricity could be reduced without cutting output in the chemicals, pharmaceuticals and plastics, food, textiles and garments and paper and other manufacturing sub-sectors and the overall sector respectively. For fuel, this potential was 26.1, 27.7, 28.5, 31.2 and 30.6 percent in respective sub-sectors and the overall sector.

Energy efficiency change was analysed by employing the Malmquist index. An improvement in electricity efficiency in the chemicals, pharmaceuticals and plastics and textiles and garments sub-sectors and a drop in electricity efficiency in the food and paper and other manufacturing sub-sectors, as well as the overall sector, was recorded. For fuel, an improvement in fuel efficiency was recorded in the food and paper and other manufacturing sub-sectors and the overall sector while a decline in fuel efficiency was observed in the chemicals, pharmaceuticals and plastics and textiles and garments sub-sectors. A decomposition of the Malmquist index revealed that the contribution of technical progress and efficiency change on energy efficiency change varied across sub-sectors. A positive shift in the frontier and a catching-up effect were responsible for the improvement in electricity efficiency in the chemicals, pharmaceuticals and plastics and textiles and garments sub-sectors respectively for both periods 2007-2013 and 2013-2018.

The decline in electricity efficiency in the food sub-sector in the two periods was attributed to both a negative shift in the frontier and a failure to catch up with the benchmark frontier. In the paper and other manufacturing sub-sector, the decline was attributed to a negative shift in the frontier in the first period and both a negative shift in the frontier and failure to catch up with the benchmark frontier in the second period. At the sectoral level, a reduction in efficiency change was responsible for the decline in electricity efficiency in the first period while both declines in efficiency change and a negative shift in frontier were responsible for the decline in electricity efficiency in the second period.

For fuel efficiency change in the period 2007-2013, both technical regress and failure to catch up with the benchmark frontier were responsible for the decline in fuel efficiency in the chemicals, pharmaceuticals and plastics sub-sector. In the textiles and garments sub-sector, the decline in fuel efficiency was attributable to technical regress. An improvement in fuel efficiency in the food sub-sector was attributable to both technological progress and the catching-up effect. In the paper and other manufacturing sub-sector, the improvement in fuel efficiency was attributable to technical progress. The catching-up effect was responsible for the improvement in fuel efficiency in the overall sector.

An investigation of the determinants of energy efficiency indicated that factors influencing energy efficiency differed not only across sub-sectors but also between electricity and fuel. This reveals inherent differences across the sub-sectors in each energy form meaning that interventions to enhance energy efficiency should not only be sub-sector specific but also energy form specific. The effect of labour productivity on electricity efficiency was found to be negative across all sub-sectors apart from the food sub-sector. The same was observed in the overall sector. It influenced fuel efficiency negatively in the four sub-sectors of interest and the overall sector. It seems that initiatives to increase labour productivity fail to provide additional weight to ensure a significant level of skill improvement needed to enhance energy efficiency.

Firm age had an ambiguous effect on energy efficiency. It promoted electricity efficiency in the chemicals, pharmaceuticals and plastics and textiles and garments sub-sectors. This means that old firms in the two sub-sectors could be employing recent equipment. The outcome could also be due to the advantages of learning-by-doing. Firm age negatively affected electricity efficiency in the food sub-sector and fuel efficiency in the chemicals, pharmaceuticals and plastics sub-sector. This implies that old firms in these sub-sectors could be using vintage technologies while younger firms could be using new efficient technologies.

Firm age squared positively affected electricity efficiency in the food and textiles and garments sub-sector. It had the same effect on fuel efficiency in the paper and other manufacturing sub-sector and the overall sector. This indicated that as firms in these sub-sectors advanced in age, there was an enhancement in energy efficiency because of learning-by-doing. In addition, it could be the case that equipment in firms in these sub-sectors became obsolete or even broke down as firms advanced in age prompting them to replace these technologies with recent equipment. The effect of firm age squared on fuel efficiency in the textile and garments sub-sector was negative. Huge sunk costs incurred in replacing old technologies could be responsible for this outcome.

The top manager's level of experience was found to positively influence electricity efficiency in the food and paper and other manufacturing sub-sectors. Experienced top managers are likely to improve processes using skills and capabilities acquired over time. Firm size ambiguously affected energy efficiency. It had a positive effect on electricity efficiency in the paper and other manufacturing sub-sector and fuel efficiency in the textile and garments sub-sector and the overall sector. This could be due to the ability of large firms to employ a highly skilled workforce, the financial ability to acquire modern equipment and the potential to capitalize on economies of scale. Firm size had a negative effect on electricity efficiency in the chemicals, pharmaceuticals and plastics and food sub-sectors. This outcome could be due to complications in the inner structure of large firms which leads to high energy use.

Foreign ownership positively influenced fuel efficiency in the food sub-sector. This implies that foreign-owned firms in this sub-sector receive technical support in addition to technical know-how from abroad. Female firm-ownership positively influenced electricity efficiency in the food sub-sector and the overall sector and fuel efficiency in the chemicals, pharmaceuticals and plastics and food sub-sector. This implies that female members promote the performance of firms by inculcating cooperation, solutions to challenges, ingenuity and invention and honesty.

Exporting was found to promote electricity efficiency in the chemicals, pharmaceuticals and plastics, food and textile and garments sub-sectors and the overall sector. A similar effect was found on fuel efficiency in the chemicals, pharmaceuticals and plastics and paper and other manufacturing sub-sectors. This outcome could be because of learning-by-exporting, especially from industrialized countries of destination. It could also be due to measures put in place by firms to improve energy efficiency as the foreign market, especially European Union deem purchasing environmentally friendly goods as key to promoting environmental quality.

R&D had a positive effect on both electricity and fuel efficiency in the chemicals, pharmaceuticals and plastics sub-sector. R&D investments could have exposed firms in these sub-sectors to innovations in energy efficiency. Nevertheless, R&D's influence on fuel efficiency was negative in the textile and garments sub-sector and the overall sector. The inability to disentangle R&D on energy efficiency from that of new product development and upgrading of existing products could be the reason for this outcome. Further, it could be possible that firms are emphasizing new product development as well as product upgrading at the expense of energy efficiency improvements.

Policy Implication

Several policy implications can be made from the findings of this study. Given the heterogeneity in drivers of efficiency across sub-sectors and energy types, the policy implications need to be sub-sector and energy-specific. The policy implications are highlighted as follows:

Enhancing technological innovation. The adoption of new technologies is the basis of energy efficiency. The National Treasury and Planning needs to increase R&D funds to enable the discovery of modern technologies and the development of new equipment. Available data shows that in 2018, R&D funding stood at only 0.48 percent of GDP. This was below the 2 percent recommended in the National Research Fund (NRF) Science, Technology and Innovation Act 2013. Further, the National Treasury and Planning may foster R&D subsidies. Low-interest loans and tax incentives could also be provided to firms that spend on R&D. The support of technological innovation will go a long way in supporting the government's effort to promote energy efficiency and conservation as highlighted in the Least Cost Power Development Plan (Republic of Kenya, 2020a).

Exporting had a positive effect on electricity efficiency across all the sub-sectors except in the paper and other manufacturing sub-sector and on fuel efficiency in the chemicals, pharmaceuticals and plastics and the paper and other manufacturing sub-sectors. There is a need for the Ministry of Industrialization, Trade and Enterprise Development to promote exports beyond the creation of export processing zones. Sourcing foreign markets is particularly important in this regard. The ministry also needs to provide specialized counselling and training to exporters on how to make the most of existing business opportunities abroad. Further, it is useful to train exporters on ways to access specific markets, for instance, those that may impose certain conditions regarding technical regulation and environmental quality standards.

Firm size had a positive effect on electricity efficiency in the chemicals, pharmaceuticals and plastics sub-sectors and fuel efficiency in the textiles and garments sub-sector. This result supports the literature that argues that large-sized firms are potentially more energy-efficient compared to small firms because of their ease of accessing financial resources, especially from third parties. Stringent requirements such as the availability of collateral limit access to credit by small firms. They also face high-interest loans because the economic risk is higher. For example, small firms have limited diversification in their product portfolio which exposes them to harmful economic shocks. There is a need for The National Treasury and Planning to offer financial inducements such as tax exemptions, low-interest loans and subsidies to small firms to help them make energy efficiency investments.

The effect of the top manager's experience on electricity efficiency in the food and paper and other manufacturing sub-sectors was positive. This demonstrates the need for manufacturing firms to persistently offer formal training to staff to polish their energy efficiency skills. Female firm-ownership was found to positively influence electricity efficiency in the food sub-sector and fuel efficiency in the chemicals, pharmaceuticals and plastics and food sub-sectors. The Ministry of Public Service, Gender, Senior Citizens Affairs and Special Programmes needs to devise policies that increase the visibility of female entrepreneurs in these sub-sectors. These include policies that support continuous education and training programmes on business skills. Publicizing success stories of successful female entrepreneurs through media and other platforms is also useful in encouraging and increasing the confidence of other potential female entrepreneurs. Women face hurdles when seeking credit, especially from formal third parties. For instance, they could be required to provide collateral for them to get loans from banks yet in most cases women do not own collateral. Accordingly, there is a need for lending institutions to rethink the requirements to advance credit to female entrepreneurs.

Other policies. There is a need for the government to promote foreign ownership, particularly in the chemicals, pharmaceuticals and plastics sub-sector where this variable was found to influence fuel efficiency. The management in foreign-owned firms needs to also utilize prevailing foreign direct policies, for instance, tax incentives promoting the importation of recent technologies from host countries. Through foreign ownership, there will be spillover effects on local firms. The Ministries of Energy and Petroleum and Mining also need to increase awareness of energy efficiency in manufacturing firms. This could be through conferences and leadership forums. For instance, if producers learn the benefits associated with energy efficiency measures, such measures may be scaled up.

Limitations of the Study

The 2018 WBES did not have information on fuel expenditure. Consequently, the analysis of fuel efficiency change was limited to one period only, that is, 2007-2013. This is unlike the analysis of electricity efficiency where electricity efficiency change was evaluated in two periods, that is, 2007-2013 and 2013-2018.

Future Research

Further research on this area can analyse the regional energy efficiency differences in Kenya's manufacturing sector. This study only concentrated on the sub-sector differences but energy efficiency could also be varying across regions. This is because the different regions could be having unique characteristics such as energy prices and electricity connectivity that may influence the energy demand. Further, with the availability of more data, this research can be extended to cover more periods allowing for more observations on each firm. The richness of information may be suitable for drawing a more discerning conclusion on the extent of energy efficiency in the manufacturing sector. Research in this area can be extended to analysing how energy efficiency changes over time by carrying out separate analyses by years. Lastly, a notable finding of this study is the significant role female firm ownership plays in enhancing energy efficiency in the manufacturing sector. However, the issue of gender and energy efficiency is an extensive area and this study might not have exhaustively covered it. Future research can investigate the role of gender in boosting energy efficiency as this can inform important policies on climate change.

CHAPTER THREE: EFFECTS OF ENERGY EFFICIENCY ON FIRM PRODUCTIVITY IN THE KENYAN MANUFACTURING SECTOR

ABSTRACT

This research explored the relationship between energy efficiency and total factor productivity in the Kenyan manufacturing sector using a sample of firms sourced from the World Bank Enterprise Survey. The relationship has not been explored in depth, particularly in sub-Saharan Africa, yet these countries heavily depend on energy to spur their economies. The probable trade-off between energy efficiency and firm productivity further fuels the need for this research. Energy intensity was applied to indicate energy efficiency. Total factor productivity was estimated by following the Levinsohn-Petrin Algorithm. A dynamic panel data model was applied in the assessment of the energy efficiency and total factor productivity relation. The empirical analysis was provided at the sectoral and sub-sector levels. The sub-sectors of concern were: chemicals, pharmaceuticals and plastics, food, textile and garments and paper and other manufacturing sub-sectors. The findings of this research showed heterogeneity in energy intensity across the manufacturing sub-sectors. Total factor productivity was also found to be heterogeneous across the sub-sectors and firms of different size and age. The estimates showed that energy efficiency significantly promoted total factor productivity. Other factors that were found to significantly affect total factor productivity include capital intensity, firm age and size, top manager's years of experience, foreign ownership and exporting status. However, the effect varied across the sub-sectors and firm sizes. Study findings suggest that policies to improve energy efficiency should be matched with policies to enhance total factor productivity.

3.1 Introduction

The International Energy Agency (IEA) has recognized energy efficiency to be the best cost-effective way to deal with energy-use-related problems (IEA, 2014). However, the effect of energy efficiency on economic performance cannot be overlooked, particularly in developing countries where dependence on environmental resources is relatively high. This is of concern because while energy efficiency is expected to lead to reduced energy consumption, developing countries need to increase energy production and consumption to spur their economies (Cantore et al., 2016). Reinforcing this opinion is an extensive view among some development economists that clean environment growth policies pose a risk more than a prospect of growth (Dercon, 2014).

This study sheds light on the relationship between energy efficiency-indicated by energy intensity - and economic performance in the Kenyan manufacturing sector by considering productivity as a measure of economic performance. Energy intensity, computed as the ratio of energy to output in monetary terms, quantifies the amount of energy needed to produce one unit of output (Haider and Bhat, 2020). An energy-intensive production system uses more energy to process a unit of output. This signals low energy efficiency (Fisher-Vanden et al., 2016). Production systems that are low energy-intensive are considered to be energy efficient. Even though some studies have criticized the use of energy intensity to measure energy efficiency because it assumes the application of one input only, studies such as Cantore et al. (2016), Fan et al. (2017), Montalbano and Nenci (2019), Haider and Ganaie (2017) have adopted the measure while investigating the energy efficiency and economic performance relation. According to Fan et al. (2017) and Haider and Ganaie (2017), energy intensity acts as a good proxy for energy efficiency in such an analysis because of its simplicity and ease of application in guiding policy assessment and design.

The manufacturing sector is a high end-user of energy through its production activities. It is also a high primary polluter. For instance, globally, the sector together with refining, mining, agriculture and construction which collectively form the industrial sector accounted for more than 50 percent of end-use energy use in 2019 (IEO, 2019). In Kenya, the manufacturing sector dominates in electricity use and it is the second-highest user of fuel after the transport sector (Republic of Kenya, 2021). In 2020, the manufacturing sector consumed 48.67 percent of the total demand for electricity in Kenya. Domestic and small commercial consumers, rural electrification and street lighting consumed 43,53, 6.956 and 0.847 percent respectively (Republic of Kenya, 2021). In the same year, the manufacturing sector consumed 10.57 percent of the total petroleum fuel sales. Sales to the transport sector were 86.69 percent and sales to other consumers were 2.74 percent (Republic of Kenya, 2021). Energy is utilized in the manufacturing sector to convert raw materials into intermediate and final capital and consumer goods, assemble and fabricate final capital and consumer goods and distribute and transport goods (Onuonga et al., 2011; Boyd and Lee, 2019).

Productivity is a suitable indicator of a manufacturing sector's economic performance. It shows the ability of a sector to create technological change because it establishes the quantity of output that can be generated from a given amount of inputs collectively (Cantore et al.,2016). It is useful in shaping the competitiveness of firms in both local and international markets (Sehgal and Sharma, 2011; Chege et al., 2014). Ideally, a firm's goods and services should compete domestically with imports and at the same time compete in foreign markets.

Lowly productive firms have a low chance of competing in either local or export markets, especially in the current open trade regimes where economies remove trade restrictions and embrace export-oriented policies (Chege et al., 2014). Firm productivity is also critical in influencing profits, wages and the overall welfare of society through poverty alleviation (Chege et al., 2014). Firm productivity is thus considered critical both in the growth of the manufacturing sector and the overall economy. At the macro level, Harris and Moffat (2015) and Seker and Saliona (2018) link differences in countries' levels of income and growth patterns to differences in productivity.

One of the reasons for the disquiet among some economists with regard to the adoption of clean environment production is that acquisition of clean technologies becomes essential leading to additional high costs to manufacturing firms. The direct implication of the technology acquisition is a decline in firm performance as the total cost of production becomes more for the same level of output (Hamamoto, 2006). Further, the acquisition of new technology may result in firms taking time to adjust to their learning curves, during which productivity may decline. The concern among researchers on the implications of clean production measures on manufacturing sector performance, particularly in developing countries, has affected climate change deliberations. According to Cantore et al. (2016), international discussions on climate change treaties are presently festering primarily because developing nations are unwilling to sign up binding emissions restraints because they are afraid that this could stifle their growth pathway.

Notwithstanding this disquiet, there is an expanding body of literature showing that the adoption of clean technologies may not necessarily stifle manufacturing sector economic performance, but may instead enhance it. For instance, Worrell et al. (2003) provide that a cut in energy use resulting from enhanced energy efficiency is one of the measures to boost a manufacturing firm's productivity. Firms enhance energy efficiency by investing in innovations and by applying recent and more efficient technologies. These technologies reduce energy consumption, provide energy cost savings and generally improve the overall production process (Worrell et al., 2003).

First among these improvements is a reduction in the cost of maintenance. Firms incur a lower total cost of production for the same level of output. Second, by adopting energy-efficient technologies, output by firms as well as the quality of products increase. New technologies can reduce wastage in input use thus resulting in the production of more output for the same level of inputs. These technologies provide clean environments for production leading to high-quality products. Third, energy-efficient technologies could result in an improvement in working conditions because of lower pollutants. Workers are less likely to get sick and their productivity is enhanced as they engage more labour hours. Finally, energy efficiency measures cut energy use in the manufacturing sector leading to a fall in overall energy demand at the national level. This implies lesser energy-infrastructure investments. The cost savings thereof could be channelled to non-energy goods leading to the creation of jobs and value addition in the economy (Celani de Macedo et al., 2020).

The additional benefits arising from the adoption of energy-efficient technologies are jointly called productivity benefits or non-energy benefits from reducing energy consumption. They enhance productivity in the manufacturing sector (Worrell et al., 2003). The cost of implementing energy efficiency programmes should incorporate the productivity benefits that may arise from such programmes. The benefits, when captured correctly will make the energy efficiency programmes to be more cost-effective. Ultimately, this will increase their uptake. Ignoring productivity benefits while designing energy efficiency programmes leads to underestimation of their cost-effectiveness.

3.1.1 Statement of the Problem

There is concern among economists regarding the effect of energy efficiency on manufacturing sector productivity. The concern is mainly fueled by the probable trade-off between energy efficiency and firm productivity. Energy forms a key input in production and an understanding of the link between energy efficiency and productivity is important in the formulation of energy efficiency programmes.

Even though energy intensity is important in indicating energy efficiency and settings goals and designs of energy policies, there is only scant research on energy intensity in Kenya's manufacturing sector. This is also regardless of the fact that this sector is among the leading energy-consuming sectors in the country. The majority of existing studies focus on developing countries in India such as Subrahmanya (2006), Sahu and Sharma (2016) and Haider and Bhat (2020) and Latin America, for example, Montalbano and Nenci (2019) leaving a gap for sub-Saharan Africa.

In the estimation of productivity, while studies such as Cantore et al. (2016) and Haider and Ganie, (2017) have adopted TFP as a measure of productivity, studies such as Subrahmanya (2006) and Montalbano and Nenci (2019) have adopted partial productivity measures, particularly labour productivity. While TFP takes into account all inputs used in production, partial productivity measures fail to recognize the contribution of other inputs in production. Failure to recognize other inputs ignores the possibility of substitution among inputs, yet firms continuously adjust their input mix when responding to changes in economic conditions and technology.

Even though various studies (such as Boyd and Pang, 2000; Worrel et al., 2003; Subrahmanya, 2006; Sahu and Narayanan, 2011; Pons et al., 2013; Cantore et al., 2016; Haider and Ganaie, 2017; Filippini et al., 2020; Montalbano and Nenci, 2019 and Celani de Macedo, 2020).) have investigated the effect of energy efficiency on manufacturing sector productivity, the direction in which energy efficiency affects manufacturing sector productivity remains unclear. While the majority of the studies such as Boyd and Pang (2000) Worrel et al. (2003), Subrahmanya (2006), Sahu and Narayanan (2011a), Cantore et al. (2016), Filippini et al. (2020), Montalbano and Nenci (2019) and Celani de Macedo (2020) find energy efficiency to positively affect productivity, Haider and Ganie (2017) find energy efficiency to negatively affect total factor productivity (TFP). Pons et al. (2013) find that the adoption of energy-efficient technologies has no significant relationship with the economic performance of the Spanish and Slovenian manufacturing sectors.

The mix of findings implies that the energy efficiency and productivity relationship could be country-specific and this calls for country-specific studies. These studies should particularly focus on developing countries. This is because the majority of the existing studies present evidence from China, Spain and U.S effectively ignoring developing countries in Africa, yet these countries heavily depend on energy to spur the growth of their economies. Energy use in developing countries is even anticipated to increase in the future and energy efficiency measures are required in this respect (Cantore et al., 2016). This study sought to present empirical evidence of energy intensity and TFP in Kenya's manufacturing sector. The research also aimed to explore the effect of energy efficiency on TFP in Kenya's manufacturing sector. In this analysis, energy intensity was applied to indicate energy efficiency.

3.1.2 Research Questions

The thesis addressed the following questions:

i. What is the level of energy intensity in Kenya's manufacturing sector?
ii. What is the level of total factor productivity in Kenya's manufacturing sector?
iii. What is the effect of energy efficiency on total factor productivity in Kenya's manufacturing sector?

3.1.3 Objectives of the Study

The general objective of this study was to analyze the effect of energy efficiency on firm productivity in Kenya's manufacturing sector. Specifically, the study sought to:

i. To determine the level of energy intensity in Kenya's manufacturing sector.
ii. To estimate the level of total factor productivity in Kenya's manufacturing sector
iii. To assess the effect of energy efficiency on total factor productivity in Kenya's manufacturing sector.

3.1.4 Significance of the Study

This study furthers extant literature on the effect of energy efficiency on manufacturing sector performance by first providing an analytical assessment of energy intensity and total factor productivity (TFP) in Kenya's manufacturing sector using recent firm-level data. Accurate measurement of TFP provides room for comparing productivity distributions within and across sub-sectors. The manufacturing sector can use the findings of this study to design policies to promote TFP in manufacturing firms. Second, the study provides analytical evidence on the relation between energy efficiency and manufacturing sector productivity in developing economies, particularly Kenya, for which evidence is scarce despite potential energy efficiency and productivity trade-off. Given potential heterogeneity in the relation between energy efficiency and productivity across different types of manufacturing firms, this study provides evidence at the sub-sector and firm size levels. Further, establishing this relationship also adds to existing literature that analyses determinants of manufacturing sector productivity. Lastly, the outcome of this study has important policy implications on how the Ministry of Energy and Petroleum should devise energy efficiency policies to incentivize the uptake of energy efficiency measures among manufacturing firms. A positive effect of energy efficiency on productivity implies that the productivity benefits of an energy efficiency programme should be incorporated when evaluating the cost-effectiveness of such a programme. Including the productivity benefits in the design of such programmes may make them appear more cost-effective compared to when only the goal of a reduction in energy consumption is captured.

3.2 Literature Review

3.2.1 Theoretical Literature Review

Literature provides four indicators to monitor energy intensity. These are thermodynamic, physical-thermodynamic, economic-thermodynamic and economic indicators (Patterson, 1996). The indicators define energy intensity as a ratio of energy input into a production process to output. Thermodynamic indicators depend solely on measurements stemming from the science of thermodynamics. However, these indicators have been criticized for failure to satisfactorily capture the end-use service needed by consumers in the measurement of output. Instead, they measure output either as heat substances or some work potential. Physical-thermodynamic and economic-thermodynamic indicators attempt to circumvent this weakness by providing hybrid pointers (Patterson, 1996). In both indicators, energy input remains quantified by thermodynamic units. Output is captured by physical units such as tonnes of produce in the physical-thermodynamic indicators, whereas the economic-thermodynamic indicators improve the measurement of output by capturing it in market prices.

Some economists have held that the two indicators are still not sufficient in monitoring energy intensity (Patterson, 1996). They argue that both input and output quantities need to be computed based on economic value because such measurement provides an accurate indication of the economic activity provided energy and output prices exhibit the demand and supply forces. The use of energy prices also offers a way out of the energy quality challenge- that is the challenge of logically summing up energy inputs of varying qualities. Economic indicators, which provide measurement for both energy inputs and output in monetary terms, are therefore more useful for policy analysis and are adopted by this study.

The concept of TFP is embedded in the neo-classical framework which attributes growth to two sources: factor accumulation and TFP growth. Most of the research has concentrated on TFP growth. According to Felipe (1999), this is because growth resulting from factor accumulation cannot be sustained in the long run due to diminishing returns to the factors. Therefore, to understand growth, the argument has to be beyond factor accumulation embedded in the production function to the discussion of how countries or institutions develop new skills, improve their organizational settings, enhance their technologies and more importantly the combination of all these which results to efficient and economical employment of factor inputs. Thus, with the optimal application of inputs in production, TFP could proxy long-run technological advancement (Haider and Bhat, 2020). Krugman (1990) holds that productivity is not the only important thing in a country but that it is the one that mainly matters in the long run.

The Porter Hypothesis provides a theoretical basis for the relationship between environmental quality and firm productivity (Porter and Van der Linder, 1995). It is a departure from the conventional view among economists that a reduction of an externality causing input such as energy stifles firm productivity by increasing the cost of production following the acquisition of new technologies and through reduced competitiveness. According to these economists, environmental quality enhancement measures such as energy efficiency require firms to assign certain inputs to pollution abatement, which is unproductive from a business point of view. The Porter hypothesis however claims that well-formulated environmental policies can result in enhanced firm productivity by promoting efficiency levels and nurturing innovations. The argument by Porter and Van der Linder, (1995) is fundamentally established on the reality that pollution is an indicator of economic waste and entails unwarranted and insufficient use of resources (Ambec et al., 2013). Therefore, curbing pollution can increase productivity through which resources are utilized.

According to the hypothesis, when a firm acquires an environmentally friendly technology, the cost of acquisition may be offset by cost savings rising from technological improvement prompted by the need for a clean environment. This is referred to as innovation offset (Porter and Van der Linder, 1995). The innovation offset in Porter's hypothesis is achieved following technological innovation rising from firm Research and Development (R&D) activities. This can have a sizeable and long-term effect on productivity improvement if environmental protection measures can stimulate the formation of more productive and environmentally friendly production processes. The Porter hypothesis, therefore, provides that adopting environmentally friendly production can achieve double dividends in which firms concurrently realize both objectives of a cleaner environment and higher productivity. Ultimately, environmentally friendly measures would not only promote private benefit but will also promote public benefit.

3.2.2 Empirical Literature Review

Considerable effort has been made to estimate energy intensity, TFP and empirically test the effect of energy efficiency on manufacturing sector productivity. This study explores three strands of literature: one reviewing studies estimating energy intensity, a second one exploring the estimation of TFP and a third one reviewing the energy efficiency and productivity relation.

Beginning with the first strand, reviewed studies show heterogeneity in energy intensity which runs from regions, clusters or industries. In India's small-scale bricks and foundry clusters, Subrahmanya (2006) calculates energy intensity as the ratio of energy cost to output value by considering 38 brick makers and 31 foundries. The findings of this study show that the brick-making cluster is more energy-intensive than the foundry cluster. The study further assesses the statistical significance of the correlation between energy intensity and capital intensity and value output among others in an attempt to establish what drives energy intensity. Findings indicate that high capital intensities in the foundries cluster could lead to increases in energy intensities. High capacity utilization and high output size are found to be accompanied by smaller energy intensities and vice versa in the brick-making cluster. However, this study focuses on only the small-scale industry by assuming this industry could be consuming a considerable amount of energy in India's total industrial demand for energy. The study ignores the larger-scale industry, yet both the small-scale and large-scale industries collectively contribute to the high energy consumption. The current study focuses on a sample of firms in the overall manufacturing sector in Kenya which is a significant consumer of energy.

Using annual survey data for the period 2002-2008, Sahu and Sharma (2016) calculate energy intensity for the Indian manufacturing sector. Findings show that energy intensity varies across various sub-sectors. An analysis of drivers of energy intensity reveals that TFP, output and firm age among others negatively influence energy intensity. The study, however, fails to capture the relationship between capital intensity and energy intensity yet literature shows that capital intensity is a key determinant of energy intensity. This study establishes how capital intensity is linked to energy intensity in the manufacturing sector in Kenya.

Still in India, Haider and Bhat (2020) calculate energy intensity based on state-level data for the paper industry covering 21 major states. Energy intensity is calculated as the ratio of fuel consumed to the gross value of output and it is found to decline from the period 2001-02 to 2013-14. Further, energy intensity is found to vary across states. In an analysis of drivers of energy intensity, capital intensity, labour productivity and TFP are found to negatively influence energy intensity while the share of gross output in total manufacturing output in the paper industry is found to positively influence energy intensity. The study considers the paper industry only, yet the manufacturing sector is composed of many industries which collectively contribute to high energy consumption. This study considers the whole of the Kenyan manufacturing sector.

In Latin America, Montalbano and Nenci (2019) compute energy intensity using World Bank Enterprise Survey (WBES) firm-level data. Results show that energy intensity varies across different countries, industries and firm size categories. However, this study does not explore the link between energy intensity and other factors, yet this analysis is important in identifying determinants of energy intensity. The current study explores how the capital intensity and output value are linked to energy intensity. Existing literature shows that capital intensity and output are important in determining energy intensity.

Moving to the second strand of literature, conventionally, a commonly applied measure of productivity is the partial factor measure of productivity. In this measure, productivity is expressed as the ratio of output to a particular input. For example, labour productivity is measured as the ratio of total sales to the number of staff. Examples of studies that have adopted this measure include Montalbano and Nenci (2019) in the manufacturing sector in thirty Latin American Caribbean States, Ulku and Pamukcu (2015) in the Turkish manufacturing sector, Gomez-Tello and Nicolini (2017) in the Spanish manufacturing sector and Heshmati and Rashdghalam (2016) in the Kenyan manufacturing and service industries.

Even though the partial factor productivity measure is simple to compute, it does not reflect a true measure of productivity given that it assumes production involves the application of only one factor of production. Total factor productivity (TFP) provides a theoretically convincing measure of productivity. TFP acknowledges that the production process is principally multi-input based. This measure permits researchers to observe how efficiently firms combine factor inputs to produce output. It has thus received attention from many researchers. Among studies that have adopted TFP include Kreuser and Newman (2018) in South Africa's manufacturing sector during the period 2010-2013. In this study, the method of Ackerberg et al. (2006) is applied to tax data obtained from South African Revenue Services (SARS). The findings of the study show significant heterogeneity in the distribution of TFP by industry, firm size and firm age. However, this study has not reported the actual firm TFP levels, yet this information is important in signalling the extent of policies needed to improve productivity. The present study provides results of firm-level TFP at the sub-sector levels in the Kenyan manufacturing sector.

In the Indian paper industry, Haider and Bhat (2020) estimate TFP using regional data for the period 2001-2013 by applying the Levinsohn and Petrin (2003) methodology. Results of this study show significant variation in TFP across regions and time. The study however fails to analyse determinants of TFP, yet such an analysis is important in revealing key factors to promoting productivity. The current study provides this analysis by investigating how energy efficiency and other factors affect TFP in the Kenyan manufacturing sector.

Blazkova et al. (2020) estimate Czech's food industry TFP in the period 2003-2017 by applying firm-level data sourced from the Magnus Web database. The study applies Ordinary least squares (OLS), instrumental variable (IV) and two-way generalised method of moments (GMM) estimators. The findings of the study show the mean TFP to be 0.5 in all estimation approaches. However, the study fails to show the distribution of TFP across various firm characteristics, even though such information is important in revealing the type of policies needed to promote productivity for the different types of firms. The present study provides the distribution of TFP across various firm characteristics in Kenya's manufacturing sector.

Ding et al. (2016) estimate TFP in China's large and medium-sized industrial firms in the period 1998-2007 using micro-level data sourced from the National Bureau of Statistics. The study employs the GMM estimator. Findings show significant heterogeneity in the distribution of TFP over time, regions, political affiliations and exporting status. Given that this study does not target small firms, the performance of these firms remains unknown, yet such firms form a significant portion of manufacturing firms and contribute significantly to GDP. The current study estimates TFP in small, medium and large firms in the Kenyan manufacturing sector.

In Kenya, Chege et al. (2014) estimate the manufacturing sector's TFP by applying firm-level data for the period 2007 obtained from the WBES. The study employs a parametric estimation technique and finds some heterogeneity in firm-level TFP across sub-sectors, firm size, exporting and legal status. However, the study does not provide an analysis of the determinants of TFP, yet such an assessment is important in identifying factors that promote productivity. The present study provides this analysis by assessing how energy efficiency and other factors affect TFP in the manufacturing sector in Kenya.

Turning to the third strand of literature, significant effort has been made to analytically investigate how energy efficiency and firm productivity are linked, but mixed results have been reported. While a bulk of the studies show that energy efficiency promotes firm productivity, few studies show a negative or no significant effect of energy efficiency on firm productivity. Beginning with studies that show a positive effect, Worrell et al. (2003) review the relationship between advancement in energy efficiency and productivity in U. S's iron and steel industry. The findings of the study reveal that energy efficiency can promote the general productivity of the industry. The study proposes that non-energy benefits should be counted in when reviewing energy efficiency policies as this would make them appear more cost-effective as opposed to when they are excluded. Even though this study provides an important investigation, the use of case review analysis fails to give quantifiable evidence. The current study provides an empirical assessment of how energy efficiency relates to firm productivity in the manufacturing sector in Kenya.

Celani de Macedo et al. (2020) investigate the extent to which energy efficiency measures can create concurrent improvements in value-added, employment and energy savings in the Republic of North Macedonia industries using input-output models. The findings of this study show that energy efficiency measures can achieve triple dividends in value-added, employment and energy saving. The study adopts value-added output and employment as indicators of performance, however, these measures do not show the capability of firms to generate technological change.

In the Indian small-scale bricks and foundry clusters and by using multiple regression analysis, Subrahmanya (2006) estimates the energy efficiency and economic performance relation. The study employs primary data obtained from 38 bricks enterprises and 31 foundries. The findings of the study indicate that energy efficiency positively influences the proportion of energy expenditure in entire variable expenditure, the value of output and factor productivities. However, this study uses returns to scale as a measure of firm performance. As in the study by Celani de Macedo et al. (2020), this measure also does not conclusively show the ability of firms to create technological change. The current study adopts TFP, which effectively shows the ability of a firm to create technology, to indicate firm performance.

By applying a standard constant return to scale Cobb-Douglas production function and pooled ordinary least squares (POLS), Montalbano and Nenci (2019) examine the linkage between energy efficiency, productivity and exporting in thirty Latin American Caribbean (LAC) states using firm-level information obtained from the WBES. The findings of this study corroborate the Porter Hypothesis. The results suggest that improving energy efficiency could result in enhanced productivity. The study also suggests that current energy reduction policies should incorporate non-energy benefits as a form of productivity benefits. However, the study fails to correct for potential reverse causality given that productivity could also influence energy efficiency positively. The present study adopts a dynamic panel data model to correct for potential reverse causality.

The findings of Worrel et al. (2003), Subrahmanya (2006) and Montalbano and Nenci (2019) are corroborated by Zhang (2016) in the Swedish Industry. The study employs a true random effects SFA model to measure energy efficiency from which it establishes its effect on productivity. The study observes that a management initiative that stresses energy efficiency is anticipated to be more cost-effective and advantageous for the general productivity of the industry. In addition, Cantore et al. (2016) explore the influence of energy efficiency on productivity and economic growth in low-income countries using fixed effects estimation. The study uses panel data on manufacturing firms from 29 developing countries obtained from the WBES. The outcome of the study indicates that improvements in energy efficiency enhance productivity and economic growth. The research proposes that policies recommending the removal of energy efficiency barriers need to be adopted by developing countries.

By resulting to cross-section data sourced from the Center for Monitoring Indian Economy Sahu and Narayanan (2011a) apply OLS in assessing the energy efficiency and Indian manufacturing productivity relation. The finding of the study reveal energy efficiency positively influences productivity. The study proposes that the Indian government should come up with financial incentives for enhancing energy efficiency. In a similar way to Montalbano and Nenci (2019), studies by Zhang (2016), Cantore et al. (2016) and Sahu and Narayanan (2011a) do not correct for potential reverse causality, which the present study does by estimating a dynamic panel data model.

Moving to studies that have found a negative effect and those that have found no significant effect, Haider and Ganaie (2017) by employing time series data and vector error correction mechanism (VECM) find energy efficiency to negatively influence productivity in India. This study establishes a unidirectional causality moving from energy efficiency to productivity. In the long run, high productivity will be realized by high energy application. The study investigates energy efficiency and productivity relation at the economy-wide level and does not provide evidence at the manufacturing sector level. This is even though the manufacturing sector is a major energy consumer. Further, analysis at the sector level is important because different sectors have different energy demands necessitating sector-specific energy policies. The current study provides empirical evidence in Kenya's manufacturing sector.

In the investigation of the influence of energy efficiency technologies on Spanish and Slovenian manufacturing sector performance using linear regression, Pons et al. (2013) find the application of energy-saving technologies has no clear impact on firm economic performance. The study establishes that energy-saving technologies positively influence environmental performance. This study proposes that policymakers should make better regulation plans and recommendations to save energy and protect the environment. Although the study adopts the rate of return as an indicator of firm performance, the indicator does not show the ability of a firm to create technological change. The present study shows the ability of a firm to create technological change by adopting TFP as a measure of productivity in Kenya's manufacturing sector.

3.2.3 Overview of Literature

Thermodynamic indicators historically dominated the modelling of energy intensity. Due to limitations with regard to how they captured output units, some alternative indicators have emerged. Among these are physical-thermodynamic and economic-thermodynamic indicators. However, these indicators still do not provide satisfactory modelling of energy intensity given that both indicators measure energy in physical units. In addition, the physical-thermodynamic indicators express output in physical units. Economic indicators, which model energy intensity by expressing energy input and output in monetary terms, are more useful in policy analysis and have been adopted by this study.

Total factor productivity is anchored in the neo-classical framework which ascribes growth to two sources: factor accumulation and TFP growth. However, given that growth resulting from factor accumulation cannot be maintained in the long run because of weakening returns to the factors, more focus in productivity literature has been directed to TFP. TFP-led growth is the growth that is not explained by an increase in inputs. It is mainly attributed to the improvement of skills, organizational settings, improvements in technology and efficient use of the factor inputs among others.

The link between environmental performance and firm productivity is mainly established by the Porter Hypothesis. This hypothesis provides that well-designed environmental quality-enhancing measures can result in productivity benefits. This hypothesis is a departure from the conventional view that provides that environmental quality-enhancing measures result in a decline in firm productivity given that they necessitate the purchase of new technologies and thus additional production costs. The Porter Hypothesis however opines that such additional costs are in the long run offset by energy cost savings making it cheaper to produce a unit of output.

Reviewed literature shows energy intensity has been used to indicate energy efficiency in some studies. In these studies, energy intensity is found to be heterogeneous across regions, industries and even different firm sizes. Several studies have made effort to evaluate the relation between energy intensity and other factors. Key among these factors are capital intensity and the size of the output. However, such analysis remains inconclusive, yet it is important in determining factors that could drive energy intensity. More studies calculating energy intensity and establishing the relationship between energy intensity and its suspected driving factors are needed, particularly for developing countries in Africa where empirical evidence is scarce.

The studies assessed further show that two broad measures of productivity exist: single-factor productivity measure and total factor productivity measure. The single-factor productivity measure has received criticism among researchers on the account that it ignores the application of many inputs in the production process. The total factor measure acknowledges that manufacturing is a multi-input production process and has gained the attraction of many researchers. While some studies have provided analysis of determinants of productivity, some have not, yet this information is important in identifying factors that are key in promoting productivity. Further, some studies have not provided the distribution of TFP across various firm characteristics, yet such distribution is important in identifying areas that require more policies to promote productivity. There is a need for more empirical estimation of firm-level TFP and assessment of the distribution of this TFP across various firm characteristics, particularly for the manufacturing sector in Africa where empirical evidence is limited. Such an analysis needs to also be extended to the identification of factors that promote TFP.

Reviewed literature on the effect of energy efficiency on firm productivity shows evidence for countries in Asia, Europe and America. Evidence for Africa is scanty yet developing countries in Africa are anticipated to consume large amounts of energy to support their growing economies. A mixture of findings on the energy efficiency and firm performance relation is reported in the studies reviewed. While a bulk of the studies, for instance, Worrel et al. (2003), Celani de Macedo et al. (2020), Subrahmanya (2006), Montalbano and Nenci (2019), Zhang (2016) Cantore et al. (2016) and Sahu and Narayanan (2011a) report a positive effect, Haider and Ganaie (2017) report a negative effect and Pons et al. (2013) report no significant effect. More studies analysing the relationship between the two variables may be required to help build a consensus. These studies should in particular be concentrated in developing countries.

Examined studies have mainly adopted models such as simple linear regression, fixed effects, input-output, multiple regressions, GMM and VECM among others to explore the influence of energy efficiency on firm productivity. Some studies have used rate of return, value-added and employment as indicators of firm performance. These indicators however do not show the capability of a firm to create technological change. Further, some studies have assessed the effect of TFP on energy efficiency and there is empirical evidence indicating that TFP influences energy efficiency positively. This indicates a possibility of feedback causality moving from TFP to energy efficiency. This causality needs to be corrected as it may result in endogeneity. However, reviewed literature shows that there are studies that have not corrected the feedback causality. This study sought to attend to the existing research gap by presenting analytical evidence on the effect of energy efficiency on productivity in Kenya's manufacturing sector by adopting TFP as a productivity measure and by employing the dynamic panel data model to correct for potential endogeneity resulting from reverse causality.

3.3 Methodology

3.3.1 Theoretical Framework

This study models energy intensity through economic indicators, which provide measurement in monetary terms. According to Subrahmanya (2006), given a measure of energy (*E*) and output (*Q*), energy intensity (*EI*) is expressed as the ratio of energy to output.

$$EI = \frac{Energy\ input\ into\ the\ process}{Useful\ output\ out\ of\ a\ process} = \frac{E}{Q} \tag{3.01}$$

From equation (3.01), energy efficiency is modelled as the inverse of energy intensity

$$EF = \frac{1}{EI} \tag{3.02}$$

where *EF* represents energy efficiency.

Analysis of TFP is founded on the theory of the firm, which describes how firms convert inputs into output using some given technology. TFP is a suitable productivity measure because it considers the employment of several factor inputs in a production process (Cantore et al., 2016). This is unlike partial productivity measures, for example, labour productivity which assumes that the production process involves the use of only one input. By taking into account other inputs, TFP also acknowledges the role of input substitution, particularly when responding to changes in technology and economic conditions.

Following Van Beveren (2012) and Harris and Moffat (2015), the study adopted a Cobb Douglas production specification and the Solow Residual approach in measuring TFP. The Cobb-Douglas function was expressed as:

$$Q = A\, K^{\alpha_k} L^{\alpha_l} \tag{3.03}$$

In equation (3.03), output, Q, is expressed as a function of capital, K, labour, L, and Hicks neutral measure of efficiency, A, which denotes the productivity index. The productivity index measures the efficiency in the utilization of the factor inputs (labour and capital). α_k and α_l denote the output elasticities of capital and labour respectively. Output elasticity measures the percentage change in output resulting from a percentage change in capital or labour. Following Cantore et al. (2016), the Cobb Douglas specification in equation (3.03) can be extended to include materials, M, as follows:

$$Q = A\, K^{\alpha_k} L^{\alpha_l}\, M^{\alpha_m} \tag{3.04}$$

where α_m represents the output elasticity of materials. From equation (3.02), TFP is derived as follows:

$$TFP = A = \frac{Q}{K^{\alpha_k} L^{\alpha_l}} \tag{3.05}$$

From equation (3.05), TFP was expressed as a ratio of output to inputs collectively. Including materials explicitly,

$$TFP = A = \frac{Q}{K^{\alpha_k} L^{\alpha_l} M^{\alpha_m}} \tag{3.06}$$

According to Felipe (1999), TFP is exogenously determined and can be interpreted as an index of other factors besides capital, labour and materials which are not explicitly considered in the equation but participate in the creation of output all the same. Such factors include R&D, managerial abilities and organizational proficiency and technology uptake (Felipe, 1999). The TFP derived, in this case, is suitable for evaluating the impact of various policy measures (Van Beveren, 2012). It was applied in the present study to investigate how energy efficiency impacts manufacturing firms' productivity.

3.3.2 Analytical Model

The analytical framework in this study followed a three-stage process. With the availability of panel data, in the first stage, the study estimated energy intensity in a firm by dividing energy input by output produced.

$$EI_{it} = \frac{E_{it}}{Q_{it}} \tag{3.07}$$

where *EI* is energy intensity, *i* denotes the *i*th firm, *t* indicates time. Energy efficiency was obtained by taking the inverse of energy intensity

$$EF_{it} = \frac{1}{EI_{it}} \tag{3.08}$$

Where EF_{it} is the energy efficiency for firm *i* at time *t*. The study linearized equation (3.04) in the second stage as a step towards getting TFP by taking natural logs.

$$q_{it} = \beta + \alpha_k k_{it} + \alpha_l l_{it} + \alpha_m m_{it} + \varepsilon_{it} \tag{3.09}$$

and $ln\ A_{it} = \beta + \varepsilon_{it}$ (3.10)

where lower-case letters denote natural logarithms, β measures the average efficiency across firms and time. ε_{it} denotes time- and firm-specific variation from the average efficiency and it is further decomposable into discernible and indiscernible elements (Van Beveren, 2012). The decomposition yielded the following expression:

$$q_{it} = \beta + \alpha_k k_{it} + \alpha_l l_{it} + \alpha_m m_{it} + v_{it} + u_{it}{}^q \tag{3.11}$$

where $\varphi_{it} = \beta + v_{it}$ denotes firm-level productivity and $u_{it}{}^q$ is an i.i.d term that represents random variations from the mean. The variations emanate from measurement error, unpredicted interruptions or other exogenous factors beyond the firm's control.

To solve for φ_{it} , equation (3.11) would have to be estimated. Estimating this equation using the ordinary least squares (OLS) method would provide biased and inconsistent parameter estimates because of simultaneity bias (Van Beveren, 2012). OLS estimates would be correct if only factor inputs were exogenous, that is, if factor inputs were determined separately from the firm's productivity level. However, input choices are affected by firm productivity. For instance, the number of employees or the amount of materials procured hinges on unseen managerial capability, which is a feature of TFP unobservable to a researcher but known to the firm. Thus, the amounts of inputs chosen are correlated with unobserved productivity shocks resulting in simultaneity bias (De Loecker, 2011).

Several alternatives to OLS have been proposed including fixed effects estimation. According to Levinsohn and Petrin (2003), by supposing that φ_{it} is firm-specific and time-invariant, a fixed effects model could be applied in the estimation of equation (3.11) The equation could be rewritten as:

$$q_{it} = \beta + \alpha_k k_{it} + \alpha_l l_{it} + m_{it} + \varphi_i + u_{it}{}^q \qquad (3.12)$$

Equation (3.12) could be analyzed in levels by Least Square Dummy Variable (LSDV) or in first differences. As long as φ_{it} remains time-invariant, this estimation would give unbiased and consistent coefficients for the inputs. As pointed out in Wooldridge (2009), for the fixed effects model to be applied, the inputs need to be strictly exogenous, conditional on firm heterogeneity. This implies that the selection of inputs must not be in response to productivity shocks. In reality, however, this notion might not hold. (Wooldridge, 2009).

A second alternative to OLS is the instrumental variable approach, where endogenous explanatory variables are instrumented. Unlike the fixed effects estimation method, this method does not require strict exogeneity of inputs (Wooldridge, 2009). For the IV estimator to be consistent, the instruments have to satisfy three conditions. First, there should be correlation between the instruments and the endogenous variables. Second, there should be no direct entry of the instruments into the production function. Third, there should be no correlation between the instruments and the error term. However, it is often difficult to obtain valid instruments for the endogenous regressors in a production function. Input prices are often employed as instruments, but they are not often reported by firms. In cases where they are reported, they are in an unsuitable manner. Annual accounts, for example, record labour expenses as mean wage per worker. If this variable were to signal exogenous labour market price, then it would be a valid instrument. Nevertheless, wages often tend to change with the skills and quality of employees. Given that these factors affect firm-level productivity, a correlation between the instrument and productivity prevails making the instruments to be invalid (Van Beveren, 2012).

A third alternative to OLS is the Olley-Pakes estimation algorithm. The method, which was developed by Olley and Pakes (1996), builds a consistent semi-parametric estimator. The estimator applies firm investment decisions to proxy unobserved productivity shocks as a step towards solving for simultaneity bias. For an estimator to be consistent, some assumptions have to be observed. First, it is assumed that at the firm level, productivity is the only unobserved state variable. This variable is presumed to grow as a first-order Markov process, implying that future unobserved productivity is only contingent on current unobserved productivity. Second, monotonicity of the investment variable is assumed, implying that investments should expand with productivity improvements, contingent on the amounts of all state factors. This assumption implies that only positive values of investment are utilized. Lastly, if industry-level price indices are employed in deflating input and output values for them to proxy respective quantities, an assumption is made that all firms in the industry are exposed to the common input and output prices (Olley and Pakes, 1996).

However, the monotonicity assumption undermines its empirical application. According to Van Beveren (2012), given the assumption that investments should only take positive values, there may be a substantial loss in efficiency contingent on the available data. Further, if investments take zero values in a substantial number of observations, the soundness of the monotonicity assumption may be put into question. Following this concern, Levinsohn and Petrin (2003) developed the Levinsohn-Petrin (LP) estimation algorithm. This algorithm replaces investments as a proxy for unobserved productivity shocks with intermediate inputs. This is on account that firms report positive values for materials and energy used every year and keep records of these observations. When this is the case, the monotonicity precondition is likely to bind. The method appealed to this study.

Materials are shown to be hinged on capital and productivity, that is $m_{it} = m(k_{it}, \varphi_{it})$. Given that monotonicity condition binds and that materials are strictly increasing in φ_{it}, this equation could be inverted to allow unobserved productivity shock to be expressed as a function of observable inputs, that is $\varphi_{it} = \varphi(k_{it}, m_{it})$, where $\varphi(.) = m^{-1}(.)$. Using this expression, equation (3.12) is rewritten as:

$$q_{it} = \beta + \alpha_k k_{it} + \alpha_l l_{it} + m_{it} + \varphi(k_{it}, m_{it}) + u_{it}{}^q \tag{3.13}$$

According to Levinsohn and Petrin (2003), the estimation of equation (3.13) takes place in two steps. In the first step, the following conditional moments are estimated $E(q_{it}|k_{it}, m_{it})$ and $E(l_{it}|k_{it}, m_{it})$ by, for instance, regressing q_{it} on k_{it} and m_{it}. The locally weighted quadratic least-squares approximation is used for each conditional mean[3]. The expectation of equation (3.13) conditional on (k_{it}, m_{it}) is then deducted from equation (3.13) to get:

[3] The local weighed quadratic least squares estimation utilizes weighted least squares to build predictions of q_{it} given (k_{it}, m_{it}) and using the regressors as grounds for a second-order polynomial approximation in (k_{it}, m_{it}). Given any particular point $(\bar{k}_{it}, \bar{m}_{it})$ where an estimate of the expected value of q_{it} is required, the regression weights most often rely on observations that are nearest to $(\bar{k}_{it}, \bar{m}_{it})$. The intercept from the local quadratic regression gives a consistent estimator of $E(q_{it}|k_{it} = \bar{k}_{it}, m_{it} = \bar{m}_{it})$.

$$q_{it} - E(q_{it}|k_{it}, m_{it}) = \alpha_l(l_{it} - E(l_{it}|k_{it}, m_{it})) + u_{it}{}^q \tag{3.14}$$

Equation (3.14) is estimated using the OLS regression method without an intercept to obtain consistent coefficients of labour. To estimate the coefficients of capital, materials and a measure of firm-level productivity requires a second step. The step uses two population moment conditions to ascertain α_k and α_m. The first-moment condition ascertains α_k by presuming that capital is invariant of innovations in productivity ξ_{it}. The second moment ascertains α_m by observing that the selection of materials in the last period should not be correlated with the innovations in productivity in the current period (Levinsohn and Petin, 2003). The two-moment conditions are as follows:

$$E[(\xi_{it} + u_{it}{}^q)k_{it}] = E[\xi_{it}k_{it}] = 0 \tag{3.15}$$

and

$$E[(\xi_{it} + u_{it}{}^q)m_{it-1}] = E[\xi_{it}m_{it-1}] = 0 \tag{3.16}$$

An estimate of the residual is then gotten from the following function:

$$\xi_{it} + u_{it}{}^q(\alpha^*) = q_{it} - \hat{\alpha}_l l_{it} - \alpha_m^* m_{it} - \alpha_k^* k_{it} - E[\varphi_{it}|\varphi_{it-1}] \tag{3.17}$$

The residual is directly referenced as a function of two parameters α_m^*, α_k^* (that is, $\alpha^* = (\alpha_m^*, \alpha_k^*)$). $E[\varphi_{it}|\varphi_{it-1}]$ is a measure of expected unobserved productivity shocks and is estimated using values of φ_{it} obtained from first-stage estimation. The Generalized Method of Moments (GMM) is then applied to get estimates of α_k and α_m. To achieve this, five over-identifying conditions are included, leading to a total of seven population moment conditions obtained by the following vector of expectations as given by Levinsohn and Petrin (2003):

$$E[(\xi_{it} + u_{it}{}^q)Z_{it}] \tag{3.18}$$

where Z_{it} is a vector of instruments provided by $Z_{it} = \{k_{it}, m_{it-1}, l_{it-1}, k_{it-1}, m_{it-2}\}$. The estimates of $\hat{\alpha}_m$ and $\hat{\alpha}_k$ are obtained by minimizing the following GMM equation:

$$Q_N(\alpha^*) = min_{\alpha^*} \sum_{h=1}^{5} (\sum_i \sum_{t=T_{i0}}^{T_{i1}} (\xi_{it} + u_{it}{}^q(\alpha^*))Z_{iht})^2 \tag{3.19}$$

where h represents the five instruments and T_{i0} and T_{i1} denote the previous and current period respectively. The estimated productivity is then computed as follows:

$$\widehat{\varphi_{it}} = \hat{\beta} + \widehat{v_{it}} = q_{it} - \widehat{\alpha_k} k_{it} - \widehat{\alpha}_l l_{it} - \widehat{\alpha_m} m_{it} \tag{3.20}$$

TFP in levels is obtained by taking the exponential of $\widehat{\varphi_{it}}$, that is

$$TFP_{it} = exp(\widehat{\varphi_{it}}) \tag{3.21}$$

Equations (3.13) to (3.21) mark the second stage estimation. The third stage estimation follows Sahu and Narayanan (2011a), Cantore et al. (2016), Haider and Ganaie (2017) and Montalbano and Nenci (2019) where TFP is modelled as a function of energy efficiency.

$$TFP_{it} = g(EF_{it}) \tag{3.22}$$

where EF_{it} denotes energy efficiency or the inverse of energy intensity while TFP_{it} stands for total factor productivity in levels. *i* represents the *i*th firm and *t* represents time. The analytical model is then expressed as:

$$\ln TFP_{it} = \gamma + \theta_{ef} \ln EF_{it} + \mu_{it} \tag{3.23}$$

γ is an intercept and μ_{it} is i.i.d error term. Following Cantore et al. (2016) equation (3.23) could be further expanded as in equation (3.24) to allow for other controls of firm-level TFP.

$$\ln TFP_{it} = \gamma + \theta_{EF} \ln EF_{it} + \theta_c C_{it} + \theta_w W_i + \mu_{it} \tag{3.24}$$

C_{it} and W_i are vectors of firm-specific variables which are time-variant and time-invariant, respectively. θ_c and θ_w are vectors of coefficients for time-variant and time-invariant controls, respectively. Estimating equation (3.24) using the OLS method could lead to biased estimates of energy efficiency since the variable is potentially endogenous. According to Cantore et al. (2016), there are two probable sources of endogeneity. First is omitted variables in form of unobserved firm characteristics. Such variables are likely to influence both energy efficiency and TFP. For instance, managerial ability could potentially influence the uptake of energy efficiency technologies by firms and at the same time affect firm TFP. To solve the endogeneity problem, the constant coefficient is allowed to vary across firms, hence capturing unobserved heterogeneity across firms that may be correlated with energy efficiency.

$$\ln TFP_{it} = \gamma_i + \theta_{EF} \ln EF_{it} + \theta_c C_{it} + \theta_w W_i + \mu_{it} \tag{3.25}$$

Cameron and Trivedi (2005) provide that the fixed effects (FE) and random effects (RE) techniques could be used to estimate equation (3.25). The main difference between the two techniques lies in the relationship between firm-specific effects and other regressors. In the fixed effects approach, an assumption that correlation prevails between firm-specific effects and the covariates is made. In the random effects approach, an assumption that the firm-specific effects are uncorrelated with the covariates is made.

The second potential cause of endogeneity is reverse causality from TFP to energy efficiency which could result in inconsistent estimates (Cantore et al., 2016). To deal with this problem and following Haider and Bhat (2020), a dynamic panel data model is recommended. This model entails the inclusion of the past period explained variable as an independent variable in equation (3.25) as follows:

$$\ln TFP_{it} = \theta_P \ln TFP_{it-1} + \theta_{EF} \ln EF_{it} + \theta_c C_{it} + \theta_w W_i + \gamma_i + \mu_{it} \tag{3.26}$$

The lagged independent variable reduces the feedback effect from TFP to energy efficiency. The logic behind this is that the resolution to improve technology is made in preceding periods, persuaded by the firm's performance. The fixed effects and random effects models could be assessed using the first difference estimator and the within (fixed) estimator. The first difference estimator gets rid of the unobserved heterogeneity (γ_i) by applying the first difference transformation. The first difference of equation (3.26) is:

$$\ln TFP_{it} - \ln TFP_{it-1} = \theta_P(\ln TFP_{it-1} - \ln TFP_{it-2}) + \theta_{EF}(\ln EF_{it} - \ln EF_{it-1})$$

$$+\theta_c(C_{it} - C_{it-1}) + \theta_w(W_i - W_i) + (\gamma_i - \gamma_i) + (\mu_{it}\text{-}\mu_{it-1}) \tag{3.27}$$

Equation (3.27) could be re-written as:

$$\Delta\ln TFP_{it} = \theta_P \Delta\ln TFP_{it-1} + \theta_{EF}\Delta\ln EF_{it} + \theta_c \Delta C_{it} + \Delta\mu_{it} \tag{3.28}$$

The first difference transformation of equation (3.26) eliminates the unobserved heterogeneity by subtracting the lagged equation from the level equation. However, this transformation does not completely wind out endogeneity. The first difference of the error term could be correlated with the first difference of the lagged TFP (that is, Cov (μ_{it}-$\mu_{it-1}, TFP_{it-1} - \ln TFP_{it-2}$)≠0) because TFP_{it-1} is correlated with μ_{it-1}.

The within estimator handles unobserved heterogeneity (γ_i) by applying a time-demeaned transformation. Applying the transformation on equation (3.26) yields:

$$\ln TFP_{it} - \ln\widehat{TFP_i} = \theta_P(\ln TFP_{it-1} - \ln\widehat{TFP_{i,-1}}) + \theta_{EF}\left(\ln EF_{it} - \ln\widehat{EF_i}\right) + \theta_c\left(C_{it} - \widehat{C_i}\right) +$$

$$\theta_w(W_i - W_i) + (\gamma_i - \gamma_i) + (\mu_{it} - \widehat{\mu_i}) \tag{3.29}$$

Equation (3.29) could be re-written as:

$$\ln TFP_{it} - \ln\widehat{TFP_{\iota}} = \theta_P(\ln TFP_{it-1} - \ln\widehat{TFP_{\iota,-1}}) + \theta_{EF}\left(\ln EF_{it} - \ln\widehat{EF_{\iota}}\right) + \theta_c\left(C_{it} - \widehat{C_{\iota}}\right) + (\mu_{it} - \widehat{\mu_{\iota}}) \quad (3.30)$$

Even though the estimator eliminates unobserved firm heterogeneity, endogeneity could still be a potential problem. The time demeaned error term could be correlated with the time demeaned lagged TFP (that is, Cov $(\mu_{it}\text{-}\widehat{\mu_{\iota}},\ \ln TFP_{it-1} - \ln\widehat{TFP_{\iota,-1}}) \neq 0$) because $\ln\widehat{TFP_{\iota,-1}}$ is correlated with $\widehat{\mu_{\iota}}$. Therefore, using the first difference estimator and the within estimator on a dynamic panel model could give inconsistent parameter estimates.

According to Cameron and Trivedi (2005), the instrumental variable approach could be used to manage the endogeneity problem in a dynamic panel model. For panel data, Cameron and Trivedi (2005) argue that it is easier to find instruments compared to cross-sectional data. In panel data, exogenous covariates in other periods could be used as instruments for endogenous covariates in the present period. A valid instrument is one with no correlation with the error term but with a strong correlation with the endogenous regressor (Cameron and Trivedi, 2005).

Anderson and Hsiao (1981) on instrumental variables require that equation (3.26) be transformed by first differencing as provided in equation (3.28) and then $\ln TFP_{it-2}$ is used as an instrument for $(\ln TFP_{it-1} - \ln TFP_{it-2})$. This is a valid instrument because $\ln TFP_{it-2}$ is uncorrelated with $(\mu_{it}\text{-}\mu_{it-1})$, under the assumption that the errors μ_{it} are serially uncorrelated. In addition, $\ln TFP_{it-2}$ is a good instrument because it is correlated with $(\ln TFP_{it-1} - \ln TFP_{it-2})$. To use this method, at least three-period data for each observation is required (Cameron and Trivedi, 2005). Alternatively, $\Delta\ln TFP_{it-2}$ could be used as an instrument for $\Delta\ln TFP_{it-1}$, but this requires at least four-period data for each observation. Nevertheless, the method has been challenged because it requires that the instrumental variable be specified and defined. Therefore, this method may provide consistent estimators, but the estimators may not be efficient, since the instrumental variable estimation under this approach fails to utilize all the existing moment conditions (Arellano and Bond, 1991).

A more efficient estimator could be got by employing an instrument obtained from lagging the dependent variable more times (Arellano and Bond, 1991). For instance, $\ln TFP_{it-2}$ and $\ln TFP_{it-3}$ could be better instruments. With these, the model is overidentified, and so estimation should either be by two-stage least squares (2SLS) or panel GMM (Cameron and Trivedi, 2005). Further, the higher the periods, the higher the number of instruments. In a three-time period, only $lnTFP_{it-2}$ is available as an instrument, in four time periods, $\ln TFP_{it-2}$ and $\ln TFP_{it-3}$ are available and so on. Arellano and Bond (1991) recommended panel GMM estimators which use more diverse instrument sets. The resulting estimator is referred to as the Arellano-Bond estimator and is adopted in this study. For the estimator to be feasible, the order condition must be satisfied. The number of instruments should be equal to or more than the parameters of the endogenous variables (r$\geq K$) (Cameron and Trivedi, 2005). The validity of the instruments is ascertained by the Sargan-Hansen test of overidentifying restrictions.

To obtain the Arellano-Bond estimator, all *T* observations for the *ith* firm in equation (3.28) are first stacked as follows:

$$\widetilde{y_i} = \widetilde{x_i}\theta + \widetilde{\mu_i} \qquad (3.32)$$

$y_i$is the dependent variable, x_i is a vector of the explanatory variables, θ is a vector of parameters to be estimated, μ_i is the error term and $\sim$ denotes differencing transformation. Assuming there is a $T\times r$ matrix of instruments Z_i and *G* parameters to be estimated, where $r\geq G$ is the number of instruments that meet the *r* moment conditions

$$E[Z_i'\widetilde{\mu_i}] = 0. \qquad (3.33)$$

Given the moment conditions, the GMM estimator is obtained by minimizing the following associated quadratic form

$$Q_N(\theta) = [\textstyle\sum_{i=1}^{N} Z_i'\widetilde{\mu_i}]'\, W_N\, [\sum_{i=1}^{N} Z_i'\widetilde{\mu_i}] \qquad (3.34)$$

where W_N represents an $r \times r$ weighting matrix. Since $\widetilde{\mu_i} = \widetilde{y_i} - \widetilde{x_i}\theta$, algebraically solving for the minimized quadratic form (3.34) yields the following Arellano-Bond estimator

$$\widehat{\theta_{AB}} = [(\textstyle\sum_{i=1}^{N} \widetilde{x_i' Z_i}) W_N\, (\sum_{i=1}^{N} Z_i'\widetilde{x_i})]'(\sum_{i=1}^{N} \widetilde{x_i' Z_i}) W_N\, (\sum_{i=1}^{N} Z_i'\widetilde{x_i}) \qquad (3.35)$$

In the case of a model over-identification, it is useful to verify whether the available data suits a panel GMM estimator or a two-stage least squares (2SLS) estimator. Pagan and Hall (1983) test of heteroscedasticity in the error term helps in making this verification (Baum et al., 2003). The GMM estimator is relatively more efficient than 2SLS if heteroscedasticity prevails. However, in the absence of heteroscedasticity, the 2SLS estimator is relatively more efficient. Nonetheless, applying the GMM estimator in case heteroscedasticity is present comes at a price. According to Hayashi (2000), the optimal weighting matrix is a function of fourth moments, and a large sample is needed to guarantee logical estimates. If this is not available, the GMM estimator may possess poor small sample properties.

3.3.3 Definition and Measurement of Variables

Table 3.1:Definition and Measurement of Variables

Variable	**Definition and measurement**	**Source of variable and data**
Output	Finished goods produced by manufacturing firms. Measured as total annual sales (Ksh).	Van Beveren (2012), World Bank Enterprise Survey (WBES).
Capital	Physical machinery and equipment used in production. The total replacement value of machinery and equipment is used as a measure of capital(Ksh).	Van Beveren (2012), World Bank Enterprise Survey (WBES).
Labour	The physical and mental workforce provided for wages and salaries. The total wages paid to permanent, full-time employees are used as a measure of capital (Ksh).	Van Beveren (2012), World Bank Enterprise Survey (WBES).
Materials	Finished goods used in the final production of other goods and services. Measured as the cost of raw materials (Ksh).	Van Beveren (2012), World Bank Enterprise Survey (WBES).
Energy	Electricity and fuel used in production. Measured by the total cost of electricity and fuel (Ksh).	Cantole et al. (2016), World Bank Enterprise Survey (WBES).
Energy efficiency	Energy consumed per unit of output. The inverse of energy intensity, which is expressed as energy per unit of out is used as a measure of energy efficiency.	Cantole et al. (2016), World Bank Enterprise Survey (WBES).
Firm age	The duration an establishment has been in existence. It is measured in years.	Kreuser and Newman (2018), World Bank Enterprise Survey (WBES).
Firm size	Number of permanent full-time employees in a firm	Kreuser and Newman (2018), World Bank Enterprise Survey (WBES).
R&D	The activity of discovering new products or services or enhancing the quality or mode of production of existing goods and services. A dummy variable, 1 if a firm has R&D activities and 0 if it does not is used as a measure of R&D.	Kreuser and Newman (2018), World Bank Enterprise Survey (WBES).
Foreign ownership	Whether a firm is foreign-owned. Measured as a dummy variable with a value of 1 if foreign-owned and 0 if otherwise.	Harris and Moffat (2015), World Bank Enterprise Survey (WBES).

Exporting status	Whether a firm exports or not. Measured as a dummy variable with a value of 1 if a firm exports and 0 if otherwise.	Kreuser and Newman (2018), World Bank Enterprise Survey (WBES).
Capital intensity	The extent of mechanization in the production process. Measured as a ratio of capital to labour.	Kreuser and Newman (2018), Rath, 2018, World Bank Enterprise Survey (WBES).
Top manager's experience	Skills gained by working. Measured as the number of years the top manager has been working	Fernandes (2008), World Bank Enterprise Survey (WBES).

Source: Author's compilation

3.3.4 Justification for Inclusion of the Various Variables in the Models

In the investigation of the effect of energy efficiency on TFP, several explanatory variables were included in addition to energy efficiency. Following Kreuser and Newman (2018), Harris and Moffat (2015), Satpathy et al (2017), Fernandes (2008), Rath (2018) and Seker and Saliola (2018), the variables include firm age, firm size, foreign ownership, exporting status, capital intensity, R&D and top manager's experience.

Firm age was included to investigate whether younger firms that are characterized by relatively new equipment produce with higher efficiency compared to old firms. Further, this variable helped in testing whether productivity is enhanced by learning-by-doing. Learning-by-doing effects take place when firms improve their productivity as they learn new production techniques and they integrate these advancements into their production schedules (Coad et al., 2013). The relation between productivity and firm age is related to the Jovanovic (1982) theory. According to the theory, firms are born with fixed productivity levels which they learn as they advance in age. Low productivity firms exit the market as highly productive firms thrive. Consequently, the average productivity of a certain age cohort increases as the age of this cohort advances (Coad et al., 2013). Firm age is anticipated to have an unclear effect on productivity given that young firms could have higher TFP because of their relatively new technologies, but older firms could have greater TFP because of learning-by-doing effects. A positive effect has been reported in Sahu and Narayanan (2011a) and Kreuser and Newman (2018) while a negative effect has been reported in Schiffbauer and Ospina (2010) and Harris and Moffat (2015).

Firm size entered the model to test whether larger firms are more productive because they have easier access to recent technologies and learning-by-doing effects obtained from their long experience or small firms are more productive because they are more flexible and have less complex management structures. Firm size is anticipated to have an unclear effect on TFP. A positive effect has been recorded in Schiffbauer and Ospina (2010), Satpathy et al. (2017) and Kreuser and Newman (2018) while a negative effect has been reported in Fernandes (2008) and Seker and Saliola (2018).

R&D entered the model because it is hypothesized that R&D enhances TFP via two channels (Harris and Moffat, 2015). First, R&D activities promote TFP by encouraging process innovation which allows production to be made at a greater efficiency (mainly through reduced costs). R&D also allows product innovation which enhances TFP if new products are created more efficiently than existing products. In the second channel, R&D enhances TFP by developing firms' absorptive capacity. This promotes a firm's capability to detect, absorb and utilize external knowledge from other firms and R&D actors for instance universities and research institutions (Fernandes, 2008; Harris and Moffat, 2015; Ding et al., 2016). The concept of absorptive capacity is premised upon the fact that certain knowledge is implicit and difficult to obtain except if a firm is engaged in R&D activities. R&D is found to promote TFP in Harris and Moffat (2015), Satpathy et al. (2017) and Kreuser and Newman (2018).

Foreign ownership was included to investigate whether firms with foreign ownership had relatively higher TFP. According to Harris and Moffat (2015), foreign-owned firms, particularly from developed countries, which are believed to be superior in technologies, have higher TFP. Foreign firms establish or acquire firms in the domestic market because of attributes that give them an upper hand in, for instance, cost over domestic firms. Such attributes include special skills in production and management or marketing skills. Nevertheless, if cultural differences between foreign owners and local workers create disharmony, this could undermine TFP, particularly in the immediate period after acquiring ownership of a local enterprise. But as foreign owners become familiar with the domestic operating environment, the problem is resolved (Ding et al., 2016).

Further, foreign-owned firms could be anticipated to have lower TFP if they opt to have high-valued production in host countries and lower-valued production in their subsidiaries abroad. Consequently, they may employ a low-skilled workforce and old technologies abroad. Nevertheless, foreign ownership was expected to influence TFP positively in this study as in Fernandes (2008), Schiffbauer and Ospina (2010), Sahu and Narayanan, (2011a) and Harrris and Moffat (2015).

The variable of exporting status was introduced in the model to help investigate whether exporting firms had relatively higher TFP. Existing literature shows that exporting firms learn from foreign buyers about new production technologies which helps them to enhance their TFP. It is also possible that exporting firms improve their production technology to take advantage of the stringent but more profitable foreign markets (Fernandes, 2008). The variable was expected to positively influence TFP in this study. Studies that find exporting status to positively influence TFP, include, Fernandes (2008), Schiffbauer and Ospina (2010), Sahu and Narayanan (2011a), Kreuser and Newman (2018) and Montalbano and Nenci (2019).

The variable of top manager's experience was included in the study based on findings in the literature that firms run by highly experienced top managers are likely to have relatively higher TFP. Experienced managers are expected to have skills and techniques to guide production towards improved productivity. The variable was expected to influence TFP positively as in Fernandes (2008).

Capital intensity was included in the model to establish whether firms with higher use of capital per unit of labour were more productive compared to firms that used lower levels of capital per unit of labour. Capital intensity was expected to be associated with high firm TFP. According to Rath (2018), a combination of high capital and labour inputs is likely to improve productivity. Further, firms with high capital intensity have modern and advanced processes that improve productivity. Studies that report capital intensity to positively influence TFP include Kreuser and Newman (2018) and Montalbano and Nenci (2019).

3.3.5 Data Type and Sources

This research applied an unbalanced panel got from the World Bank Enterprise Surveys (WBES). The data is useful in understanding the business environment faced by private sector firms and in developing policies to improve the business environment. The data on manufacturing and service firms was collected through stratified random sampling. The levels of stratification are regions, sub-sectors and firm sizes. The surveys present information on specific firm features, infrastructure and services, sales and supplies, competition, finance, performance and business environment relations, crime, labour and land. They are available in many waves for 169,000 firms in 146 countries. This gives room for the comparison of enterprise performance across countries and across time. The data can be used to create a firm-level panel to monitor variations in the business environment over time and evaluate the impact of reforms.

The surveys try to match variables across waves. If desired, variables can be matched by changing variable names in older waves to variable names in the most current wave. The panel used in this study was for 2007, 2013 and 2018 where firms were followed over time. The panel was unbalanced due to natural causes such as the entry and exit of firms during the study period. In total, the panel had 2439 observations for both manufacturing and service firms from which a panel of 1265 observations for manufacturing firms was drawn. The manufacturing firms in the panel were broadly categorized into four sub-sectors: chemicals, pharmaceuticals and plastics; food; textiles and garments and paper and other manufacturing sub-sectors. According to Saliola and Seker (2011), the categorization of firms gives room for sub-sector level analysis. Some variables of interest had missing observations and the multiple imputation technique was applied to fill the gaps.

3.4. Results and Discussions

The first section contains descriptive statistics of the covariates applied in the estimations.

3.4.1 Descriptive Statistics

Table 3.2 contains summary statistics of capital intensity in firms.

Table 3.2Descriptive statistics of capital intensity in Kenya's manufacturing sector

Sub-sector	Mean	SD	Minimum	Maximum
Chemicals, Pharmaceuticals and Plastics sub-sector				
2007(N=28)	12.46	28.60	0.069	144
2013(N=52)	11.30	19.68	0.028	107.7
2018(N=98)	14.21	41.34	0.004	355.6
Food sub-sector				
2007(N=110)	8.305	19.53	0.005	153.8
2013(N=154)	43.18	323.7	0.0001	3891.7
2018(N=140)	11.80	37.95	0.004	383.3
Textiles, and Garments sub-sector				
2007(N=111)	0.8963	19.79	0.003	130
2013(N=51)	38.36	146.9	0.028	1009.1
2018(N=50)	21.96	81.37	0.002	420
Paper and other manufacturing sub-sector				
2007(N=147)	7.250	4.020	1	15
2013(N=157)	25.13	8.07	1	35
2018(N=167)	50.82	22.68	1	103

Source: own computation from WBES data.

Table 3.2 reveals that paper and other manufacturing sub-sector had on average higher capital intensity than other sub-sectors. This implies that the paper and other manufacturing sub-sector employed relatively more capital per unit of labour than other sub-sectors. Capital intensity was observed to increase over time in this sub-sector, but no clear pattern was observed in other sub-sectors.

The descriptive statistics of factor inputs used in the production function, firm size, firm age, top manager's level of experience, foreign ownership, exporting and R&D status were shown in chapter two of the thesis.

3.4.2 Energy Intensity in Kenya's Manufacturing Sector

Table 3.3 shows the results of average energy intensity, average total energy consumption and capital intensity across the four sub-sectors of the Kenyan manufacturing sector.

Table 3.3:Average energy intensity, total energy consumption and capital intensity scores in the Kenyan manufacturing sector

Sub-sector	Energy intensity	Total energy consumption ('000' shillings)	Capital intensity
Chemicals, pharmaceuticals and plastics	0.120	896,883.3	12.66
Food	0.413	889,595.6	21.10
Textile and Garments	0.064	482,031.4	20.41
Paper and other manufacturing	0.225	2,268,268.3	27.73

Source: Own computation from WBES data

The food sub-sector had the highest energy intensity score of 0.413. Theoretically, this implies that firms in this sub-sector had the highest amount of energy to produce a unit of output. It signals the least energy efficiency among the four sub-sectors. The paper and other manufacturing sub-sector followed with a score of 0.225 and the chemicals, pharmaceuticals and plastics sub-sector with 0.120. The textiles and garments sub-sector had the least energy intensity score of 0.064, implying that this sub-sector was the most energy-efficient.

Comparing energy intensity and total energy consumption by firms in the various sub-sectors, results showed that the textiles and garments sub-sector besides having the least energy intensity also had the least average energy consumption. This suggested that energy efficiency was associated with less energy consumption in this sub-sector. However, in the other sub-sectors, there was no clear pattern between energy consumption and energy intensity. The finding is consistent with the outcome of Subrahmanya (2006). Subrahmanya (2006) explains that the lack of a clear pattern between energy consumption and energy intensity could be expounded by the fact that holding other factors constant, energy intensity depends on capacity utilization rate and amount of output.

Subrahmanya (2006) observes that higher capital intensity can potentially lead to more energy consumption and energy intensity. The food sub-sector and paper and other manufacturing sub-sector, which were more capital-intensive than other sub-sectors, were also more energy-intensive. The textiles and garments and chemicals, pharmaceuticals and plastics sub-sectors were less intensive in capital and energy. Some correlation analyses to test for statistical significance between energy intensity and capital intensity and energy intensity and value of output were done. The results are presented in Table 3.4.

Table 3.4:Correlation between energy intensity and capital intensity and energy intensity and value of output in Kenya's manufacturing sector

	C, P and P	Food	P and O M	T and G
Capital Intensity	0.0323^{**}	0.1711^{***}	0.1911^{***}	0.0714
Value of output	-0.3180^{***}	-0.2786^{***}	-0.3232^{***}	-0.3700^{***}

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
C, P and P is chemicals, pharmaceuticals and plastics, T and G is textiles and garments and P and O M is paper and other manufacturing.
Source: own computation from WBES data

Table 3.4 reveals that at 5 percent level of significance, capital intensity and energy intensity were positively related in all the four sub-sectors except the textiles and garments sub-sector. This signalled that higher capital intensities led to high energy use. The consequence was higher energy intensity. Therefore, a high level of capital investment in the three sub-sectors did not result in high energy efficiency. This finding is consistent with Subrahmanya (2006) in the foundry industry in India.

Concerning energy intensity and the value of output, Table 3.4 shows that at 5 percent level of significance, energy intensity was negatively related to the value of output. This implies that higher capacity utilization could produce higher output at lower energy intensity. According to Subrahmanya (2006), if capacity use and size of output in a firm were low, energy intensity would be high. A steady expansion of capacity utilization, as well as the size of output, allows firms to lower energy intensity.

3.4.3 The Production Function in Kenya's Manufacturing Sector

The study estimated a production function as a step towards measuring TFP in Kenya's manufacturing sector. Parameter estimates of the production function were applied in the calculation of TFP. A linearized Cobb-Douglas production function was estimated using the Levinsohn-Petrin (LP) estimation algorithm for each sub-sector based on the assumption that firms in a particular sub-sector use common technology (Kreuser and Newman, 2018). The log of output was regressed on the log of factor inputs - labour, capital and materials. The coefficients showed elasticity of output with respect to a change in a factor input. Table 3.5 provides LP and OLS estimates of the production function in each sub-sector. OLS estimates were provided for robustness check.

Table 3.5:Parameter estimates of production functions in Kenya's manufacturing sector

	LP				OLS			
	T and G	C, P and P	Food	P and OM	T and G	C, P and P	Food	P and OM
Dependent variable: lnQ								
ln*L*	0.571***	0.497***	0.429***	0.408***	0.558***	0.535***	0.432***	0.435***
	(0.0890)	(0.115)	(0.0560)	(0.0728)	(0.0637)	(0.0643)	(0.0442)	(0.0429)
ln*K*	0.133	0.0396	0.135	0.332**	0.117***	-0.00894	0.0538	0.0214
	(0.0836)	(0.228)	(0.137)	(0.139)	(0.0383)	(0.0539)	(0.0331)	(0.0285)
ln*M*	0.121	0.831***	0.443***	0.0907	0.310***	0.398***	0.451***	0.497***
	(0.129)	(0.277)	(0.144)	(0.196)	(0.0473)	(0.0544)	(0.0364)	(0.0348)
RTS	0.825	1.368	1.007	0.831	0.985	0.924	0.937	0.953
Wald test								
Chi2	1.720	0.85	0.00	2.90				
P value	0.190	0.358	0.962	0.089				

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
C, P and P is chemicals, pharmaceuticals and plastics sub-sector, T and G is textiles and garments sub-sector and P and O M is paper and other manufacturing sub-sector.
Source: own computation from WBES data

LP results show that the elasticity of output with respect to labour was statistically significant in all the sub-sectors at 5 percent level of significance. The elasticity of output with respect to materials was only statistically significant in the chemicals, pharmaceuticals and plastics and food sub-sectors at 5 percent level of significance. The elasticity of output with respect to capital was only statistically significant in the paper and other manufacturing sub-sector at 5 percent level of significance. The coefficient of labour was higher in OLS than in LP estimation in all the sub-sectors except in the textiles and garments sub-sector. According to Kreuser and Newman (2018), this indicates that labour was positively correlated with productivity shocks. Therefore, the labour coefficient in OLS estimation was biased upwards. The finding is consistent with Fernandes (2008) and Kreuser and Newman (2018). OLS underestimated the coefficient of labour in the textile and garments sub-sector. This suggested that labour employed in this sub-sector had a negative correlation with productivity shocks. Therefore, the labour coefficient in OLS estimation was biased downwards.

All the coefficient estimates of capital were higher in LP than in OLS. This suggested that capital was negatively correlated with productivity shocks. Consequently, the coefficient of capital in OLS estimation was biased downwards. The finding is consistent with Fernandes (2008) and Kreuser and Newman (2018). The coefficient estimates of materials in OLS were larger than those of LP in all the sub-sectors except in the chemicals, pharmaceuticals and plastics sub-sector. This suggested that materials were positively correlated with productivity shocks. Thus, the coefficient of materials in OLS estimation was biased upwards. The outcome is in line with Goncalves and Martin (2016).

All the factor elasticities had economically plausible signs. Holding all other factors constant, an increase in any one input resulted in increased output. A unit increase in labour increased output across all the sub-sectors by a bigger margin compared to a unit increase in capital. The result corroborates the findings of Fernandes (2008), Kreuser and Newman (2018), Saleem and Zaki (2018) and Seker and Saliola (2018). Saleem and Zaki (2018) explain that this is because labour includes both the skilled and unskilled components which are crucial elements in production. The textile and garments sub-sector had the highest elasticity of output with respect to labour (0.571). The Paper and other manufacturing sub-sector had the least elasticity in this regard (0.408).

The elasticity of output with respect to materials was in some instances higher and in others lower than the elasticity of output with respect to capital or labour. A unit change in material input brought the highest change in output in the chemicals, pharmaceuticals and plastics sub-sector (0.831) and the least change in the paper and other manufacturing sub-sector (0.0907). This indicated that material inputs were important in the production of goods in the chemicals, pharmaceuticals and plastics sub-sector. The paper and other manufacturing sub-sector had the highest capital elasticity (0.332) while the chemicals, pharmaceuticals and plastics sub-sector had the least (0.0396). The textile and garments sub-sector and food sub-sector had almost similar capital elasticities at 0.135 and 0.133, respectively. However, capital elasticity was significant in the paper and other manufacturing sub-sector only.

The sum factor elasticities give an insight into returns to scale in each sub-sector. Where the sum exceeds one, that shows increasing returns to scale. A sum less than one shows decreasing returns to scale and a sum equal to one denotes constant returns to scale. The study found increasing returns to scale in the chemicals, pharmaceuticals and plastics (1.368) and food (1.007) sub-sectors. The textiles and garments (0.825) and paper and other manufacturing (0.831) sub-sectors had decreasing returns to scale. A proportional rise in factor inputs in the chemicals, pharmaceuticals and plastics and the food sub-sectors resulted in a more than proportional rise in output. A proportional rise in inputs in the textiles and garments and paper and other manufacturing sub-sector led to a less than proportional rise in output. The study performed a Wald test to investigate the null hypothesis that there existed constant returns to scale in all the sub-sectors. The findings show that at 5 percent level of significance, the null hypothesis was rejected in the four sub-sectors of interest. However, in the paper and other manufacturing sub-sector, the finding was weakly in line with the Wald test at 10 percent level of significance.

3.4.4 Estimated Average TFP in Kenya's Manufacturing Sector.

The average productivity in each sub-sector is presented in Table 3.6.

Table 3.6:Average TFP in the Kenyan manufacturing sector

Sub-sector	Average TFP
Chemicals, pharmaceuticals and plastics	3.071
Food	2.925
Textile and Garments	2.079
Paper and other manufacturing	2.722

Source: own computation from WBES data

Table 3.6 reveals that the chemicals, pharmaceuticals and plastics sub-sector had an estimated average TFP of 3.071, the food sub-sector had 2.925, the paper and other manufacturing sub-sectors had 2.722 and the textiles and garments sub-sector had 2.079. The average TFPs are not directly comparable across the sub-sectors given that production functions are different across sub-sectors. Technology is assumed to be common within the sub-sectors but different across them. Nevertheless, TFP distribution across sub-sectors could be compared (Kreuser and Newman, 2018). TFP distribution is more useful in explaining the extent of heterogeneity in productivity levels within and across the sub-sectors. According to Tybout (2000), heterogeneity in productivity across firms prevails significantly, even when the manufacturing sector is narrowly defined.

Appendix 2 presents plots of the TFP distribution of each sub-sector. The y-axis contains densities of the distributions while the x-axis contains logarithms of TFP. A widely dispersed plot denotes greater heterogeneity across firms within a sub-sector. Of concern also is whether firms are highly concentrated in the higher segment or lower segment of the TFP distribution. A tight dispersion in TFP distribution was witnessed in the paper and other manufacturing sub-sector as well as the chemicals, pharmaceuticals and plastics sub-sector. This was indicative of less heterogeneity in productivity in these sub-sectors. The distribution of TFP in the food sub-sector showed tight dispersion but not as in the paper and other manufacturing and chemicals, pharmaceuticals and plastics sub-sectors. This also signalled minimal heterogeneity in productivity.

The textiles and garments sub-sector TFP distribution showed that this sub-sector had the widest dispersion, especially on the lower parts of the plot, and a relatively sizable density below the mean. This pointed to relatively sizable heterogeneity in TFP, implying the coexistence of high-productivity and low-productivity firms in the sub-sector. According to Kreuser and Newman (2018), such a distribution signals the existence of rigidities or other distortions that hinder the efficient allocation of resources within the sub-sector.

3.4.5 TFP by Sub-Sector and Firm Size in Kenya's Manufacturing Sector

The heterogeneity of TFP in Kenya's manufacturing sector was further analyzed on firm attributes of age and size. The empirical literature provides that these characteristics are major sources of heterogeneity in productivity (Van Biesebroeck, 2005; Fernandes, 2008). The analysis is crucial in singling out firm characteristics with the highest potential to improve productivity and receive the most resources. Table 3.7 shows the average TFP by firm size within the sub-sectors. The WBES categorization of small (5-19 employees), medium (20-99 employees) and large (over 100 employees) firms was followed.

Table 3.7:Average TFP by firm size in the Kenyan manufacturing sub-sectors

Sub-sector	Size category		
	small	medium	large
Chemicals, pharmaceuticals and plastics	2.923	2.658	3.865
Food	2.784	2.669	3.395
Textile and garments	2.303	1.969	1.938
Paper and other manufacturing	3.200	2.432	2.650

Source: Own calculations from WBES data

In the chemicals, pharmaceuticals and plastics and food sub-sectors, TFP was highest in large firms. In these sub-sectors, TFP was higher in small firms compared to medium firms. That large firms possessed the highest TFP could probably be because they had better access to financial resources that allowed them to upgrade their production technology and achieve better performance. It could also be that workers here had better skills and productivity. This finding is in line with Van Biesebroeck (2005), and Seleem and Zhaki (2018).

In the textile and garments and paper and other manufacturing sub-sectors, small firms had the highest TFP. This could be because small firms in these sub-sectors were more flexible with less complex management structures. The results for the textiles and garments sub-sector show that productivity decreased monotonically with an increase in firm size. The outcome of this study conforms with the results of Fernandes (2008) and Seleem and Zhaki (2018) which show the performance of small firms is devoid of the disadvantages of scale inefficiencies. Productivity was higher in large firms than in medium firms in the paper and other manufacturing sub-sector.

3.4.6 TFP by Sub-sector and Firm Age in the Kenyan Manufacturing Sector

Table 3.8 presents the average TFP of firms of different ages and sub-sectors. The age categories are 1-10, 11-20, 21-30, 31-40 and 40+ years.

Table 3.8:Average TFP by firm age in the Kenyan manufacturing sub-sectors

	Firm age in years				
Sub-sector	1-10	11-20	21-30	31-40	40+
Chemicals, pharmaceuticals and plastics	3.666	6.038	3.513	1.336	2.441
Food	1.395	3.062	3.359	5.292	1.982
Textile and garments	1.776	2.874	1.550	1.130	2.451
Paper and other manufacturing	2.796	2.789	1.709	3.176	3.390

Source: Own calculations from WBES data

The results reveal an unclear pattern of firm age and productivity relation across the sub-sectors. In the chemicals, pharmaceuticals and plastics sub-sector, young firms, particularly in the first two age cohorts had on average greater productivity compared to older firms. The result agrees with the literature that links young firms with recent and more productive technologies. Another possible explanation for this finding as pointed out by Coad et al. (2013) is that old firms could suffer from inertia effects, which manifest in two forms. First, old firms could be susceptible to the liability of obsolescence, a situation in which old firms fail to adapt to changing business environments. Second, they could be susceptible to the liability of senescence, a situation in which old firms become rigid by accrued rules, habits and organizational configurations. This finding is in line with Seleem and Zhaki (2018).

The food sub-sector exhibited an inverted U relationship between productivity and firm age. TFP was low in firms aged 1-10 years but increased in successive age cohorts to reach the highest level in firms of 31-40 years then fell drastically in firms beyond 40 years. According to Fernandes (2008), the inverted U life cycle pattern is an indication that firms begin at low TFP but learn by doing. They, for instance, venture into new investments, take part in foreign markets, or achieve economies of scale and improve TFP. However, after attaining a particular age (40 years in the sample used), firm know-how, operations and production turn out to be obsolete, inertia strikes and TFP declines. This finding is consistent with Fernandes (2008).

The paper and other manufacturing sub-sector exhibited a U relationship between firm productivity and age. After ranking the firms, TFP was high in firms aged 1-10 years and decreased entered the 11-20 age bracket. The decrease continued in the 21-30 age bracket but increased in subsequent years. The firms in this sub-sector begin at high TFP probably because they have new and efficient technologies but as they grow old, these technologies become outdated and TFP declines to low levels. The poor performance then makes the firms rethink their operations and change their technologies or make new investments. Their flexibility in making technology change investments could be because of the ease of access to financial resources. According to Coad et al. (2013), old firms have ease of access to long-term credit, have large equity capital, which facilitates access to external financing, and have good internal cash flow. Finally, the textiles and garments sub-sector showed no clear pattern of TFP change with firm age.

3.4.7 Effect of Energy Efficiency on TFP in Kenya's Manufacturing Sector

Table 3.9 provides the results of panel GMM regression. The statistical significance was tested by applying the dynamic panel data estimation using a clustered robust technique to deal with potential heteroscedasticity.

Table 3.9:Regression results of the effect of energy efficiency on TFP in Kenya's manufacturing sector

TFP	Overall Sector	Food Sub-sector	T and G Sub-sector	P and O M Sub-sector
TFP_{t-1}	0.0821	-0.180	0.048	0.253
	(0.0674)	(0.227)	(0.045)	(0.250)
Energy efficiency	0.220***	3.246***	0.001***	0.227*
	(0.0432)	(0.819)	(0.0003)	(0.129)
Capital Intensity	0.00136*	1.738**	0.0121***	-0.342***
	(0.000744)	(0.818)	(0.00265)	(0.0768)
Firm age	0.0299***	0.500*	-0.247	1.367***
	(0.0107)	(0.292)	(0.449)	(0.320)

Firm size	0.0546**	-0.152	-0.068	0.00145**
	(0.0268)	(0.591)	(0.069)	(0.000698)
Top Manager's experience	0.210*	0.0734	0.015	0.00916
	(0.116)	(0.135)	(0.010)	(0.0142)
Foreign owned	0.222	-1.672	0.616*	-1.333
	(0.209)	(3.740)	(0.315)	(1.008)
Export	-0.162	0.894	0.739**	-0.593
	(0.157)	(3.286)	(0.367)	(0.536)
R&D	0.114	1.390	0.831***	-0.443
	(0.162)	(3.327)	(0.170)	(0.395)
Year(base year: 2007)				
2013	-3.152***	-22.50*	0.171**	2.337
	(0.718)	(12.66)	(0.343)	(3.827)
2018	-3.381***	-23.36	0.294	-0.640
	(0.787)	(15.60)	(0.032)	(3.425)
Region(base region: Nyanza)				
Central	0.565	0.643	1.564	-0.718
	(0.436)	(6.839)	(2.747)	(1.574)
Coast	0.368	4.312	-2.828	-1.752
	(0.406)	(6.350)	(3.102)	(1.681)
Nairobi	0.481	4.058	0.215	-1.297
	(0.389)	(6.351)	(2.413)	(1.590)
RV	0.354	5.485	-0.258	-2.074
	(0.415)	(6.588)	(2.773)	(1.823)
Sub-sector(base C P and P)				
Food	0.194			
	(0.261)			
T and G	-0.0819			
	(0.244)			
P and O M	-0.0299			
	(0.289)			
Endogeneity Test				
H0: Exogenous				
Chi-sq	4.349	3.936	3.215	6.280
Prob> chi-sq	0.037	0.047	0.067	0.012
Heteroscedasticity test				
H0: Homoscedasticity				
Chi-sq	38.44	30.19	32.35	52.21
Prob> chi-sq	0.042	0.088	0.028	0.000
Sargan-Hansen test				
Chi-sq	6.410	8.051	9.252	4.684
Prob> chi-sq	0.698	0.781	0.160	0.585

Dependent variable: TFP
Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
T and G is textiles and garments and P and O M is paper and other manufacturing. RV is Rift Valley and D denotes a dummy variable. TFP_{t-1} is the first lag of TFP.
Source: own computation from WBES data

Table 3.9 provides results of the assessment of the effect of energy efficiency on TFP. Analysis was done at the overall manufacturing sector and sub-sector levels. In the overall sector model, the null hypothesis of exogeneity of energy efficiency was rejected at 5 percent level of significance. It indicated the presence of endogeneity which could be addressed by adopting a 2SLS or panel GMM estimator. At 5 percent level of significance, the Pagan and Hall (1983) test confirmed the presence of heteroscedasticity. The GMM estimator was therefore the suitable estimator. The Sargan-Hansen test of the null hypothesis of validity of overidentifying restrictions was accepted at 5 percent level of significance. Therefore, all the instruments adopted in the overall sector model were valid.

The effect of energy efficiency on TFP was positive. This finding was consistent with the Porter Hypothesis which argues that the adoption of clean production can lead to the achievement of double dividends, where higher productivity is realized in the process of ensuring clean production. According to the hypothesis, the cost of acquiring clean production technologies is offset by cost savings arising from the use of such technologies, a phenomenon known as innovation offset. This finding is useful in dispelling fear, particularly in developing countries, where there is disquiet about the implications of reductions in energy use on growth. The finding corroborates the results of Sahu and Narayanan (2011a) in the manufacturing sector in India and Cantore et al. (2016) in manufacturing firms in 29 low-income countries. However, the result contrasts Haider and Ganaie (2017) who find energy efficiency to negatively influence TFP in India and Montalbano and Nenci (2019) who finds the effect of energy efficiency on productivity in Latin America's manufacturing sector to be insignificant.

Capital intensity, expressed as a ratio of capital to labour, positively influenced TFP. Theoretically, higher capital intensity indicates that usage of capital per employee has improved. The result of this study suggests that capital deepening and widening have a favourable effect on TFP. High capital intensity is probably associated with recent and advanced technology, which promote TFP. The finding corroborates Kreuser and Newman (2018) and Montalbano and Nenci (2019).

Firm age was found to positively affect TFP. This implies that TFP was higher in old firms compared to young firms. The finding was in line with the Jovanovic (1982) theory that postulates that at the time of establishment, firms have fixed productivity which they understand as they grow old. In the process, firms possessing low productivity leave the market as those with high productivity thrive. According to Coad et al. (2013), this process makes the average productivity of firms that survive attrition increase with time. Further, the outcome of this study could be expounded by the learning-by-doing effect. Firms learn modern production techniques and integrate them over time. This outcome is in line with Sahu and Narayanan (2011a) and Kreuser and Newman (2018).

Firm size was found to positively influence TFP. This indicates that TFP was higher in large firms compared to smaller firms. The outcome was in agreement with theoretical frameworks on industrial dynamics which project large firms to produce at higher productivity compared to small firms (Jovanovic, 1982). The models provide that while entering the industry, firms are of small size and have low productivity. Many depart shortly after joining, while the surviving ones expand and quickly converge to the industry average size and productivity level. Departure from the industry is first preceded by a period of decreasing firm size and productivity (Van Biesebroeck, 2005). It is also probable that productivity is relatively high in large firms because of their better access to formal credit compared to smaller firms. Access to credit helps them acquire new technologies which are essential in boosting productivity. Their better financial position also enables them to run formal training programs that provide workers with the skills necessary to improve productivity. This finding corroborates the outcome of Van Biesebroeck (2005), Schiffbauer and Ospina (2010), Satpathy et al. (2017), and Montalbano and Nenci (2019). Fernandes (2008) on the other hand finds productivity to be more in small firms compared to large firms.

The coefficient of top manager's years of experience was shown to be positive and statistically significant. Highly experienced managers were associated with higher TFP. According to Fernandes (2008), a top manager's experience captures management ability. The outcome of this study indicates that top managers in the Kenyan manufacturing sector are of high ability. The finding is consistent with Fernandes (2008).

Exporting had an insignificant effect on TFP. Though literature provides that exporting is linked to higher TFP, the view is not supported by the study findings. The composition of Kenya's exports may explain this unexpected outcome. For instance, according to the Republic of Kenya (2019), even though export levels increased by 14.1 percent in the five years 2014-2018, there was a varying growth rate in key export components. Agricultural exports which account for the largest component of exports had horticulture and tea grow by 14.36 percent and 9.92 percent respectively in the same period. On the other hand, exports of manufactured products such as leather products and medicinal and pharmaceutical products declined by 11.72 percent and 1.5 percent respectively. This may reflect that policies to promote exports were more concentrated in agriculture, with less emphasis on manufacturing products and hence the results of no TFP premiums by exporting activities. The finding corroborates the outcome of Vu et al. (2016). On the other hand, Montalbano and Nenci (2019) and Kreuser and Newman (2018) find exporting to promote TFP.

Foreign ownership had a positive but insignificant coefficient contrary to the study's prediction. This finding contradicted the results of both Fernandes (2008) in the Bangladesh manufacturing industry and Harris and Moffat (2015) in the majority of the foreign-owned groups of firms in Great Britain, who find foreign ownership to positively influence TFP.

The effect of R&D on TFP was not significantly different from zero. This implies that there was no noticeable TFP advantage from engaging in R&D activities. It was expected that R&D would significantly influence TFP through the process and product innovation and through developing firms' absorptive capacity but this was not evident. The low R&D investments in firms in the sample could partly be the reason for this finding. It is also possible that the absorptive capacity for the few firms engaging in R&D activities was not advanced enough to permit productivity improvements. The outcome is in line with Van Biesebroeck (2005) and Rath (2018). However, Harris and Moffat (2015), Satpathy et al. (2017) and Kreuser and Newman (2018) find R&D to positively influence TFP.

With regards to year dummies, the study found TFP to decrease in 2013 and 2018 relative to the 2007 level. This indicates that the business environment for the Kenyan manufacturing sector was less conducive in 2013 and 2018 compared to 2007.

3.4.8 Effect of Energy Efficiency on TFP by Sub-sector in Kenya's Manufacturing Sector

Following Montalbano and Nenci (2019), this study accounted for heterogeneity by performing separate regressions for the different sub-sectors. The findings are provided in Table 3.9. The Sub-sectors of concern were: chemicals, pharmaceuticals and plastics, food, textile and garments and paper and other manufacturing sub-sectors. The chemicals, pharmaceuticals and plastics sub-sector had low sample sizes and the estimation failed convergence tests. Consequently, this sub-sector was dropped.

Table 3.9 shows that in all the models, the null hypothesis for exogeneity of energy efficiency was rejected at 5 percent level of significance, except for the textile and garments sub-sector where the null hypothesis was weakly rejected at 10 percent level of significance. This was indicative of the presence of endogeneity which could be addressed by adopting a 2SLS estimator or panel GMM estimator. At 5 percent level of significance, the Pagan and Hall (1983) test confirmed the presence of heteroscedasticity across all the sub-sectors apart from the food sub-sector where it was confirmed at 10 percent level of significance. A panel GMM estimator was thus the suitable estimator for the sample used in the study. The Sargan-Hansen test of the null hypothesis of overidentifying restrictions was accepted at 5 percent level of significance. Thus, all the instruments adopted in the models were valid.

Energy efficiency was found to positively affect TFP across all the sub-sectors. This means that energy efficiency in each sub-sector yielded double dividends in terms of promoting a clean environment and realizing higher TFP. The finding was in line with the Porter Hypothesis. It agreed with Cantore et al. (2016) in a majority of sub-sectors in 29 low-income countries and Montalbano and Nenci (2019) in a majority of the sub-sectors in Latin America's manufacturing sector.

The findings from the regression analysis showed evidence of heterogeneity in other TFP correlates across the sub-sectors. The coefficient of capital intensity was positive and significant in the food and textile and garments sub-sectors. This implies that high capital intensity was linked to higher TFP. This could mean that high capital-intensive firms in these sub-sectors have recent technologies and advanced production processes which play a big role in enhancing TFP. This outcome corroborates the findings of Montalbano and Nenci (2019) who find capital intensity to positively influence TFP in the food, textiles and apparel and chemicals and minerals sub-sectors in Latin America and Rath (2018) who find capital intensity to boost TFP in India's textile sub-sector. Nevertheless, the coefficient of capital intensity in the paper and other manufacturing sub-sector was negative and significant. This implies that firms with high levels of capital achieved lower TFP. The finding was in line with Van Biesebroeck (2005) in nine countries in Africa.

The coefficient of firm age was found to be positive and significant in the food and paper and other manufacturing sub-sectors. Old firms in these sub-sectors had higher TFP than younger firms. The finding was in line with the Jovanovic (1982) theory, which provides that firms learn their productivity capabilities as they advance in age. In the process, low-productivity firms leave the industry as the high productive firms thrive. The finding also suggested the presence of learning-by-doing effects. Firms learned new production techniques with time and assimilated them into their production processes, ultimately boosting their TFP. This outcome is in line with Sahu and Narayanan, (2011a) and Kreuser and Newman (2018).

Firm size had a positive effect on TFP in the paper and other manufacturing sub-sector. Large firms in this sub-sector had higher TFP compared to smaller firms. This outcome was in line with the Jovanovic (1982) theory which explains that firms start small. Many of them exit and the remaining ones grow in size and quickly converge into the industry average size and productivity. Before exiting, firms decline in size and productivity (Van Biesebroeck, 2005). The good performance in TFP by large firms in the paper and other manufacturing sub-sector could also be because they had easy access to credit compared to small firms. The credit could have helped them to update their technology and provide formal training to workers. Trained workers have skills that enhance TFP. The finding contradicts Montalbano and Nenci (2019) who find firm size to positively influence TFP in all the Latin America manufacturing sub-sectors apart from the other manufacturing sub-sector where firm size has no significant effect on TFP.

Foreign ownership had a positive and significant coefficient in the textiles and garments sub-sector. This indicates that foreign ownership was linked to higher TFP. It could be argued that for foreign investors to find it justifiable to establish or acquire local ownership, they must have characteristics that give them an upper hand in cost over local firms. Such characteristics include better technologies, management and access to delivery and advertising means (Fernandes, 2008; Harris and Moffat, 2015). This outcome corroborates the results of Fernandes (2008), Schiffbauer and Ospina (2010), Sahu and Narayanan (2011a) and Harrris and Moffat (2015).

Exporting status positively affected TFP in the textiles and garments sub-sector. This indicates that there were TFP premiums for exporting firms. Probably, exporting firms in this sub-sector learned ways to boost their productivity from their foreign clients. Exporting firms could also be producing using advanced technologies to meet the strict but profitable requirements of foreign clients. They also learn to meet commodity demands on time and to assure commodity quality in competitive markets. It could also be that high TFP firms self-select into foreign markets. Fernandes (2008), however, observes that self-selection and learning-by-exporting are not mutually exclusive given that high TFP firms with the advantage of accessing export markets could persistently have better TFP due to acquaintance with exporting. This outcome agrees with the result of Montalbano and

Nenci (2019) who establish that exporting positively influences TFP across all Latin America's manufacturing sub-sectors apart from the machinery and other manufacturing sub-sectors where exporting does not affect TFP.

R&D positively influenced TFP in the textiles and garments sub-sector. This implies that firms with R&D activities had higher TFP. Probably, engaging in R&D activities led to process and product innovations which boosted TFP. Moreover, R&D activities could have enhanced the firm's absorptive capacity thereby boosting the firm TFP. This finding corroborates Harris and Moffat (2015), Satpathy et al. (2017) and Kreuser and Newman (2018).

TFP decreased in 2013 relative to 2007 in the food and textiles and garments sub-sector. Probably, the operating environment for this sub-sector was less conducive in 2013.

3.4.9 Effect of Energy Efficiency on Kenya's Manufacturing Sector TFP by Firm Size

The study further accounted for firm heterogeneity by analyzing the effect of energy efficiency on Kenya's manufacturing sector's TFP by firm size. The findings are provided in Table 3.10.

Table 3.10:Regression results of the effect of energy efficiency on Kenya's manufacturing sector's TFP by firm size

TFP	small firms	medium firms	large firms
TFP_{t-1}	-6.343	0.167	0.205
	(4.069)	(0.167)	(0.196)
Energy efficiency	5.346^{***}	0.572^{***}	0.0000536
	(1.507)	(0.134)	(0.000720)
Capital intensity	0.455^{***}	0.011^{*}	0.247^{*}
	(0.0831)	(0.006)	(0.141)
Firm age	0.973^{**}	-0.461^{*}	1.388^{**}
	(0.421)	(0.263)	(0.685)
Manager's experience	0.103	-0.001	0.000705
	(0.562)	(0.021)	(0.0388)
Foreign owned	-8.182	1.198^{*}	-0.464
	(11.60)	(0.627)	(1.222)
Export	12.63^{**}	-0.601	1.013
	(6.121)	(0.400)	(0.864)
R&D	-11.80	0.403	0.145
	(17.06)	(0.394)	(0.846)
Year(base year: 2007)			
2013	-37.99	-1.306	-6.085
	(58.47)	(1.375)	(4.901)
2018	-58.44	-1.273	-6.070
	(55.63)	(1.540)	(5.597)
Region(base region: Nyanza			
Central	-26.17	-1.602^{*}	1.655
	(24.05)	(0.965)	(1.209)

Coast	-12.75	-1.607***	0.712
	(31.01)	(0.791)	(1.053)
Nairobi	3.737	-1.625***	0.933
	(31.72)	(0.746)	(1.132)
Rift Valley	-32.54	-1.039	1.069
	(32.41)	(0.768)	(2.568)
Sub-sector(base C P and P)			
Food	73.52***	-0.401	0.551
	(25.86)	(0.579)	(0.781)
P and OM	25.03	-0.351	-0.197
	(23.07)	(0.546)	(0.882)
T and G	31.72	-0.651	-0.388
	(22.35)	(0.576)	(0.851)
Endogeneity Test			
H0: Exogenous			
Chi-sq	6.923	5.285	3.134
Prob> Chi-sq	0.009	0.022	0.077
Heteroscedasticity Test			
H0: Homoscedasticity			
Chi-sq	36.83	34.65	34.62
Prob> Chi-sq	0.025	0.042	0.043
Sargan-Hansen test			
Chi-sq	2.792	10.45	9.022
Prob> chi-sq	0.732	0.729	0.425

Dependent variable: TFP
Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
C, P and P is chemicals, pharmaceuticals and plastics, T and G is textiles and garments and P and O M is Paper and other manufacturing. TFP_{t-1} is the first lag of TFP.
Source: Author's computation from WBES data

From the endogeneity test as shown in Table 3.10, the null hypothesis for exogeneity of energy efficiency was rejected in small and medium firms at 5 percent level of significance. In large firms, it was rejected at 10 percent level of significance. The test indicated endogeneity in the model. The problem could be resolved by adopting a 2SLS or panel GMM estimator. The null hypothesis of homoscedasticity was rejected at 5 percent level of significance in all firm sizes. Thus, the panel GMM was the suitable estimator in this study. From the Sargan-Hansen test, the null hypothesis of validity of overidentifying restrictions was accepted at 5 percent level in each of the size cohort models. Thus, the instruments adopted in each of the cohort models were valid. The robust standard errors in the separate panel data regressions took care of any potential standard heteroscedasticity in the models.

The coefficient of energy efficiency was found to be positive and significant in all size categories, except in large firms. Energy efficiency in the manufacturing sector was in general associated with high TFP except in large firms. The outcome was consistent with the Porter Hypothesis. The finding corroborates the outcome of Montalbano and Nenci (2019). However, for Montalbano and Nenci (2019), energy efficiency positively influenced TFP in micro, medium and large firms but had an insignificant effect in small firms.

Capital intensity had a positive effect on TFP across all the firm sizes. Firms that produce with a large capital stock per employee were linked to higher TFP. Probably, the high levels of capital were characterized by modern technologies which are key to boosting TFP. This finding is in line with Montalbano and Nenci (2019) for Latin American manufacturing firms.

Firm age had a mixed effect on TFP in the different firm sizes. It had a positive influence on TFP in small and large firms. This finding confirmed the Jovanovic (1982) theory. Older firms in the two firm size categories had higher TFP. In the medium firms, the coefficient of firm age was negative and significant, implying that younger firms had higher TFP than old firms. The finding was consistent with sections of literature that postulate that young firms potentially have high productivity compared to old firms because they use new technologies and produce at higher efficiency levels. Further, the high TFP in young firms could be a result of their flexibility to technological changes. Old firms suffer from inertia effects, which show in two forms. According to Coad et al. (2013), old firms are susceptible to the liability of obsolescence, a scenario in which old firms fail to be flexible enough to accommodate changing business environments. They are also susceptible to the liability of senescence, a scenario in which old firms become inflexible due to accrued rules, norms and organizational settings. The outcome of this study contradicts Seleem and Zhaki, (2018) who find the firm size to negatively affect TFP in large firms and has no significant effect in small and medium firms.

The coefficient of foreign ownership was positive and significant in the medium firms, implying that foreign-owned medium firms had higher TFP than medium local firms. Probably, foreign firms possessed characteristics that gave them an edge in cost reduction over local firms. Such characteristics could include better technology, management or access to delivery and advertising means (Fernandes, 2008; Harris and Moffat, 2015). Such characteristics boost TFP (Fernandes, 2008; Harris and Moffat, 2015). The finding contrasts Seleem and Zhaki (2018) who find foreign ownership to significantly affect TFP in small firms but have no significant effect in medium and large firms.

The coefficient of exporting status was positive and significant in small firms. This implies that in this size category, TFP was higher in exporting firms compared to non-exporting firms. Probably, exporting firms learnt useful lessons from their foreign clients. It could also be that exporting firms operate with higher technology to satisfy the stringent but profitable requirements of foreign markets. They also learn to meet orders on time and to guarantee commodity quality in competitive markets. Moreover, firms with high TFP self-select into export markets. Nevertheless, as discussed earlier, self-selection and learning-by-exporting are not mutually exclusive. High TFP firms with access to export markets could maintain better TFP because of acquaintance with exporting (Fernandes, 2008). Montalbano and Nenci (2019) find exporting status to promote TFP in medium firms. However, exporting status has no significant effect on TFP in small and large firms.

TFP was reported to decrease in Nairobi, Central and Coast regions relative to the Nyanza region in medium-sized firms. Probably, the business environment in these sub-sectors was less conducive compared to that of the Nyanza region. With regards to sub-sector dummies, TFP was found to increase in the food sub-sector relative to the chemicals, pharmaceuticals and plastics sub-sector in small firms. This suggests that the business environment could be more conducive in the food sub-sector compared to the chemicals, pharmaceuticals and plastics sub-sector in small firms.

3.5 Summary, Conclusion, Policy Implication and Areas for Further Research

Summary and Conclusion

Energy efficiency is considered to be the best approach for dealing with energy-use-related issues. However, there is concern among economists on the firm productivity outcome of energy efficiency. This study used an unbalanced micro-panel for the years 2007, 2013 and 2018 got from the World Bank Enterprise Survey (WBES) to measure energy intensity and TFP and to test energy efficiency and TFP relation in Kenya's manufacturing sector.

Given that Kenya's manufacturing sector is comprised of several sub-sectors, average energy intensity scores were summarized by sub-sectors. The sub-sectors of concern were: the chemicals, pharmaceuticals and plastics sub-sector, food sub-sector, textiles and garments sub-sector and paper and other manufacturing sub-sector. Energy intensity was largest in the food sub-sector at 0.413 followed by the paper and other manufacturing sub-sector at 0.225. The chemicals, pharmaceuticals and plastics had a score of 0.120. The textile and garments sub-sector had the least energy intensity score of 0.064. Further analysis of the capital intensity and output value relation with energy intensity revealed that in general, energy intensity had a significant positive correlation with capital intensity. With regards to the value of output, energy intensity had a significant negative correlation with the value of output. The results indicate that large capital investment did not translate to efficient energy use. However, the production of a higher level of output was accompanied by efficient energy use.

The study estimated TFP by use of the Levinsohn-Petrin (LP) estimation algorithm. The average TFP in the chemicals, pharmaceuticals and plastics was 3.071, food 2.925, paper and other manufacturing 2.722 and textiles and garments 2.079. The study further established the level of heterogeneity of TFP in the Kenyan manufacturing sector by providing distributions of TFP for each sub-sector. The paper and other manufacturing and chemicals, plastics and pharmaceuticals sub-sectors had tightly dispersed distribution plots, implying that there was less heterogeneity in productivity in these sub-sectors. The distribution TFP in the food sub-sector had a tight dispersion but was lower than the paper and other manufacturing and chemicals, pharmaceuticals and plastics sub-sectors. The textiles and garments sub-sector had widely dispersed distribution plots, particularly on the lower parts of the plot and with a sizable density below the mean. This signalled more heterogeneity in TFP, implying that there coexisted high-productivity and low-productivity firms in this sub-sector. Such a dispersed distribution signals the existence of rigidities or other distortions that hinder the efficient allocation of resources within a sub-sector. Further, results showed heterogeneity in average firm-level TFP across the different firm-size categories for each sub-sector and different age categories for each sub-sector.

In the evaluation of the effect of energy efficiency on productivity, the study adopted panel GMM to deal with potential endogeneity resulting from unobserved heterogeneity and feedback causality. Energy efficiency was found to significantly affect TFP in the Kenyan manufacturing sector. Higher energy efficiency was related to higher TFP. The finding was in line with the Porter Hypothesis. Capital intensity influenced TFP positively. This signals that capital deepening and widening had a favourable effect on TFP.

Firm age was found to positively influence TFP, a finding that was in line with the Jovanovic (1982) theory. The outcome can also be explained by learning-by-doing effects. Firm size was found to positively influence TFP, a finding consistent with the Jovanovic (1982) theory. It is also probable that large firms have better access to credit which they used to acquire new and advanced technologies and to train their employees, thereby boosting productivity. The top manager's experience positively influenced TFP. A top manager's experience is an indicator of management ability and can potentially lead to higher TFP. The learning-by-doing effect associated with top managers with high experience could also be at play in Kenya's manufacturing sector. TFP was found to decrease in 2013 and 2018 relative to 2007. This suggests that the business environment for the Kenyan manufacturing sector could have been less favourable in 2013 and 2018 compared to 2007.

Separate regressions for the manufacturing sector by sub-sector and firm sizes were performed to take account of heterogeneity. The sub-sectors of concern were: textiles and garments, food and paper and other manufacturing sub-sectors. The chemicals, pharmaceuticals and plastics sub-sector had low sample sizes and the estimation failed convergence tests. The sub-sector was therefore dropped. Energy efficiency was found to positively influence TFP across all the sub-sectors. Energy efficiency was linked to high TFP. This was consistent with the Porter Hypothesis. A positive effect of capital intensity on TFP was found in the food and textile and garments sub-sectors. This indicates that high capital investments boosted TFP. However, in the paper and other manufacturing sub-sector, it was found to have a negative influence.

Firm age was found to positively influence TFP in the food and paper and other manufacturing sub-sectors. This can be explained by learning-by-doing effects. Firm size was reported to promote TFP in the paper and other manufacturing sub-sector. Probably, large firms had better access to credit which helped them acquire better technologies and train their staff, thereby enhancing TFP. Foreign ownership was found to boost TFP in the textiles and garments sub-sector. Probably, foreign-owned firms had some cost advantage over local firms. Exporting status was found to promote TFP in the textile and garments sub-sector. Probably, exporting firms in this sub-sector learnt better ways to produce from export markets. R&D was found to enhance TFP in the textile and garments sub-sector. This indicates that through R&D, there are TFP premiums of process and product innovations. R&D activities could also have improved the absorptive capacity of firms. TFP was found to decline in 2013 relative to 2007 in the food and textiles and garments sub-sectors. This indicates that the business environment for the two sub-sectors was less conducive in 2013 compared to 2007.

In the firm size analysis, sizes of interest were: small, medium and large. Energy efficiency had a positive influence on TFP in small and medium firms. High energy efficiency was associated with TFP premiums in these firm sizes. Capital intensity was found to positively influence TFP across all size categories. Capital deepening and widening had favourable effects on TFP. There were mixed findings on the effect of firm age on TFP. While firm age positively influenced TFP in small and large firms, it had a negative effect in medium firms. Younger firms had higher TFP than old firms in the medium-size category. Probably, younger firms had recent and advanced technologies. There is a need for older firms to adopt newer technologies and overcome inertia to boost productivity. Better access to credit could explain the outcome in small and large firms.

Foreign ownership was found to positively affect TFP in medium firms. Foreign-owned firms could be having some cost advantage over domestic firms, which promoted TFP. Small exporting firms were found to have higher TFP. They probably learnt about new technologies from their counterparts.

Policy Implication

In general, higher energy efficiency was found to be related to stronger TFP. The result reveals that policies to promote energy efficiency also promote firm productivity contrary to fears in some quarters. There is a need for the manufacturing sector to enhance energy efficiency through technological innovation. The National Treasury and Planning could provide a platform where manufacturing firms get credit at a low-interest rate to help them acquire new technologies. The government needs to devise policies that increase foreign investments in the manufacturing sector as this could promote the flow of knowledge and technological progress. Exporting has the same effect and should be promoted by the Ministry of Industrialization, Trade and Enterprise Development. Through exporting, the sector improves energy efficiency by learning-by-exporting which leads to improvement in TFP. Policies that help in the dissemination of information regarding energy efficiency and potential benefits such as improvement in TFP should also be formulated. Incorporating productivity benefits in the energy efficiency measures could make them even more cost-effective.

More policies to enhance TFP can be drawn from the findings of the control covariates. The study established strong heterogeneity by sub-sector and firm sizes revealing that there can be no common solution across the sub-sectors and firm size categories. Policies to improve productivity should therefore be sub-sector and firm size specific. Capital intensity was in general found to positively affect TFP, signalling that capital deepening and widening provides a viable channel to promote productivity. This study recommends the National Treasury and Planning to develop policies that increase the uptake of capital, especially technologically superior investments associated with modern and advanced technologies and innovations, be designed.

Firm age had a positive influence on TFP in the majority of the sub-sectors and firm sizes, implying that old firms enjoy the gains of learning-by-doing effects and better technology. However, in the medium firms, firm age was found to negatively influence firm-level TFP, implying that young firms enjoy the benefits of recent and advanced technologies and flexible working structures. This study recommends that policies encouraging startups for instance through access to formal credit at ease be designed by the Ministry of Industrialization, Trade and Enterprise Development. Top manager’s experience positively affected TFP in the overall model. This study recommends manufacturing firms to develop structures that continuously equip staff with formal training to sharpen their skills.

Foreign ownership positively influenced TFP in the textile and garments sub-sector and the medium firms. This study recommends that policies that facilitate an increase in the number of foreign investors be designed by the Ministry of Industrialization, Trade and Enterprise Development. Exporting was found to positively affect TFP in the textile and garments sub-sector and small firms. The insignificant effect of exporting on TFP across other sub-sectors and medium and large-size firms could be a result of declining manufacturing sector export performance. Since exports create learning-by-exporting effects, the study recommends the promotion of manufacturing sector exports by the Ministry of Industrialization, Trade and Enterprise Development.

Limitations of the Study

The chemicals, pharmaceuticals and plastics had a low sample size and thus failed convergence tests in the estimation of the effect of energy efficiency on TFP. This sub-sector was therefore dropped in the analysis.

Future Research

Given that policies to improve energy efficiency could also promote TFP, further research should seek to understand why in many cases uptake of energy efficiency measures is low even though energy efficiency has TFP premiums. Policies from this research may help remove impediments to energy efficiency in Kenya's manufacturing sector. In addition, there is a need to extend this research to the investigation of how energy efficiency affects profitability in Kenya's manufacturing sector. This analysis is important given the huge sunk cost of acquiring energy-efficient technologies.

CHAPTER FOUR: ENERGY AND NON-ENERGY INPUT SUBSTITUTION IN KENYA'S MANUFACTURING SECTOR

ABSTRACT

Energy substitution is viewed as one of the pivotal processes in reducing energy consumption. Debate on the direction and extent of substitution has been wide but with little consensus. This study employed the translog cost function at the sub-sector and firm size levels to analyze energy and non-energy input substitution possibilities in Kenya's manufacturing sector. The iterated seemingly unrelated regression technique was applied on a micro panel drawn from World Bank Enterprise Survey and Energy and Petroleum Regulatory Authority for the years 2007, 2013 and 2018. The sub-sectors of concern were: chemicals, pharmaceuticals and plastics, food, textile and garments and paper and other manufacturing sub-sector while the firm sizes of interest were small, medium and large. The overall sector was also included for robustness check. The findings revealed that in general, energy is the highest price-sensitive input across sub-sectors and firm sizes. The Morishima elasticities of substitution revealed that capital and labour could substitute energy across all sub-sectors and firm sizes. Substitutability of capital for energy increased with firm size. However, no consistent pattern was found in the substitutability of labour for energy. Findings suggest that energy price policies could be important in reducing energy use and in boosting capital investments and employment.

4.1 Introduction

The current mode of industrial production is heavily reliant on non-renewable energy. The use of this form of energy has several attendant problems that include resource depletion, environmental pollution and a limit on firm competitiveness. Reliance on non-renewable energy resources could be reduced through two approaches: technical change and input substitution (Fiorito and van den Bergh, 2015). Technical change is achieved through advancements in the efficiency of input use. Input substitution possibilities are often assessed through the evaluation of elasticities of substitution. The evaluation quantifies the extent of flexibility of an economy in producing output with the application of various input combinations.

Globally, the debate on whether energy and non-energy inputs, particularly capital and labour, are substitutes or complements took centre stage following the oil price shocks in the 1970s (Haller and Hyland, 2014). It has further been stimulated by rising environmental consciousness in societies and governments (Koetse et al., 2008). Early studies in this regard were motivated by the need to determine optimal energy taxes and evaluate the effect of oil price shocks on economies. Recent studies on energy and non-energy input substitution are driven by the necessity to cut energy use and harmful emissions stemming from the combustion of fossil fuels. They are also driven by a desire to predict future energy demand and to identify the implication of an environmental policy, such as energy tax, on the utilization of energy and non-energy inputs (Arnberg and Bjorner, 2007; Fiorito and van den Bergh, 2015).

An assessment of the energy and non-energy inputs substitution possibilities focuses on assessing how demand for non-energy inputs reacts to variations in energy prices. Energy price uncertainties significantly affect the selection of other factor inputs and this has effects on output, productivity, capacity utilization and prices of goods and services (Apostolakis, 1990). If capital and labour are substitutes for energy, a rise in energy price, either due to growing energy scarcity or high cost of energy production and distribution, will lead to more demand for capital and labour inputs to compensate for a reduction in energy use (Apostolakis, 1990; Berndt and Wood, 1975). In the context of production functions, demand for more capital in reaction to high energy prices is captured by the adoption of energy-saving technologies (Koetse et al., 2008). Therefore, the substitution of capital and labour for energy could result in more capital formation and, thereby an improvement in labour productivity, more employment of labour and scarce energy resources cannot form a major bottleneck to growth (Apostolakis, 1990; Berndt and Wood, 1975).

On the other hand, if capital and labour complement energy in production, a rise in energy price would reduce demand for not only energy but also capital and labour (Apostolakis, 1990). This would imply a reduction in capital formation and productivity, which heavily depends on capital accumulation and a decline in employment. Ultimately output would also decline (Arnberg and Bjorner, 2007; Haller and Hyland, 2014). According to Apostolakis (1990) and Berndt and Wood (1975), it is also possible that energy and non-energy inputs could have limited substitution possibilities which means that adjustments by the manufacturing sector to higher energy prices may be challenging, that cost of production may increase sharply, that the constitution of output might move away from energy-intensive goods and that considerable adjustments in the underlying technological structure may be needed. Therefore, the enquiry of whether energy and non-energy inputs are substitutes or complements is central, particularly following the high energy prices and global financial and economic crisis in the last decade (Fiorito and van den Bergh, 2015). It has important policy implications on capital intensity, rate of capital formation, investment behaviour, employment and environment.

As discussed earlier, the Kenyan manufacturing sector is one of the central sectors of the economy both in its economy-wide contribution and final energy consumption. Even though the total requirement of electricity in the country is almost fully met by domestic production (for example, 98.82 percent in 2020), the total fuel requirement is met from imports (Republic of Kenya, 2021). This contributes significantly to the country's total import bill. For instance, in 2020, from an import bill of Ksh. 1643.6 billion, oil imports, even though severely reduced by COVID-19, accounted for Ksh. 201.1 billion, which was 12.24 percent of the total import bill (Republic of Kenya, 2021). With total export earnings of Ksh. 567.37 billion in the same year, it implies that 35.45 percent of the export earnings went to cover the oil import bill. Further, the high oil import bill contributed significantly to the balance of trade deficit in the country, which stood at Ksh. 999.85 billion in that year (Republic of Kenya, 2021).

The heavy reliance on energy by this sector constrains its growth by increasing the total cost of production. For instance, in the textile and garments sub-sector, the cost of electricity can increase to a high of 40 percent of the unit cost of manufacture (KAM, 2018b). In the metal and allied sub-sector, electricity cost averages between 40-50 percent of the total conversion cost (KAM, 2018b). The high electricity cost is in part due to high tariffs. For example, in 2018, the manufacturing sector electricity tariff in Kenya was third-highest after that of Rwanda and Burundi in the East Africa region as shown in Table 4.1.

Table 4.1:Manufacturing electricity tariffs in the East Africa region, 2018

	Ethiopia	Tanzania	Sudan	Uganda	Kenya	Rwanda	Burundi
Tariff (Ksh/KWh)	1.66	6.88	10.58	12.26	13.65	13.82	20.11

Source: KAM (2019).

Dependence on petroleum fuels by this sector makes it vulnerable to price volatility from unstable global oil supplies and economic sanctions (Republic of Kenya, 2018). The high energy prices and associated high total cost of production results in high product prices. Moreover, the electricity supply in the country is often characterized by frequent blackouts and low voltage which results in losses in production and sales and the breakdown of equipment (KAM, 2018a). Ultimately, the shortcomings impact negatively on the cost of production and undermine the competitiveness of Kenya's manufactured goods locally and internationally (KAM, 2018a).

The energy situation in Kenya begs the question of whether non-energy inputs could substitute energy inputs in the manufacturing sector. The increased global concern over the effects of energy use on environmental quality (depletion of energy resources and release of greenhouse gases, GHGs), further fuels this debate. Kenya's input to GHG emissions on a universal level is small, but the country's fast-increasing populace and enlarging economic activity can result in a substantial upsurge in its future GHG levels. This would aggravate climate change (Dalla Longa and van der Zwaan, 2017). Kenya in its Intended Nationally Determined Contribution (INDC) has undertaken to cut its GHG emissions by 30 percent in 2030 (Republic of Kenya, 2015). The undertaking is in reaction to resolutions agreed upon at the 21st sitting of the Conference of the Parties to the United Nations Framework Convention on Climate Change (UNFCCC) of 2015 in Paris (Dalla Longa and van der Zwaan, 2017).

The World Development Indicators show that in Kenya, the majority of carbon dioxide emissions, which are the main GHG emissions, are from liquid fuel combustion. For instance, over the last decade, carbon dioxide emissions from fuel consumption accounted on average 79 percent of the total carbon dioxide emissions in the country. Therefore, analysis of the energy and non-energy input substitution potential in the manufacturing sector is also important in indicating whether Kenya can meet its emission reduction commitment by substituting capital or labour for energy. This is on account that the manufacturing sector is one of the highest consumers of liquid fuel in the country.

The ability to substitute non-energy inputs for energy is likely to vary across sub-sectors and firm sizes. This is because production technology varies across sub-sectors and firm sizes. Therefore, information on sub-sector and firm-size energy and non-energy input substitution possibilities may be of policy relevance. There is a need to investigate the effect of a policy instrument on various sub-sectors and firms of different sizes since there may be heterogeneity in their reaction to energy prices. The sub-sectors of concern were: chemicals, pharmaceuticals and plastics, food, textile and garments and paper and other manufacturing sub-sectors. The firm sizes of interest were small, medium and large.

4.1.1 Statement of the Problem

The global concerns about the implications of energy use in production on environmental quality and the manufacturing sector's competitiveness have fueled debate on whether non-energy inputs could substitute energy in production.

The question has been investigated extensively with mixed findings. Starting with energy-capital substitution possibilities, Koetse et al. (2008), Onuonga et al. (2011), Smyth et al. (2011), Krishnapillai and Thompson (2012), Zha and Ding (2014), Haller and Hyland (2014) and Wang et al. (2019) have found capital to be a substitute for energy. Others such as Arnberg and Bjorner, (2007), Tovar and Iglesias (2013), Fiorito and van den Bergh (2015) and Deininger et al. (2018) have found capital to be a complement for energy. Only a few studies have examined energy-labour substitution possibilities. The majority of these studies for instance Onuonga et al. (2011), Symth, et al. (2011) and Dissou et al. (2014) have established that labour is a substitute for energy. In contrast, Dahl and Erdogan (2000), Zha et al. (2012) and Wang et al. (2019) have found labour to be a complement for energy.

The mixed findings suggest that energy and non-energy substitution possibilities in production is a worthy research theme, especially in sub-Saharan Africa where evidence is scanty. In Kenya, Onuonga, et al. (2011) have found capital and labour to be substitutes for energy using macro time-series data. However, macro data suffer from aggregation bias and capture more than technical substitution (Leon-Ledesma et al., 2010). Micro-level data is arguably unbiased. In addition, the study does not capture recent substitution potential, yet production relationships adjust over time, under the stimulation of shifting preferences or tastes and technological change (Fiorito and van den Bergh, 2015). More recent studies are needed to inform on recent developments with implications on energy and non-energy input substitution possibilities in the manufacturing sector. Further, the study fails to assess whether the substitution potential varies across sub-sectors and firm sizes. Such analysis is important because different sub-sectors and sizes could be operating at varying technologies. This analysis is useful in identifying the sub-sectors and firm sizes that are more flexible in altering their input mix following changes in factor prices.

This study sought to fill the existing research gaps by analysing energy and non-energy inputs substitution potential inputs in the Kenyan manufacturing sector at sub-sector and firm size levels using the most recent firm-level data.

4.1.2 Research Questions

The study addressed the following questions

i. What are the energy-capital substitution possibilities in Kenya's manufacturing sector?
ii. What are the energy-labour substitution possibilities in Kenya's manufacturing sector?
iii. How do energy and non-energy inputs substitution possibilities vary across firms of different sizes in Kenya's manufacturing sector?

4.1.3 Objectives of the Study

The general objective of the study was to establish the energy and non-energy inputs substitution possibilities in Kenya's manufacturing sector. Specifically, the study sought to analyze:

i. The energy-capital substitution possibilities in Kenya's manufacturing sector.
ii. The energy-labour substitution possibilities in Kenya's manufacturing sector.
iii. Whether energy and non-energy substitution possibilities vary across firm sizes in Kenya's manufacturing sector.

4.1.4 Significance of the Study

This research furthers the literature on input substitution by assessing energy and non-energy inputs substitution potential using recent surveys of Kenyan manufacturing firms. This is a developing economy in sub-Saharan Africa where analytical evidence on the matter is scant.

Second, by using firm-level data, the research adds to the current literature by carrying out estimation at the decision-making unit (the firm) where evidence is scanty. Third, this research furthers extant literature by presenting sub-sector as well as firm-size level evidence on energy and non-energy substitution potential. This is important in taking into account heterogeneity in production. Lastly, the findings of the study could inform the National Treasury and Planning and EPRA on the implications of changing energy prices and macroeconomic implications of energy price shocks on investment behaviour, employment and environmental quality.

4.2 Literature Review

4.2.1 Theoretical Literature Review

Theoretical literature shows that input substitution has extensively been a matter of intense controversy among economists. This is underscored by the Georgescu-Roegen versus Solow/Stiglitz debate (Daly 1997a, b; Stiglitz, 1997). At the centre of the disagreement was whether the energy and capital relation was of substitution or complementary nature. The concern on this subject dates back to the theoretical works of Georgescu-Roegen (1971) who opined that energy and materials were constraining factors to economic growth because of their exhaustible nature. Georgescu in the fund-flow model of the production process argued that what is often referred to as "production" is in real sense transformation - of natural resources into valuable goods and waste products (Daly, 1997b).

In this modelling, labour and capital inputs are opined to be agents of transformation, while natural resources are observed to be the material to be transformed. Therefore, one agent of transformation can often be substituted for another, or one natural resource can be substituted for another, but the relationship between agents of transformation and natural resources is primarily one of a complementary nature, not of a substitution nature (Daly, 1997b). However, neoclassical economists led by Stiglitz (1974) opposed the suggestion that limited natural resources present a constraint to growth. According to Stiglitz (1974), there exist at least two economic forces to offset the limits compelled by natural resources: technical change and substitution of capital for natural resources.

More specifically, machines that are made from fairly ample resources can cut the wastage of scanty natural resources. Technical change, some of which results from investments in research and development (R&D), which is a type of capital, can help moderate the quantities of physical capital and natural resources needed to produce output (Stiglitz, 1997). In general, economists show confidence in the reduction of energy along with other material intensity through these economic forces, which are observed to be steered to a large extent by price mechanisms (Dasgupta and Heal, 1974; Stiglitz, 1974). Consequently, the neoclassical production framework forms the basis for analysing the energy and non-energy input substitution possibilities in Kenya's manufacturing firms. Under this framework, it is possible to assess how demand for inputs changes following changes in the price of the inputs. According to Sakai (1973), variation in the price of one input, *j*, brings a change in the demand for input *i* by changing the input price ratios which prompts technical substitution among the inputs along the old isoquant frontier.

4.2.2 Empirical Literature Review

Considerable effort has been employed in analysing energy and non-energy input substitution possibilities. Mixed findings have been found across various studies. This study focuses on reviewing three strands of literature: one showing energy-capital substitution possibilities, another one showing energy-labour substitution possibilities and a third one showing whether firm size matters in the relationship between energy and non-energy inputs. Beginning with the first strand of literature, Zha et al. (2012) by adopting a translog cost model in the Chinese electricity industry use annual time-series data obtained from various China Statistical Yearbooks for the period 1985-2007. Capital is found to be a substitute for energy. However, the results obtained by this study are likely to suffer from aggregation bias. According to Solow (1987), aggregation bias may be a result of the use of aggregate data. This is because estimates of factor substitutability encapsulate more than technical substitution. For instance, Arnberg (2007) argues that what may appear as factor substitution at the aggregate level may be arising from demand effects, which cause adjustments in the output shares of firms. Solow (1987) therefore holds that input substitution is a microeconomic effect that is best analysed using micro-level data as variations in energy intensities are wide and aggregate outcomes will be propelled by composition effects. Consequently, this study employs a micro-panel of firm-level data.

Smyth et al. (2011) employ a translog production function and annual time series data drawn from China Statistical Yearbooks for the period 1978-2007 in China's energy-intensive iron and steel sector. Findings reveal a strong substitution possibility between energy and capital. Estimates from a production function are however subject to bias given that input factors are highly likely to be endogenous (Koetse et al., 2008). The study has not corrected this problem and thus estimates are likely to be biased. In the Chinese power sector, Zha and Ding (2014) employ a translog cost function and aggregate time-series data for the period 1995-2008 drawn from various statistical Yearbooks. Results of the study show that energy and capital substitute each other.

Still, in China and in a more recent study, Wang et al. (2019) also adopt the translog cost function to examine the elasticity of factor substitution and the determinants of energy intensity in China’s Industry. The study focuses on three sectors namely the mining and quarrying industry, the manufacturing industry and the electricity, gas and water industry for the period 1984-2011. Aggregate time series data is drawn from various China Statistical Yearbooks. The study finds capital and energy to be very strong substitutes. Studies by Symth et al. (2011), Zha and Ding (2014) and Wang et al. (2019) also use aggregate data and their estimates are also likely to suffer from aggregation bias.

By use of a micro panel for the period 1991 to 2009, Haller and Hyland (2014) employ a translog cost function in Irish manufacturing firms. The findings of the study reveal that energy and capital substitute each other. A similar outcome has been found by Krishnapillai and Thompson (2012) in the U.S manufacturing industry. The study adopts a translog production function and cross-section data obtained from the 2007 U.S. Census Bureau report. Estimates from a production function in this study are also likely to be biased because the factor inputs used in the function are likely to be endogenous.

By use of panel data running from 1993 to 1997 sourced from energy surveys conducted by the Denmark Statistics, Arnberg and Bjorner (2007) employ a translog cost function and a linear logit function in the Denmark industrial companies. In both models, energy and capital are observed to be complements. In a more recent study using a similar modelling approach, Deigner et al. (2018) use a micro panel running from 1997 to 2008 to estimate energy-capital substitution in Swiss, manufacturing companies. The study finds energy and capital to substitute each other in the less energy-intensive companies, but in the more energy-intensive companies, energy and capital are found to complement each other. Fiorito and van den Bergh (2015) apply a translog cost function in seven OECD countries and aggregate time-series data during the period 1970-2005. The study finds energy and capital to be complements. As observed earlier, the use of aggregate data is likely to lead to estimates with aggregation bias, which this study seeks to circumvent by using firm-level data.

Turning to Kenya, Onuonga, et al. (2011) apply a translog cost function and aggregate time-series data for the period 1970-2005. The study finds energy to be a substitute for capital. However, the use of aggregate data makes estimates of this study to be susceptible to aggregation bias. In addition, given that some years have passed since the study was done, its findings may not correctly provide the current energy-capital substitution possibilities. This is because production relationships adjust over time, under the stimulation of shifting preferences or tastes and technological change (Fiorito and van den Bergh, 2015). This study seeks to provide evidence for energy-capital substitution possibilities for Kenyan manufacturing firms using recent micro firm-level panel data.

Moving to the second strand of literature, Zha et al. (2012) employ a translog cost function and aggregate time-series data obtained from various China Statistical Yearbooks for the period 1985-2007 in China's electricity industry. The findings of the study show that labour is a complement for energy. However, given that the study uses aggregate time-series data, estimates are highly likely to suffer from aggregation bias. This study circumvents this problem by using micro-level panel data. Smyth et al. (2011) apply a translog production function and annual time series data drawn from China's statistical Yearbooks for the period 1978-2007 in China's energy-intensive iron and steel sector. The study finds energy and labour to be substitutes. These estimates are however likely to be biased given that factor inputs could be potentially endogenous. This study shuns the problem of endogeneity by employing a cost function. In China's power sector, Zha and Ding (2014) establish that energy and labour are weak substitutes. Still, in China, Wang et al. (2019) establish that energy and labour complement each other in the manufacturing industry. Estimates of energy-capital substitution possibilities obtained by Smyth et al. (2011), Zha and Ding (2014) and Wang et al. (2019) are also susceptible to aggregation bias given that they use aggregate time-series data. This study bypasses this potential problem by using micro panel data.

Haller and Hyland (2014) establish that energy and labour are substitutes in the Irish manufacturing firms, an outcome that is similar to that of Krishnapillai and Thompson (2012) in U.S manufacturing. However, estimates of energy-labour substitution possibilities obtained by Krishnapillai and Thompson (2012) are also likely to be biased given that the study applies a production function and input factors are subject to endogeneity. This study avoids the problem of endogeneity by using a cost function. In the Swiss manufacturing firms, Deininger et al. (2018) find that energy and labour substitute each other. Dissou et al. (2015) apply a constant elasticity of substitution (CES) production function and time-series data running for the period 1962-1997 in the Canadian manufacturing industries. The study reports that energy and labour substitute each other. However, because the study employs time-series data, estimates of energy-capital substitution have a likelihood of suffering from aggregation bias. Further, the estimates are potentially biased because factor inputs applied in a production function are likely to be endogenous.

For the Kenyan case, Onuonga et al. (2011) establish that energy and labour are substitutes. Nevertheless, these estimates are likely to suffer from aggregation bias. Further, they do not show the current energy-labour substitution possibilities as they rely on old data, yet as observed earlier, production relationships vary over time, under the influence of varying preferences or tastes and technological change. To avoid potential aggregation bias and to provide current energy-labour substitution possibilities, this study employs a panel of recent firm-level data.

On the third strand of literature, Nguyen and Reznek (1993) seek to analyse possible variation in input substitution in U. S's small and large manufacturing firms using cross-section data retrieved from the Census Bureau's LRD for 1977 and 1982. A translog production function is adopted for five four-digit industries. The Findings of the study show that capital and materials and materials and labour substitute each other. The study finds that the magnitude of substitution in the three inputs is common through all firm sizes, implying that small enterprises are as flexible as large enterprises. However, estimates from this study are prone to bias given that factor inputs applied in the translog production function are likely to be endogenous. Further, this study does not handle energy as a separate input in the production process and thus findings do not reveal the energy and non-energy inputs relation.

Nguyen and Streitwieser (1999) seek to establish whether plant size matters in U. S's manufacturing using the 1991 Manufacturing Energy Consumption Survey and 1991 Annual Survey of manufacturers cross-section data set. A translog production function is adopted. Findings show that energy and capital and energy and labour are substitutable to one another. The magnitude of substitution among the inputs is found to be generally similar across all plant sizes, implying that small and large plants are equally flexible in substituting factor inputs. Estimates from this study are also prone to bias given that factor inputs applied in the translog production function are likely to be endogenous.

The findings of Nguyen and Streitwieser (1999) are corroborated by the results of Haller and Hyland (2014) in Irish manufacturing. The study finds no consistent pattern of elasticity of capital with respect to energy prices in Irish manufacturing. Bardazzi et al. (2015) seek to establish whether firm size matters in reaction to energy prices by Italian manufacturing firms. The study applies a translog cost function and an unbalanced panel drawn from the Italian Enterprise Integrated and Systematized Information System and Manufacturing Product Survey for the years 2000-2005. Firms are categorized into small and medium firms and large firms. The study finds capital to be a substitute for energy and labour to be a substitute for energy. Large enterprises have higher elasticities of capital and labour with respect to changes in energy prices, which means that large enterprises are more flexible in factor substitution than small and medium enterprises. While Bardazzi et al. (2015) findings provide valuable insights into the issue of energy and non-energy substitution across firm sizes, the failure to treat small and medium establishments as separate enterprises does not permit analysis of whether factor substitution varies across the two sizes.

Reviewed studies show mixed findings for energy-capital and energy-labour substitution possibilities. Some researchers have attempted to reconcile the varying findings. First, differences in findings have been attributed to differences in data types (Apostolakis, 1990). Estimation based on cross-sectional data is considered to measure the long-run relationship between inputs and is thus argued to show a substitution relationship between energy and non-energy inputs. In contrast, time-series data is argued to seize short-run factor relationships since adjustments to factor prices take time (Solow, 1987). Studies using this data are thus argued to find that energy and non-energy inputs have a complementary relationship.

The idea that energy and non-energy inputs complement each other in the short run is supported by the results of Fiorito and van den Bergh (2015) for the energy-capital substitution and Wang et al. (2019) for the energy-labour substitution. That of energy and non-energy inputs being substitutes is supported by the results of Krishnapillai and Thompson (2012). However, the avenue for reconciliation based on the type of data used is not conclusive as there are studies using time series data such as Smyth et al. (2011), Zha and Ding (2014), Onuonga et al. (2011) for energy-capital substitution and Wang et al. (2019) for energy-labour substitution which find energy and non-energy inputs to substitute each other. Further, some studies which use cross-sectional data such as Arnberg and Bjorner (2007) find the energy and non-energy inputs to complement each other.

A second avenue for reconciliation of the varying results is provided by Berndt and Wood (1979), who note that variations in findings can be because of the number of factor inputs incorporated in the model. The study holds that studies that involve three-factor inputs (that is capital, labour and energy) report substitutability, for example, between energy and capital while those that include materials as a fourth factor report a complementary relationship. Although this argument is theoretically convincing, there exist some studies whose findings are not consistent with this theoretical argument. For instance, Haller and Hyland (2014) establish that energy and capital substitute each other yet the study adopts four-factor inputs in its cost function and Arnberg and Bjorner (2007) establish that energy and capital are complements even though the study adopts three-factor inputs. This means that the theoretical argument does not tell the story.

A third avenue is the measurement of factor inputs. Specifically, the disaggregation of capital into physical capital and working capital is argued to provide differences in findings. Physical capital implies real machinery, while working capital implies other forms of capital, such as buildings and constructions, land and monetary assets (Koetse et al. 2008). Solow (1987) however notes that such disaggregation has failed to provide clear reconciliation. In an attempt to provide more convincing avenues for variations in findings, Koetse et al. (2008) provide a meta-analysis to assess the capital-energy substitution in North America and Europe using different data and time. The study finds that heterogeneity in findings can be explained by differences in the measurement of energy, where aggregate energy information is used or a distinction between fuel and electricity is made. Other reasons for heterogeneity provided by the study are variations in model specification, location and time. Nevertheless, Zha and Ding (2014) note that sources of heterogeneity in findings remain unresolved. This necessitates more analytical elucidation on the energy and non-energy input substitution possibilities. This study builds on previous studies to analyse energy and non-energy inputs substitution possibilities in Kenya's manufacturing sector.

4.2.3 Overview of Literature

The theoretical literature on energy and non-energy substitution potential is mainly anchored on the neoclassical production framework. The framework shows how firms change energy and non-energy input combinations in reaction to varying energy prices. The framework is a departure from the conventional view that energy and materials are constraining factors to economic growth because these resources are exhaustible. The neoclassical economists oppose the conventional view and note that the growth limits compelled by natural resources can be offset by technical change and substitution of manmade factors (for example capital) for natural resources.

The reviewed literature reveals mixed findings on energy and non-energy input substitution possibilities. For energy-capital substitution, the majority of the studies, for example, Onuonga et al., (2011), Smyth et al. (2011), Krishnapillai and Thompson (2012), Haller and Hyland (2014), Zha and Ding (2014), Deigner et al. (2018) and Wang et al., 2019) have found energy and capital to substitute each other. In contrast, few studies, for example, Fiorito and van den Bergh (2015) have found energy and capital to be complements. On energy-labour substitution, some studies, for instance, Onuonga et al. (2011), Smyth et al. (2011), Krishnapillai and Thompson (2012), Deininger et al. (2018) and Haller and Hyland (2014) have found energy and labour to be substitutes while others such as Dahl and Erdogan (2000) and Wang et al. (2019) have found them to be complements. On whether firm size matters in the energy and non-energy input substitution possibilities, empirical evidence on this subject is scarce. For the few existing studies, mixed findings are found. Nguyen and Streitwieser (1999) and Haller and Hyland (2014) find small firms to be as flexible as large firms in substituting non-energy inputs for energy while Bardazzi et al. (2015) find larger firms to be more flexible than small and medium establishments.

The majority of the studies have used a cost function to model energy and non-energy input substitution possibilities. However, few have adopted a production function and their estimates are potentially biased because input factors used in the production function could be endogenous. Applying a cost function overcomes this problem. Moreover, some studies have applied micro-level data while others have applied aggregate time-series data. Nevertheless, the use of aggregate data is observed to provide estimates that suffer from aggregation bias as aggregate data capture more than responses to price changes.

Finally, some studies have attempted to provide avenues for reconciling differences in findings across studies. Among the avenues suggested are the type of data used (Solow, 1987), number of factor inputs incorporated in the model (Berndt and Wood, 1979), measurement of factor inputs, variations in the model specification (Solow, 1987; Koetse et al., 2008), location of study and study period (Koetse et al., 2008). Nevertheless, the source of heterogeneity in findings remains contentious. Therefore, the demand for more empirical elucidation on energy and non-energy substitution possibility becomes significant. This study locates itself to provide empirical evidence for the manufacturing sector in Kenya, where there is a dearth of research in this area. A notable existing study for the Kenyan manufacturing sector is by Onuonga et al. (2011). This study is however found to have applied aggregate data on a translog cost function and hence findings are likely to suffer from aggregation bias. The study also fails to provide empirical analysis at the disaggregate sub-sector and firm size levels. The use of a uniform policy instrument may result in varying impacts on different subsectors and firm sizes given the heterogeneity in the reaction of sub-sectors and firm sizes to varying market conditions. Further, the study does not give the current substitution possibilities as it relies on old data. This study addresses the research gap by employing the most recent firm-level data on a cost function. The empirical analysis is provided at the sub-sector and firm size level.

4.3 Methodology

4.3.1 Theoretical Framework

The study followed the works of Berndt and Wood (1975, 1979) and Tovar and Iglesias (2013) to develop a framework for modelling energy and non-energy inputs substitution possibilities. The study assumed that manufacturing firms have a twice differentiable, weakly separable and strictly quasi concave production function exhibiting the functional relation between output, Q, and inputs capital, K, labour, L, and energy, E. The production function takes the following general form:

$$Q = f(KLE) \qquad (4.01)$$

It was further assumed that the production function is characterized by constant returns to scale, separable in factor inputs and any technical change affecting K, L and E is Hicks-neutral. A common problem while estimating production functions is that factor inputs are likely to be endogenous due to simultaneity bias leading to biased estimates (Koetse, 2008; Haller and Hyland, 2014). The dual to the production function is a cost function that reflects the production technology. The application of factor prices in the cost function alleviates the problem of endogeneity. Hence a cost function is preferable to a production function (Koetse, 2008). The cost function takes the following general form:

$$C = C(Q, P_k, P_l, P_e, T) \qquad (4.02)$$

where C is the total cost, P_k, P_l, P_e are the input prices of K, L and E, respectively and T captures Hicks-neutral technical change (changes in output brought about by technological change). In minimizing total costs subject to constraints and following Tovar and Iglesias (2013), equation (4.02) could be expressed as follows:

$$C = C(Q, P_i, T) = \min_i\{P'i: f(i), i \gg 0\} \qquad (4.03)$$

Where P is a vector of input prices with $(P_k, P_l, P_e)' \gg 0$, i is input demand and $f(\cdot)$ is the production function. It is assumed that the cost function is homogenous of degree one in input prices, quasi-concave, twice differentiable and weakly separable. Further, the function is assumed to be non-declining in output and input prices (Haller and Hyland, 2014; Tovar and Iglesias, 2013).

4.3.2 Analytical Model

For cost function C to be assessed, a functional form needs to be specified. Following Berndt and Wood (1975, 1979), Tovar and Iglesias (2013) and Haller and Hyland (2014), this study adopted a transcendental logarithmic (translog) cost function, which was suggested by Christensen et al. (1973). The cost function is flexible, twice differentiable and does not demand advance assumptions on the link between the factor inputs (Berndt and Wood, 1975; Haller and Hyland, 2014). The link is established through analysis. The function is expressed as follows:

$$\ln C_{ft} = \alpha_0 + \sum_{i=1}^{n} \delta_i \ln P_{ift} + \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \alpha_{ij} \ln P_{ift} \ln P_{jft} + \sum_{i=1}^{n} \beta_i \ln P_{ift} \ln Q_{ft} + \tau_q \ln Q_{ft} + \tau_{qq} (\ln Q)^2 + \sum_{i=1}^{n} \mu_{fi} \ln P_{ift} \qquad i,j = k,l,e \quad i \neq j \qquad (4.04)$$

where ln is the natural log, f indicates firms, i and j represent the three-factor inputs (capital, labour and energy) at time t, C is the total cost, Q is output, P is the price of each of the inputs, μ is the residual and α_0, δ_i α_{ij}, β_i, τ, and μ_{fi} are coefficients to be estimated. Efficiency in estimation is improved by augmenting the translog cost function with factor share equations as suggested by Diewert (1974). Factor share equations are got by differentiating the translog cost function with respect to input prices as suggested by Shepard's lemma. They are provided as follows:

$$S_{ift} = \delta_i + \sum_{j=1}^{n} \alpha_{ij} \ln P_{jft} + \beta_i \ln Q + \mu_{if} \quad (4.05)$$

where S indicates factor shares, δ_i and α_{ij} are distribution and substitution parameters, respectively (Christensen et al., 1973). The distribution parameters measure the change in cost-share in reaction to a change in input price as a consequence of factor substitution. The substitution parameter reflects the price elasticity of substitution between the various inputs.

Given that firms differ in various ways, accounting for firm heterogeneity is essential. However, according to Haller and Hyland (2014), in the case of joint estimation of cost function and share equations, controlling for firm heterogeneity by adding firm-level fixed effects is not computationally practical. This is because the intercept in the share equation (δ_i) is the coefficient on price in the translog cost function. Following Iqbal (1986) and Haller and Hyland (2014), this study adopted a panel-pooled model and exploited the available data to model firm heterogeneity directly by incorporating foreign ownership and exporting status dummies. Further, the study included time dummies to capture variations over time. According to Haller and Hyland (2014), time dummies provide a straightforward and often applied approach to modelling Hicks-neutral change. Controls account for the reality that cost functions are not homogenous across firms, and that firms in dissimilar sub-sectors use different production technologies. The resulting cost function was expressed as follows:

$$\ln C_{ft} = \alpha_0 + \sum_{i=1}^{n} \delta_i \ln P_{ift} + \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \alpha_{ij} \ln P_{ift} \ln P_{jft} + \sum_{i=1}^{n} \beta_i \ln P_{ift} \ln Q_{ft} + \tau_q \ln Q_{ft} + \tau_{qq} (\ln Q_{ft})^2 + \sum_{i=1}^{n} \mu_{fi} \ln P_{ift} + \theta_z Z_{ft} + \theta_\gamma \gamma_t, \qquad i, j = k, l, e \quad i \neq j \quad (4.06)$$

where Z is a dummy vector of foreign ownership and exporting status, γ captures time dummies, and θ_z and θ_γ are the coefficients to be estimated. The subsequent factor share equations are provided as follows:

$$S_{if} = \delta_i + \sum_{j=1}^{n} \alpha_{ij} \ln P_{jft} + \beta_i \ln Q_{ft} + \mu_{if} \quad (4.07)$$

To make certain that the cost function is symmetric and homogenous of degree one in input prices, the following constraints are imposed:

$\sum_{i=1}^{n} \delta_i = 1$; $\sum_{i-1}^{n} \alpha_{ij} = 0$; i, j =1,…, n; $\sum_{i=1}^{n} \beta_i = 0$ (for homogeneity condition)

$\alpha_{ij} = \alpha_{ji}$, i, j = k, l, e; $i \neq j$ (for symmetry) (4.08)

Equations (4.06) and (4.07) were jointly analysed using Zellner's iterated seemingly unrelated regression (iSUR) method. According to Haller and Hyland (2014), this technique takes care of possible correlation between errors in the equations. Given that the factor shares must add up to one, one of the factor shares (in this case capital) was arbitrarily dropped and it was calculated as a residual. Employing iSUR ensured that the estimated parameters remained unchanged with regard to the dropped factor (Haller and Hyland, 2014).

The joint estimation of the translog cost function and the factor share equations provided the initial step of a two-step process. In the second step, elasticities were calculated directly from the estimated parameters of the translog cost function and predicted cost shares. The study first estimated own - and cross-price elasticities of demand (PED). Own-price elasticities provide the percentage change in demand for an input following a percentage change in its price. Cross-price elasticities provide the percentage change in demand for an input in reaction to a one percent change in the price of another factor input. The price elasticity of demand was calculated as follows:

$$\epsilon_{x_i P_i} = \sigma_{ii} \times S_i = \frac{\alpha_{ii} + S_i \times S_i}{S_i} \tag{4.09}$$

$$\epsilon_{x_i P_j} = \sigma_{ij} \times S_i = \frac{\alpha_{ij} + S_i \times S_j}{S_i} \tag{4.10}$$

Where $\epsilon_{x_i P_i}$ is own-price elasticity and $\epsilon_{x_i P_j}$ is cross-price elasticity.

For the cross-price elasticity, if $\epsilon > 0$, the variable inputs were taken to be substitutes. This means that a rise in the relative price of one input increased demand for the other input. If $\epsilon < 0$, the inputs were considered to be complements. This implies that a rise in the relative price of one factor reduced demand for the other input. Haller and Hyland (2014) note that own-and cross-price elasticities can be helpful to policymakers who might desire to identify the potential effect of, for instance, a carbon tax on demand for energy and other factor inputs. The elasticities measure the actual change in demand for non-energy inputs following an increase in energy price. Nevertheless, some literature has opined that price elasticity of demand is not a satisfactory measure of factor substitutability because it fails to measure the ease of substitution or curvature of the production function (Haller and Hyland 2014; Zha and Ding 2014). In addition, Zha and Ding (2014) note that the own- and cross-elasticities of substitution are measures of absolute substitution and do not reveal changes in factor input ratios, yet they are of important economic interpretation.

Allen elasticity of substitution (AES) and Morishima elasticity of substitution (MES) are theoretically better measures of substitution (Haller and Hyland 2014; Zha and Ding 2014). According to Frondel (2004), they reveal the scenario in which substitution possibilities are determined entirely by technology. AES was first proposed by Hicks and Allen (1934) and was later improved by Allen (1938) and Uzawa (1962). It is thus often referred to as Allen–Uzawa elasticity of substitution and is expressed as follows:

$$AES_{x_i P_j} = \frac{\epsilon_{x_i P_j}}{S_j} \tag{4.11}$$

AES estimates the actual percentage change in demand for factor input *i* in reaction to variation in factor *j*'s price and has the same sign as cross-price elasticity. However, Blackorby and Russell (1989) note that this measure suffers from three weaknesses: first, AES does not measure the ease of substitution or curvature of the production function and it adds no information to cross-price elasticities; second, the measure does not provide evidence of relative factor shares, yet this is the rationale for the elasticity of substitution; lastly, it cannot be elucidated as a derivative of a quantity ratio with respect to a price ratio, implying that it is entirely unproductive. In addition, Zha and Ding (2014) note that this measure provides partial elasticities as it considers a case of two inputs only. This means that AES fails to permit for optimum alteration of all inputs to a variation in price ratio.

MES provides an alternative to AES. It was first developed by Morishima (1967) and Blackorby and Russell (1989). The measure gives a natural generality of the two-factor elasticity of substitution to a situation of more than two-factor inputs. It alters along an isoquant, thus giving an accurate measure of factor substitution (Zha and Ding, 2014). Further, Blackorby and Russell (1989) note that MES is a measure of ease of substitution, provides information about relative factor shares and is a derivative of the quantity ratio with respect to the price ratio. MES is therefore preferred to AES in this study. It is calculated as follows:

$$MES_{ij} = \frac{\partial \ln(X_i/X_j)}{\partial \ln P_j} = \epsilon_{x_i P_j} - \epsilon_{x_j P_j} \tag{4.12}$$

where X_i and X_j are demands for factor inputs *i* and *j* and $\epsilon_{x_i P_j}$ and $\epsilon_{x_j P_i}$ are cross- and own-price elasticities. Equation (4.12) reveals that MES corrects cross-price elasticity for variations in the requirement for a factor input when its price varies. It describes the change in the ratio of two factors (X_i/X_j) when the price of one-factor input (P_j) varies and exemplifies the technical substitution possibility between the inputs. Based on this measure, factors *i* and *j* are substitutes if the *i/j* input ratio increases (MES > 0) following a rise in price P_j. Thus, in case of a rise in the price of energy input, the demand for both the energy and non-energy input, say capital, drops but the demand for capital falls less. In this case, capital and energy would be categorized as Morishima substitutes. This is indicative of the reality that the production process is now more capital-intensive. If on the other hand MES < 0, the two-factor inputs *i* and *j* are labelled MES – complements.

4.3.3 Data Type, Source and Measurement of Variables

The study applied an unbalanced panel data of 1265 observations obtained from the World Bank Enterprise Surveys (WBES) for the most recent years (2007, 2013 and 2018). Data was also sourced from various Energy and Petroleum Regulatory Authority electricity tariffs and maximum retail pump prices of petroleum releases. WBES provide data on manufacturing and service firms collected through stratified random sampling. The stratification is based on regions, sectors and firm size. WBES contain data on demographic information of firms, infrastructure and services, sales and supplies, competition, finance, performance and business environment relations, crime, labour and land. The data is available in many waves thus giving room for panel data analysis. In this study, the data of interest was firm total sales and expenditure on electricity, fuel and capital, wages and the wage rate per employee.

The study computed the average price of a tonne of equivalent (TOE) of electricity and fuel from the Energy and Petroleum Regulatory Authority data. EPRA prescribes tariffs, charges and rates to be charged by KPLC to consumers of electricity after every three years. It also revises fuel prices for various regions in the country every 14th of the month taking into account the landing cost of fuel, storage and distribution costs, margins for oil marketing companies and various taxes and levies. The average maximum pump price of a TOE of electricity and the average price of a TOE of fuel was computed to give room for energy price aggregation. Information on the specific type of fuel consumed was not available and thus light diesel was used as a proxy for fuel. This is the fuel used by manufacturing firms to run power generators.

Table 4.2:Definition, measurement and sources of variables

Variable	Definition and measurement	Source of variable and data
Energy	Electricity and fuel used in production. Measured by the total cost of electricity and fuel (Ksh).	Tovar and Iglesias (2013), Haller and Hyland (2014) and Zha and Ding (2014) World Bank Enterprise Surveys (WBES).
Output	Finished goods produced by manufacturing firms. Measured as total annual sales (Ksh).	Arnberg and Bjorner (2007), Haller and Hyland (2014) and Zha and Ding (2014) World Bank Enterprise Survey (WBES).
Labour	The physical and mental workforce provided for wages and salaries measured by total wages paid to permanent, full-time employees (Ksh).	Arnberg and Bjorner (2007), Haller and Hyland (2014) and Zha and Ding (2014) World Bank Enterprise Surveys (WBES).
Capital	Physical machinery and equipment used in production. Measured by the total value of machinery and equipment (Ksh).	Arnberg and Bjorner (2007), Haller and Hyland (2014) and Zha and Ding (2014) World Bank Enterprise Surveys (WBES).
Foreign ownership	Whether a firm is foreign-owned. This variable was included as a control for heterogeneity. Measured by a dummy variable with a value of 1 if foreign-owned and 0 if otherwise	Haller and Hyland (2014) World Bank Enterprise Surveys (WBES).
Exporting status	Whether a firm exports or not. This variable was included as a control for heterogeneity. Measured by a dummy variable with a value of 1 if a firm exports and 0 if otherwise.	Haller and Hyland (2014) World Bank Enterprise Surveys (WBES).
Year dummies	Year when data collection was done. The variable was introduced to capture Hicks-neutral technical change. The dummy variable assumes a value	Haller and Hyland (2014) World Bank Enterprise Surveys (WBES).

	of 1 in the year of observation and 0 if otherwise.	
Total cost	The total cost incurred in the production of goods. Measured by the summing capital, labour and energy costs (Ksh).	Tovar and Iglesias (2013), Haller and Hyland (2014) and Zha and Ding (2014) World Bank Enterprise Surveys (WBES).
Factor shares	Proportions of the cost of each factor of production in the total cost of production. Calculated by obtaining the ratio of the expenditure on each factor to the total cost of production.	Tovar and Iglesias (2013), Haller and Hyland (2014) and Zha and Ding (2014) World Bank Enterprise Surveys (WBES).
Price of capital	The price of capital was defined as the user cost of capital. According to Romer (2012), the user cost of capital, which is the implied rate of renting capital, is drawn from the investment behaviour of firms established on the neoclassical theory of capital accumulation. In this case, it is expressed as a function of real interest rate, depreciation rate and capital gains. Data on user cost of capital was not available for this study and hence total replacement cost of capital was used as a proxy (Ksh).	World Bank Enterprise Surveys (WBES).
Price of labour	Mean wage earnings per employee. Obtained by dividing the total wages paid to permanent, full-time employees by the number of permanent, full-time employees (Ksh).	Arnberg and Bjorner (2007), Haller and Hyland (2014) and Zha and Ding (2014) World Bank Enterprise Surveys (WBES).
Price of energy	Defined as the cost of a unit of energy expressed in Kenya shillings per tonne of equivalent. Following Haller and Hyland (2014), this study computed the price of energy based on the price of electricity and fuel, weighted by firm-level electricity and fuel consumption. The price of electricity was defined as the average spending per TOE on electricity (Ksh). The price of fuel was defined as the average	Haller and Hyland (2014). Energy and Petroleum Regulatory Authority (EPRA)

	maximum retail pump price of fuel per TOE (Ksh).	

Source: Author's compilation

4.4 Results and Discussions

This section covers descriptive statistics, findings of cost shares, estimates of the translog cost function and own-price, cross-price elasticities and MES.

4.4.1 Descriptive Statistics of Variables Used in the Estimation

Summary statistics of labour, capital and energy, exporting and foreign ownership are provided in chapter two of the thesis. Table 4.3 provides summary statistics of the remaining variables of the price of capital, energy and labour.

Table 4.3: Summary statistics of input prices by manufacturing sub-sector in Kenya, 2007, 2013 and 2018

Statistics	Price of capital	Price of labour	Price of electricity	Price of fuel
Chemicals, Pharmaceuticals and Plastics sub-sector				
2007(N=28)				
Mean	304.32	66.04	135.95	615.13
SD	394.43	69.99	0.615	1.573
Minimum	5.5	2.039	135.84	614.50
Maximum	2000	269.2	139.91	618.92
2013(N=52)				
Mean	207.29	3078.4	153.11	950.23
SD	392.35	12833.2	2.838	11.25
Minimum	0.55	1.579	149.33	924.14
Maximum	2000	91666.6	158.40	971.15
2018(N=98)				
Mean	18533.48	7096.41	187.64	934.02
SD	172652.6	44445.1	3.275	7.784
Minimum	0.4	0.286	186.20	907.47
Maximum	1710000	428571.4	195.50	953.23
Food sub-sector				
2007(N=110)				
Mean	484.61	1262.7	142.12	615.98
SD	2477.48	3470.8	6.132	2.095
Minimum	0.3	0.216	139.09	614.50
Maximum	25000	17669.4	156.19	618.92
2013(N=154)				
Mean	11408.88	2033.9	158.86	953.43
SD	137777.4	6561.2	3.922	13.70
Minimum	0.07	0.038	151.42	924.14
Maximum	1710000	70000	172.59	971.15
2018(N=140)				
Mean	1771.20	12977.8	195.39	938.59
SD	12972.16	75725.2	3.977	122.98
Minimum	0.005	0.217	183.41	907.47
Maximum	150000	70000	211.78	955.84
Paper and other manufacturing sub-sector				
2007(N=147)				
Mean	220.84	3167.9	138.14	615.97

SD	628.23	14236.9	2.700	2.087
Minimum	0.12	0.200	135.84	614.50
Maximum	7000	133333.3	142.35	618.91
2013(N=157)				
Mean	13014.08	1648.46	155.58	948.54
SD	159598.4	4503.3	2.720	14.25
Minimum	0.08	0.065	149.33	924.14
Maximum	2000000	33333.33	172.58	971.15
2018(N=167)				
Mean	6244.99	7410.4	190.47	935.49
SD	56477.59	49189.3	5.172	13.46
Minimum	0.04	1.25	183.41	907.47
Maximum	700000	625000	211.78	955.84
Textile and garments sub-sector				
2007(N=111)				
Mean	117.00	818.3	143.47	615.77
SD	398.33	2261.8	3.579	2.008
Minimum	0.06	0.429	142.35	614.50
Maximum	4000	16950	154.80	618.91
2013(N=51)				
Mean	187.90	1047.1	157.91	950.14
SD	494.08	2293.8	1.253	11.09
Minimum	0.21	0.677	154.80	924.14
Maximum	3050	13000.1	158.40	971.15
2018(N=50)				
Mean	4682.24	27473.1	195.19	936.70
SD	28253.15	176496.2	1.581	9.271
Minimum	0.07	0.588	186.20	907.47
Maximum	200000	1250000	195.50	952.78

Source: Author’s computation from WBES and EPRA data

Notes: The prices of labour, electricity and fuel are expressed in thousands of Kenya shillings while the price of capital is in millions of Kenya shillings.

In each of the sub-sectors, the price of labour was found to increase over time, except for the paper and other manufacturing sub-sector where it declined in the year 2013. A probable explanation for this trend is that employees were able to successfully negotiate for higher wages to cushion themselves from inflation or firms engaged more expensive skilled labour because of evolving complexities in production. The wage was found to vary significantly across sub-sectors. The food sub-sector paid the highest wage in 2007 while the chemicals, plastics and pharmaceuticals sub-sector paid the least. In 2013, the chemicals, plastics and pharmaceuticals sub-sector paid the highest wage while the textile and garments sub-sector paid the least. In 2018, the textile and garments sub-sector paid the highest wage while the paper and other manufacturing sub-sector paid the least.

The price of capital, proxied by the replacement cost of capital, was found to vary significantly across time and sub-sectors. In 2007, the average price of capital was highest in the food sub-sector and least in the textile and garments sub-sector. In 2013, the average price of capital was highest in the paper and other manufacturing sub-sector and least in the textile and garments sub-sector. In 2018, the chemicals, plastics and pharmaceuticals sub-sector recorded the highest average price of capital while the food sub-sector recorded the least.

The average price of electricity increased with time across the sub-sectors. An increase in electricity price over time reflected price adjustments on electricity tariffs by EPRA to capture changes in non-fuel costs and fuel costs incurred in electricity production, foreign exchange rate fluctuation adjustment, inflation adjustment, security support facility costs, water levy and taxes and levies. The chemicals, plastics and pharmaceuticals sub-sector paid the lowest average price of electricity in the period under review. The textile and garments sub-sector paid the highest average price of electricity in 2007 while the food sub-sector paid the highest average price in 2013 and 2018.

The average price of fuel varied across time and sub-sectors. 2013 recorded the highest average price of a TOE while 2007 recorded the least. Variations in fuel price over time reflected changes in the average cost of landing of the imported fuel. Differences in fuel prices across sub-sectors could be explained by differences in regional prices of fuel given that firms in various sub-sectors were located in different regions of the country and fuel prices vary across regions.

4.4.2 Average Cost Shares of Factor Inputs in the Kenyan Manufacturing Sector

Table 4.4 provides findings of the average cost shares of labour, capital and energy in Kenya's manufacturing sector.

Table 4.4:Average cost shares of labour, capital and energy in Kenya's manufacturing sector

Factor	Cost Share
Labour	0.315
Capital	0.573
Energy	0.112

Source: author's computation from WBES and EPRA data

The results in Table 4.4 show that capital cost-share was dominant at 57.3 percent followed by that of labour at 31.5 percent while the energy cost-share was the least at 11.2 percent. The finding on cost shares of capital and energy conforms with Haller and Hyland (2014) who establish that the two inputs have the highest and least cost shares respectively in the Irish manufacturing sector.

The finding on energy cost shares conforms with the results of Arnberg and Bjorner (2007) in Denmark industrial companies and Deininger et al. (2018) in Swiss manufacturing firms. However, the findings in the current study contrast Arnberg and Bjorner (2007) and Deininger et al. (2018) who find cost shares of labour to be higher than cost shares of capital.

4.4.3 Diagnostic Test

The models were assessed for heteroskedasticity using the White test, and multicollinearity using the variance inflation factor (VIF). The null hypothesis of homoskedasticity could not be rejected at 5 percent level of significance across all the sub-sectors and the overall sector model. Thus the presence of heteroskedasticity could not be accepted. VIF evaluates the effect of collinearity among explanatory variables in a regression model on the accuracy of estimates. It indicates how the presence of multicollinearity inflates the variance of an estimator (Greene, 2008). A VIF of 1 indicates no collinearity between any two explanatory variables. VIF increases with collinearity and in the limit, it can become infinite (Greene, 2008). A VIF greater than 10 is in general indicative of severe multicollinearity. The VIF scores in Table 4.5 indicated that there was minimal collinearity among variables. The values ranged between 2.12 and 2.60.

Table 4.5: Heteroskedasticity and Multicollinearity test in Kenyan manufacturing sub-sectors

	Sub-sector				
	C, P and P	Food	T and G	P and O M	Overall sector
Heteroskedasticity test					
H0:Homoskedasticity					
Chi-sq	103.95	117.86	140.11	112.24	219.38
Prob> chi-sq	0.975	0.838	0.277	0.914	0.171
Multicollinearity test					
VIF	2.220	2.230	2.600	2.250	2.120

Source: Author’s estimates from WBES and EPRA data.
C, P and P is chemicals, pharmaceuticals and plastics, T and G is textiles and garments and P and O M is paper and other manufacturing. VIF is the Variance Inflation Factor.

Table 4.6 presents heteroskedasticity and multicollinearity test results in the Kenyan manufacturing sector by firm size.

Table 4.6:Heteroskedasticity and Multicollinearity test in Kenyan manufacturing sector - by firm size

	Small firms	Medium firms	Large firms
Heteroskedasticity test			

H0:Homoskedasticity			
Chi-sq	220.43	222.31	218.28
Prob> chi-sq	0.161	0.160	0.186
Multicollinearity test			
VIF	2.830	2.120	2.380

Source: Author's estimates from WBES and EPRA data.

The null hypothesis for homoscedasticity could not be rejected at 5 percent level of significance across the various size categories. Thus, the presence of heteroskedasticity could not be accepted. The VIF estimates showed minimal collinearity among the variables with values ranging between 2.12 and 2.83.

4.4.4 Elasticity of Factor Substitution in the Kenyan Manufacturing Sector.

This section provides an analysis of the elasticity of substitution between energy and non-energy inputs in the Kenyan manufacturing sector by sub-sector. According to Nguyen and Streitwieser (2008), firms across various sub-sectors have different cost functions, partly due to their product mix. For this reason, the degree of elasticity of substitution in reaction to changes in factor inputs is likely to vary across sub-sectors. Consequently, this study estimated the translog cost function jointly with share equations, separately for each sub-sector with the adding up, homogeneity and symmetry conditions factored in. An examination of whether elasticities differ across firms in different sub-sectors is useful in identifying those sub-sectors where firms are more flexible in reacting to variations in energy prices by modifying their input mix.

The sub-sectors of interest were: the chemicals, pharmaceuticals and plastics, food, textile and garments and the paper and other manufacturing sub-sector. The study also examined the overall manufacturing sector for robustness check. Following Tovar and Iglesias (1986) and Haller and Hyland (2014), the study added three dummy variables in the overall manufacturing sector model to control for heterogeneity in cost structure in the four sub-sectors. The estimates of the cost functions are presented in Table 4.7.

Table 4.7:Translog cost function estimation results by sub-sector and overall sector

			Sub-sector		
Variable	C, P and P	Food	T and G	P and O M	Overall sector
ln*Pk*	0.338^{***}	0.347^{***}	0.316^{***}	0.333^{***}	0.346^{***}
	(0.025)	(0.016)	(0.024)	(0.016)	(0.009)
ln*Pl*	0.422^{***}	0.416^{***}	0.351^{***}	0.414^{***}	0.407^{***}
	(0.016)	(0.010)	(0.015)	(0.010)	(0.006)

			Sub-sector		
Variable	C, P and P	Food	T and G	P and O M	Overall sector
ln*Pe*	0.240***	0.237***	0.333***	0.253***	0.247***
	(0.018)	(0.014)	(0.025)	(0.012)	(0.008)
ln*q*	0.290***	0.353***	0.355***	0.289***	0.308***
	(0.038)	(0.027)	(0.037)	(0.026)	(0.015)
ln*Pk*ln*Pk*	-0.008	0.00007	0.011	0.039***	0.015**
	(0.019)	(0.010)	(0.018)	(0.011)	(0.006)
ln*Pl*ln*Pl*	0.040***	0.029***	0.033***	0.034***	0.033***
	(0.006)	(0.004)	(0.007)	(0.004)	(0.002)
ln*Pe*ln*Pe*	0.009	0.023**	0.030	0.025***	0.022***
	(0.011)	(0.009)	(0.020)	(0.008)	(0.005)
ln*q*ln*q*	0.014	0.039**	0.036	0.037***	0.039***
	(0.023)	(0.016)	(0.024)	(0.014)	(0.008)
ln*Pk*ln*Pl*	0.062***	0.004	-0.027	0.028**	0.014**
	(0.021)	(0.011)	(0.017)	(0.011)	(0.006)
ln*Pk*ln*Pe*	-0.059	0.004	-0.019	-0.027	0.065*
	(0.120)	(0.068)	(0.068)	(0.058)	(0.034)
ln*Pl*ln*Pe*	-0.009	-0.014**	-0.021**	-0.015***	-0.014***
	(0.007)	(0.005)	(0.011)	(0.005)	(0.003)
ln*Pk*ln*q*	-0.041*	0.013	0.015	-0.012	-0.002
	(0.022)	(0.013)	(0.019)	(0.010)	(0.006)
ln*Pl*ln*q*	-0.004	-0.009	-0.015	-0.003	-0.007**
	(0.010)	(0.006)	(0.009)	(0.006)	(0.003)
ln*Pe*ln*q*	0.009	0.011	0.012	0.006	0.010**
	(0.010)	(0.009)	(0.016)	(0.008)	(0.005)
Exporting	-0.267	-0.116	-0.216	-0.127	-0.032
	(0.166)	(0.100)	(0.139)	(0.095)	(0.057)
Foreign	-0.134	-0.368***	-0.075	-0.189	0.046
	(0.192)	(0.120)	(0.158)	(0.117)	(0.072)
D2013	-0.086	-0.004	-0.129	-0.101	0.311***
	(0.150)	(0.096)	(0.130)	(0.093)	(0.065)
D2018	0.037	-0.003	0.039	-0.093	0.316***
	(0.168)	(0.102)	(0.154)	(0.097)	(0.065)
Food					-0.318***
					(0.059)
T and G					-0.222***
					(0.056)
P and O M					-0.237***
					(0.064)
Intercept	0.107	-0.330***	-0.640***	-0.130*	-0.385***
	(0.125)	(0.077)	(0.105)	(0.072)	(0.043)
R^2	0.561	0.530	0.514	0.451	0.515
Adj. R^2	0.515	0.509	0.472	0.430	0.507
N	178	404	212	471	1265

Variable	C, P and P	Food	Sub-sector T and G	P and O M	Overall sector

Source: Author's estimates from WBES and EPRA data.
Note: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Dependent variable: lnTC
C, P and P is chemicals, pharmaceuticals and plastics, T and G is textiles and garments and P and O M is paper and other manufacturing
.

Table 4.7 provides coefficient estimates of the translog cost functions for the four sub-sectors considered and the overall sector. The estimates of the adjusted R-squared showed that the explanatory variables more than average explained variations in the total cost across the sub-sectors and the overall sector, except for the textile and garments and paper and other manufacturing sub-sectors.

The estimates of the translog cost function have modest insightful implications due to the complexity of the function (Haller and Hyland, 2014). Hence, the study only considered first-order coefficients of the functions. Price and output variables were normalized around the mean by dividing observed values by their mean. Thus, the first-order coefficients reflected the sensitivity of total cost to the various explanatory variables at the sample mean (Onghena et al., 2014). Therefore, the first-order coefficients were cost elasticities valued at the sample mean (Onghena et al., 2014).

The first-order price and output coefficients were statistically significant at 5 percent level of significance with the expected signs. The cost elasticity of output was positive, implying that total costs in all the sub-sectors and the overall sector increased as output increased. When output increased by 1 percent in the textiles and garments sub-sector, total costs increased by 35.5 percent. The sub-sector experienced the highest increase in costs. In the paper and other manufacturing sub-sector, when output increased by 1 percent costs increased by 28.9 percent. This was the least increase among the sub-sectors. In the chemicals, pharmaceuticals and plastics, food sub-sectors and overall sector, an increase in output by 1 percent increased costs by 29 percent, 35.3 percent and 30.8 percent respectively.

The coefficients of factor prices in the chemicals, plastics and pharmaceuticals sub-sector showed that at the sample mean capital, labour and energy accounted for 33.8 percent, 42.2 percent and 24 percent of total cost, respectively. In the food sub-sector, respective inputs accounted for 34.7 percent, 41.6 percent and 23.7 percent of the total cost. In textile and garments, the corresponding contribution to total costs was 31.6, 35.1 and 33.3 percent, respectively. In the paper and other manufacturing sub-sector, it was 33.3, 41.4 and 25.3 percent, respectively. In the overall sector, respective units accounted for 34.6, 40.7 and 24.7 percent of the total cost. Total costs decreased with foreign ownership in the food sub-sector but increased in 2013 and 2018 relative to 2007. Across the sub-sectors, total costs decreased in food, textile and garments and paper and other manufacturing sub-sectors relative to the chemicals, plastics and pharmaceuticals sub-sector.

Before the sub-sector elasticities of substitution were computed, the study first tested whether the sub-sector and overall sector translog cost functions were well-behaved. This involved establishing whether the estimated translog cost functions satisfied monotonicity and quasi-concavity conditions in factor prices. According to Hunt (1984), for the monotonicity condition to be satisfied, cost shares fitted at all data points need to be positively signed. For this study, fitted cost shares were positive for all observations in all sub-sectors and overall sector models. The quasi-concavity condition is fulfilled if the Hessian matrix from the analysis is negative semi-definite implying that own-price elasticities are negative at every observation (Haller and Hyland, 2014). Own-price elasticities were found to be negative at all observations across all the sub-sectors and the overall sector. Having satisfied monotonicity and quasi-concavity conditions, the translog cost functions were well-behaved and elasticities of factor substitution were calculated from their estimates. The findings on monotonicity and quasi-concavity conditions are largely in line with the results of Haller and Hyland (2014). However, for this study, 99.9 percent of the fitted cost shares are positive and data points with negative fitted cost shares are dropped. Further, only 0.3 percent of the observations failed to meet the quasi-concavity condition. Table 4.8 provides findings of sub-sector own-price and cross-price elasticities.

Table 4.8:Own and cross-price elasticities of demand for factor inputs in the Kenyan manufacturing sector

	Sub-sector				
PED	C, P and P	Food	T and G	P and OM	Overall sector
ϵ_{kk}	-0.692	-0.653	-0.649	-0.530	-0.606
ϵ_{kl}	0.642	0.427	0.261	0.511	0.452
ϵ_{ke}	0.030	0.248	0.271	0.160	0.454
ϵ_{lk}	0.303	0.356	0.234	0.406	0.383
ϵ_{ll}	-0.471	-0.512	-0.550	-0.495	-0.504
ϵ_{le}	0.215	0.202	0.269	0.214	0.210

ϵ_{ek}	0.091	0.364	0.259	0.225	0.611
ϵ_{el}	0.383	0.355	0.286	0.355	0.350
ϵ_{ee}	-0.722	-0.665	-0.577	-0.648	-0.664

Source: Author's estimates from WBES and EPRA data. Notes: C, P and P is chemicals, pharmaceuticals and plastics, T and G is textiles and garments and P and O M is paper and other manufacturing.
PED is the price elasticity of demand, ϵ_{kk} is the own-price elasticity of capital, ϵ_{ll} is own-price elasticity of labour, ϵ_{ee} is own-price elasticity of energy, ϵ_{kl} is cross-price elasticity of labour for capital, ϵ_{ke} is cross-price elasticity of energy for capital, ϵ_{lk} is cross-price elasticity of capital for labour, ϵ_{le} is cross-price elasticity of energy for labour, ϵ_{ek} is cross-price elasticity of capital for energy and ϵ_{el} is cross-price elasticity of labour for energy.

Table 4.8 shows that sub-sector own-price elasticities of substitution were negative. The three-factor inputs were sensitive to changes in their price. Holding all other factors unchanged, a one percent increase in a factor's price decreased its demand. This finding was in line with the fundamental principle of demand for a normal good. All the inputs had inelastic demand since the own-price elasticities of substitution were less than one. The study reveals that energy was the most sensitive input across all the sub-sectors except in the textile and garments sub-sector where capital was the most sensitive input. In the overall sector, energy was still the most sensitive input to own-price change. The finding suggested that changes in energy prices impact production in the manufacturing sector considerably.

Capital was the second most sensitive input to own-price changes across all the sub-sectors except for the textile and garments sub-sector where energy was the second most sensitive. In the overall sector capital was also the second most sensitive input to own-price change. Labour was the least sensitive input to own-price change across all the sub-sectors as well as in the overall sector. This suggested that it was difficult to replace labour in production (e.g., by automating operations). This was probably explained by the high sunk costs of automation or the influence of trade unions in protecting workers against lay-offs and wage cuts. The findings here broadly conform with Arnberg and Bjorner (2007). Haller and Hyland (2014) also establish that energy is the most sensitive input and labour is the least sensitive input. The findings contrast Onuonga et al. (2011) who find capital to be most responsive to own price changes followed by labour and energy is least responsive. Zha and Ding (2014) find labour to be the most responsive input to own-price changes while energy is least sensitive to own-price changes.

The own-price elasticities displayed considerable variation across the sub-sectors. Own-price elasticity of capital ranged from -0.692 in the paper and other manufacturing sub-sector to -0.530 in the chemicals, pharmaceuticals and plastics sub-sector. Own price elasticity of energy ranged from -0.722 in the chemicals, pharmaceuticals and plastics sub-sector to -0.577 in the textile and garments sub-sector. For labour, own-price elasticity ranged from -0.550 in the textile and garments sub-sector to -0.471 in the chemicals, pharmaceuticals and plastics sub-sector. Findings of heterogeneity in own-price elasticities across sub-sectors are in line with Nguyen and Streitwieser (2008) and Wang et al. (2018).

The estimates of cross-price elasticities were positive and this indicated that all factor inputs in Kenya's manufacturing sector were substitutes in the production process. The elasticities were inelastic for all factor inputs across all the sub-sectors and the overall sector. The elasticities of substitution were also in general asymmetric. The textile and garments sub-sector exhibited the highest cross-price elasticity of capital for energy (ϵ_{ke}= 0.271) followed by the food sub-sector (ϵ_{ke} = 0.248) and paper and other manufacturing sub-sector (ϵ_{ke} = 0.160). An increase in the price of energy in these sub-sectors was associated with more capital investment and investment in energy-efficient equipment.

The chemicals, plastics and pharmaceuticals sub-sector exhibited the least cross-price elasticity of substitution of capital for energy (ϵ_{ke} = 0.030). While this estimate denotes that increasing energy prices would not result in a decline in capital formation, the finding reveals that the complexity in adjusting capital may result in a steep increase in the cost of production, ultimately compelling a radical change away from energy-intensive production processes. The overall sector also displayed inelastic demand for capital following variations in energy prices. The elasticity of substitution of capital for energy in the overall sector (ϵ_{ke} = 0.454) was however higher than in individual sub-sectors.

On substitution of energy for capital, results showed that except for the paper and other manufacturing sub-sector, the elasticities were higher than those of substitution of capital for energy. These elasticities were also less than one suggesting that energy demand was inelastic to changes in capital price. The elasticities ranged from ϵ_{ek} = 0.091 in the chemicals, plastics and pharmaceuticals to ϵ_{ek}= 0.364 in the food sub-sector. In the textile and garments sub-sector, cross-price elasticity of substitution of energy for capital was ϵ_{ke} = 0.259 while in paper and other manufacturing sub-sector, it was ϵ_{ke} = 0.225. The cross-price elasticity of substitution of energy for capital in the overall sector was higher than in individual sub-sectors. The elasticity was ϵ_{ke} = 0.611 and its magnitude also indicated that energy demand was inelastic to changes in capital price. Comparing the findings of this study with those of other studies, Haller and Hyland (2014) find capital to be a weak substitute for energy (ϵ_{ke} = 0.040) and energy is a stronger substitute for capital (ϵ_{ek} = 0.920). Krishnapillai and Thompson (2012) find capital to be a substitute for energy across U.S manufacturing industries, but the cross-price elasticities of energy for capital are more than those of capital for energy. Nguyen and Streitweiser (2008) establish that energy and capital are complements in some industries such as the glass container industry. They however establish that energy and capital are substitutes in other industries such as the organic fibres industry.

Study findings show that elasticities of substitution of labour for energy were positive and less than one across all the sub-sectors and the overall sector. An increase in the price of energy resulted in more uptake of labour, albeit less than proportionately. Variation of elasticities across sub-sectors was however not huge. The elasticities ranged from $\epsilon_{le} = 0.202$ in the food sub-sector to ϵ_{le}= 0.269 in the textile and garments sub-sector. In the chemicals, pharmaceuticals and plastics sub-sector, this elasticity was ϵ_{le} = 0.215 and in the paper and other manufacturing sub-sector, it was ϵ_{le} = 0.214. The overall sector had ϵ_{le}= 0.210. Haller and Hyland (2014) and Krishnapillai and Thompson (2012) find labour to be a weak substitute for energy.

Results show elasticities of substitution of energy for labour were positive and less than one across all sub-sectors and the overall sector. An increase in labour price led to an increase in demand for energy even though less than proportionately. The elasticities were, however, higher than those of substitution of labour for energy and variation across sub-sectors was not to a large extent, except in the textile and garments sub-sector. They ranged from ϵ_{el}= 0.286 in the textile and garments to ϵ_{el}= 0.383 in the chemicals, pharmaceuticals and plastics sub-sector. The overall sector had ϵ_{el}= 0.350. Haller and Hyland (2014) and Krishnapillai and Thompson (2012) find energy to be a substitute for labour.

Table 4.8 further shows that capital and labour were substitutes with inelastic demand. This applied across all sub-sectors. Nonetheless, the elasticity of substitution of capital for labour was higher than that of labour for capital. This implied that there was more space to expand capital by increasing labour prices than there was to expand labour by increasing capital prices. Haller and

Hyland (2014) and Wang et al. (2018) also find capital to be a more substitute for labour than labour is a substitute for capital.

Cross-price elasticities are limited as they only provide a measurement of how one input reacts to changes in the price of another input (Nguyen and Streitwieser, 1999). MES provide a measure of the technical substitution relationship between factor inputs. Table 4.9 provides results for MES.

Table 4.9:Morishima elasticities of substitution of energy for non-energy factors in the Kenyan manufacturing sector

MES	C, P and P sub-sector	Food sub-sector	T and G Sub-sector	P and OM sub-sector	Overall Sector
MES_{kl}	1.114	0.939	0.811	1.006	0.957
MES_{ke}	0.752	0.913	0.848	0.808	1.119
MES_{lk}	1.198	1.009	0.883	0.937	0.989
MES_{le}	0.936	0.866	0.846	0.862	0.874
MES_{ek}	0.813	1.016	0.906	0.756	1.218
MES_{el}	0.854	0.867	0.836	0.850	0.854

Source: Author’s estimates from WBES and EPRA data

Table 4.9 presents results for Morishima elasticities of substitution (MES). All the estimates were positive confirming substitution possibilities between all factor inputs. The MES estimates were higher than cross-price elasticities. This was expected since MES correct cross-price elasticities for changes in demand for a factor input in reaction to variation in its price. This is achieved by subtracting own-price elasticities from cross-price elasticities. The elasticities had a clear asymmetry between the factor inputs. According to Krishnapillai and Thompson (2012), MES displays asymmetry because MES evaluates the sensitivity of input ratios to variations in different factor prices.

Table 4.9 shows that the capital-energy ratio was inelastic to changes in energy prices across all sub-sectors. The MES of capital for energy ranged from 0.752 in the chemicals, pharmaceuticals and plastics to 0.913 in the food sub-sector. In the textiles and garments and paper and other manufacturing sub-sectors, the elasticities were 0.848 and 0.808 respectively. The corresponding MES in the overall sector was elastic at 1.119. This elasticity was higher than for individual sub-sectors. Results of MES of capital for energy suggest that energy price policies could boost capital investments and spur investments in energy-efficient technologies without stifling growth in the manufacturing sector. The findings of this study corroborate Nguyen and Streitwieser (2008), Krishnapillai and Thompson (2012) and Haller and Hyland (2014).

Apart from the paper and other manufacturing sub-sector, the energy-capital ratio was more sensitive to variations in capital price compared to the capital-energy ratio reaction to variations in energy prices. This was across all sub-sectors and the overall sector. A probable explanation for this is that during a time of high capital price, the old machinery was still being operated with energy inefficiency as less amount of capital was invested to replace them. The results are in line with Nguyen and Streitwieser (2008), Krishnapillai and Thompson (2012) and Haller and Hyland (2014).

On labour-energy substitution, results revealed that the labour-energy ratio in the Kenyan manufacturing sector was inelastic to changes in energy price. This applied across all the sub-sectors and the overall sector. The elasticities exhibited minimal variation across all sub-sectors and the overall sector, except in the chemicals, plastics and pharmaceuticals sub-sector. They ranged from 0.846 in textiles and garments to 0.936 in the chemicals, pharmaceuticals and plastics sub-sector. The MES of labour for energy in the food and paper and other manufacturing sub-sectors and the overall sector were 0.866, 0.862 and 0.874, respectively. The findings of this study affirm that energy price policies could lead to an upward intake of labour across the sub-sectors and the overall sector. These findings are in line with Krishnapillai and Thompson (2012) and Haller and Hyland (2014). The energy-labour ratio revealed that energy was a substitute for labour, but energy demand was inelastic to changes in labour price. This applied across all the sub-sectors and the overall sector. Thus an increase in labour price could lead to more consumption of energy even though less than proportionately. These findings corroborate Krishnapillai and Thompson (2012) and Haller and Hyland (2014).

The capital-labour ratio was elastic to changes in labour price. This applied in the chemicals, pharmaceuticals and plastics sub-sector (MES_{kl}= 1.114) and paper and other manufacturing sub-sector (MES_{kl} = 1.006). The Capital-labour ratio was however inelastic in the food sub-sector (MES_{kl}= 0.939) and the textile and garments sub-sector (MES_{kl}= 0.811) and the overall sector (MES_{kl}= 0.957). The labour-capital ratio was elastic to changes in capital price in the chemicals, pharmaceuticals and plastics sub-sector (MES_{lk} = 1.198) and food sub-sector (MES_{lk} = 1.009), but inelastic in the textile and garments (MES_{lk} = 0.883), paper and other manufacturing sub-sector (MES_{lk} = 0.937) and the overall sector (MES_{lk} = 0.989).

4.4.5 Elasticity of Substitution in the Kenyan Manufacturing Sector – by Firm Size

This section provides an analysis of the energy and non-energy input substitution possibilities across firms of different sizes. The analysis is useful in identifying the size category in which firms are more flexible in response to changes in energy prices by modifying their input mix. The issue of whether small or large firms respond more with regard to altering their input use to varying factor prices is eventually an empirical one (Nguyen and Streitwieser, 1999). Firms of different sizes have different cost functions and thus varying degrees of factor substitution in reaction to changes in factor prices. According to Haller and Hyland (2014), the response is higher among larger, financially stable and more innovative firms than in small firms. However, if smaller firms are more flexible and price responsive, they react better to changes in factor prices.

The study considered three firm size categories based on the WBES classification: small (5-19 employees), medium (20-99 employees) and large (over 100 employees). The estimates of the translog cost function based on different firm sizes are provided in Table 4.10.

Table 4.10: Kenyan manufacturing sector Translog cost function parameter estimates, - by firm size

	Small firms	Medium firms	Large firms
lnPk	0.308***	0.345***	0.299***
	(0.018)	(0.016)	(0.018)
lnPl	0.439***	0.435***	0.418***
	(0.011)	(0.010)	(0.010)
lnPe	0.253***	0.220***	0.282***
	(0.013)	(0.011)	(0.014)
lnq	0.299***	0.289***	0.282***
	(0.026)	(0.024)	(0.028)
lnPklnPk	0.002	0.047***	0.014
	(0.011)	(0.015)	(0.009)
lnPllnPl	0.061***	0.051***	0.031***
	(0.005)	(0.005)	(0.005)
lnPelnPe	0.028***	0.028***	0.017**
	(0.008)	(0.007)	(0.008)
lnqlnq	0.048***	0.063***	0.023
	(0.014)	(0.015)	(0.015)
lnPklnPl	-0.018	0.028**	0.015
	(0.014)	(0.013)	(0.011)
lnPklnPe	-0.070	0.037	0.076
	(0.060)	(0.066)	(0.065)

	Small firms	Medium firms	Large firms
lnPllnPe	-0.024***	-0.021***	-0.012**
	(0.005)	(0.005)	(0.006)
lnPklnq	0.001	-0.014	0.009
	(0.015)	(0.013)	(0.010)
lnPllnq	-0.031***	-0.022***	0.003
	(0.007)	(0.006)	(0.006)
lnPelnq	0.017**	0.014**	0.014
	(0.008)	(0.007)	(0.009)
Food	-0.330***	-0.256***	-0.268**
	(0.098)	(0.090)	(0.117)
T and G	-0.324***	-0.132	-0.197*
	(0.095)	(0.088)	(0.106)
P and O M	-0.202**	-0.268**	-0.084
	(0.096)	(0.105)	(0.123)
Exporting	-0.006	0.001	-0.057
	(0.091)	(0.090)	(0.106)
Foreign	0.101	0.058	-0.047
	(0.117)	(0.110)	(0.139)
D2013	0.463***	0.172*	0.309**
	(0.109)	(0.099)	(0.127)
D2018	0.331***	0.277***	0.178
	(0.111)	(0.099)	(0.124)
Intercept	-0.396***	-0.487***	-0.410***
	(0.072)	(0.071)	(0.077)
R^2	0.599	0.563	0.463
Adj. R^2	0.578	0.546	0.435
N	386	491	388

Source: Author's estimates from WBES and EPRA data. Note: Dependent variable: ln TC

Table 4.10 provides estimates of the translog cost function of the Kenyan manufacturing sector based on firm size. The estimates of adjusted R-squared showed that the explanatory variables more than average explained variations in total cost across all firm sizes, except in the case of large firms.

All first-order input prices as well as output coefficients across the various firm sizes were statistically significant at 5 percent and had the expected signs. The cost elasticity of output was positive implying that total cost increased as output increased across firms of all sizes. When output increased by one percent, total cost increased by the highest proportion (29.9 percent) in the small manufacturing firms followed by medium firms (28.9 percent). The large firms had the least increase (28.2 percent).

The coefficients of factor prices showed that at the sample mean, capital, labour and energy accounted for 30.8, 43.9 and 25.3 percent, respectively, of the total costs in small manufacturing firms. In medium firms, the inputs accounted for 34.5, 43.5 and 22 percent of total costs, respectively. In large firms, the respective shares were 29.9, 41.8 and 28.2 percent. The total costs decreased in the food sub-sector relative to the chemicals, pharmaceuticals and plastics sub-sector across all the firm sizes. The total cost decreased in the textiles and garments sub-sector relative to the chemicals, pharmaceuticals and plastics sub-sector in small and large firms. The total costs decreased in the paper and other manufacturing sub-sector relative to the chemicals, pharmaceuticals and plastics sub-sector in small and medium firms. The total costs increased in 2013 relative to 2007 across all firm sizes. In small and medium firms, total costs increased in 2018 relative to 2007.

The study evaluated the behaviour of the translog cost function in the different firm-size levels. This was done by testing whether the functions increased monotonically and were quasi-concave in input prices. The estimated translog cost functions for the various firm-size samples reasonably met the regularity conditions. Only 0.257 percent of the fitted capital cost shares in the large firm-size sample violated the monotonicity condition. In the small firm-size sample, 0.258 percent of the fitted capital cost shares and 0.258 of the fitted labour cost shares violated the monotonicity condition. In the medium firm-size sample, only 0.204 percent of the fitted capital cost shares violated the monotonicity condition. Only 0.204 percent of the labour own-price elasticities violated the quasi-concavity condition. Nguyen and Streitwieser (1999) find the violations of monotonicity and quasi-concavity to be significantly less than 5 percent in many cases for the U.S manufacturing sector.

Given that the regularity conditions were fairly well met, the translog cost functions were found to be well-behaved and elasticities of factor substitution could be calculated from their estimates with accuracy.

Table 4.11 presents the results of the own-price and cross-price elasticities across firms of different sizes.

Table 4.11:Own and cross-price elasticities of factor inputs in the Kenyan manufacturing sector - by firm size

PED	Small firms	Medium firms	Large firms
ϵ_{kk}	-0.681	-0.504	-0.645

ϵ_{kl}	0.352	0.308	0.478
ϵ_{ke}	-0.080	0.339	0.582
ϵ_{lk}	0.262	0.418	0.338
ϵ_{ll}	-0.404	-0.430	-0.502
ϵ_{le}	0.193	0.163	0.386
ϵ_{ek}	0.024	0.521	0.571
ϵ_{el}	0.343	0.335	0.374
ϵ_{ee}	-0.635	-0.648	-0.655

Source: Author's estimates from WBES and EPRA data

The findings in Table 4.11 reveal that all own-price elasticities were negative, which is consistent with the fundamental principle of demand for a normal good. The own-price elasticities had absolute values less than one indicating that all the inputs had inelastic demand. This contrasts Nguyen and Streitwieser (1999) who find factor inputs to respond to own-price changes more than proportionately. Energy was on average the most sensitive to change in own price in the and medium firms. In small-sized firms, capital was the most sensitive factor to own price change.

Own-price elasticities of labour and energy increased with firm size. However, for energy, there was minimal variation across various firm sizes. Large firms were the most sensitive to labour own-price change (ϵ_{ll} = -0.502) followed by medium firms (ϵ_{ll} = -0.430) and small firms (ϵ_{ll} = -0.404). Large firms were the most sensitive to energy's own-price change (ϵ_{ee} = -0.655) followed by medium-sized firms (ϵ_{ee}= -0.648) and small firms (ϵ_{ee}= -0.635). No clear pattern was evident for capital own-price elasticities across the three firm sizes. Small firms were the most sensitive to capital's price change (ϵ_{kk} = -0.681) followed by large-sized firms (ϵ_{kk} = -0.645) and medium-sized firms (ϵ_{kk} = -0.504). The patterns of own-price elasticities in this study contrast Nguyen and Streitwieser (1999) who find no consistent patterns across the various firm-size categories.

The cross-price elasticities of capital with respect to changes in energy price displayed a consistent pattern across firm sizes. The elasticities were found to be positive and with absolute values less than one in medium (ϵ_{ke} = 0.339) and large-sized firms (ϵ_{ke} = 0.582). However, in the small-sized firms, the estimate was negative with a small absolute value (ϵ_{ke} = -0.080). The finding showed that capital could be a substitute for energy in medium and large firms even though less than proportionately, but not in small firms. Large-sized firms exhibited a higher substitution possibility than medium-sized firms possibly because large firms were better placed financially to replace old energy-intensive equipment with energy-efficient technologies compared to medium firms. Further, it could be that large firms channelled more resources into research and development geared towards innovation compared to smaller firms.

In small firms, capital was at best a weak complement for energy. This means that a rise in energy prices resulted in a very small decline in demand for capital. The finding implied that the cost of production in small firms could rise considerably following a rise in energy prices. In a similar study, Haller and Hyland (2014) find no consistent pattern in the cross-price elasticity of capital with respect to changes in energy price across firm sizes. Nguyen and Streitwieser (1999) find capital to be at best a weak substitute for energy in some firm sizes and a weak complement in others. The cross-price elasticity of capital with respect to energy price exhibited minimal variation across firms of different sizes in this study.

The estimates in Table 4.11 show asymmetry in cross-price elasticities of capital and energy. The cross-price elasticities of substitution of energy for capital were positive with absolute values less than one. This means that energy was a substitute for capital across firms of all sizes. A rise in capital price could result in a rise in demand for energy, although less than proportionately. The cross-price elasticities of substitution of energy for capital increased with the size of firms. Large firms had the highest cross-price elasticity of substitution of energy for capital ($\epsilon_{ek} = 0.571$) followed by medium-sized firms ($\epsilon_{ek} = 0.521$) and small firms ($\epsilon_{ek} = 0.024$). The finding for small-sized firms exhibited at best weak substitution possibility of energy for capital.

Table 4.11 shows that cross-price elasticities of labour with respect to energy prices were positive and inelastic across firms of all sizes. This implies that labour was a substitute for energy, but a change in energy price elicited less than proportionate change in demand for labour. This suggested that a rise in energy prices could result in the expansion of employment across firms of all sizes. However, the estimates revealed no consistent pattern in the elasticity of labour with respect to energy prices across the various firm sizes. Large-sized firms were the most sensitive ($\epsilon_{le} = 0.386$) followed by small firms (ϵ_{le}= 0.193) and medium firms (ϵ_{le}= 0.196). Comparing the findings of this study with others, Nguyen and Streitwieser (1999) find labour to be a weak substitute for energy across firms of all sizes except in size class 5 (firms with 500-999 employees) where it is found to be at best a weak complement for energy.

Table 4.11 shows that the substitution possibility between labour and energy was also asymmetric. Other than in large-sized firms, the elasticity of energy with respect to change in labour price was higher than the elasticity of labour with respect to change in energy price. However, there was no clear pattern in the elasticity of energy with respect to labour prices across firms of different sizes. Large firms (ϵ_{el}= 0.374) had the highest response to changes in labour price followed by small firms (ϵ_{el}= 0.343) and medium firms (ϵ_{el}= 0.335) in that order.

With regard to labour and capital substitution, estimates in Table 4.11 reveal that the elasticity of capital with respect to labour price change was positive with absolute values less than one across firms of all sizes. Capital was therefore a substitute for labour, but a rise in labour price led to a less than proportionate surge in demand for capital. Therefore, labour price policies could lead to more capital formation across all firm sizes. Nevertheless, no clear pattern in the elasticity of capital with respect to labour prices was observed. Capital in large firms was the most sensitive to changes in labour price (ϵ_{kl}= 0.478) followed by small-sized firms (ϵ_{kl}= 0.352) and medium-sized firms (ϵ_{kl}= 0.308).

The elasticity of labour with respect to change in capital price was positive with an absolute value of less than one across all firm sizes. Labour was therefore a substitute for capital. However, a rise in the price of capital led to a less than proportionate surge in demand for labour. Capital price policies could result in more employment of labour across all firm sizes. There was also no clear pattern in the elasticity of labour with respect to capital price change. Labour in medium firms was the most sensitive to changes in capital price (ϵ_{lk}= 0.418) followed by large firms (ϵ_{lk}= 0.338) and small firms (ϵ_{lk}= 0.262) in that order.

The substitution possibility between capital and labour was asymmetric. Except for medium-sized firms, elasticities of labour with respect to capital price change were higher than elasticities of capital with respect to labour price change. This implies that in large and small firms, labour price policies would lead to more capital formation than labour employment that would arise from capital price policies. In medium firms, capital price policies could lead to more labour employment than capital formation arising from labour price policies.

Nguyen and Streitwieser (1999) observe that cross-price elasticities are limited since they only provide a measurement of how one input reacts to variation in the price of another input. MES provides a measure of the technical substitution relationship among factor inputs used in production. Table 4.12 provides estimates of MES.

Table 4.12:Morishima elasticities of substitution in the Kenyan manufacturing sector – by firm size

MES	Small firms	Medium firms	Large firms
MES_{kl}	0.756	0.738	0.980
MES_{ke}	0.555	0.987	1.237
MES_{lk}	0.943	0.921	0.983
MES_{le}	0.828	0.811	1.042
MES_{ek}	0.705	1.025	1.216
MES_{el}	0.747	0.765	0.876

Source: Author's estimates from WBES and EPRA data.

The MES estimates in Table 4.12 were positive confirming that there existed substitution possibilities between the factor inputs under consideration across all the firm sizes. The MES estimates were higher than the cross-price elasticities reported in Table 4.11. This is because MES alters cross-price elasticities for variations in demand of a factor input following a change in its price. This was realized by subtracting the negatively signed own-price elasticities, from cross-price elasticities. MES estimates in Table 4.12 also displayed asymmetric behaviour.

Considering the capital-energy MES estimates, results showed that the capital-energy ratio increased with firm size and captured the possibility of substitution of capital for energy. Large-sized firms had the highest capital-energy ratio (MES_{ke}= 1.237) followed by medium firms (MES_{ke}= 0.987) and small firms (MES_{ke}= 0.555) in that order. Therefore, large firms were relatively more flexible in substituting capital for energy compared to smaller firms. As alluded to earlier, large firms have the financial capacity to replace old energy-intensive equipment with energy-efficient technologies which smaller firms do not have. Large firms could also be more innovative than smaller firms.

The capital-energy MES estimate for large firms was more than unity and this showed that these firms were highly responsive to variations in energy prices. In small and medium firms, the capital-energy ratio was less than one indicating that changes in energy price led to less than proportionate change in the capital-energy ratio. Even though cross-price elasticities of substitution of capital for energy showed that capital was at best a weak complement for energy, MES estimates showed that capital was a substitute for energy. This brings out the fact that cross-price elasticities do not tell the whole story as they only provide the measurement of how one input reacts to variation in price in another input (Nguyen and Streitwieser, 2008). MES provides a measure of technical substitution among inputs and thus presents theoretically superior estimates of factor substitution (Nguyen and Streitwieser, 2008).

Comparing the results of this study with similar studies, Nguyen and Streitwieser (1999) find capital-energy ratio estimates to be positive and more than unity across all firm sizes in the U.S. manufacturing sector. The estimates show the degree of substitution among the factor inputs to be similar in general across the various firm sizes. This implies that small firms are as flexible as large firms in factor substitution. Haller and Hyland (2014) find no significant variation in capital-energy ratio across firms of different sizes. The study finds the largest firms to be most responsive to variations in energy prices.

In consideration of the energy-capital ratio, Table 4.12 MES estimates show that the ratio increased with firm size. The energy-capital ratios in medium and large firms were more than unity, implying that these firms were greatly responsive to variations in capital price. The energy-capital ratio was more responsive to variations in capital price than the capital-energy ratio was to changes in energy price. This applied across firms of all sizes except in large firms where the capital-energy ratio was found to be relatively more responsive to variations in energy price than the energy-capital ratio was to changes in capital price.

On the labour-energy ratio, the MES estimates showed no consistent pattern across firms of different sizes. The ratio was highest in large firms (MES_{le}= 1.042) followed by small firms (MES_{le}= 0.828) and medium firms (MES_{le}= 0.811) in that order. The MES estimates showed that large firms were highly sensitive to variations in energy prices. In small and medium firms, the labour-energy ratio changed less than proportionately to variation in the price of energy. The findings of the labour-energy ratio support the notion that labour could replace energy in production. Energy could be reduced by increasing labour without hampering production across firms of different sizes. These findings are in line with the outcome of Nguyen and Streitwieser (1999) who find no consistent pattern in labour-energy ratios.

The MES of energy for capital was higher than that of energy for labour in medium and large firms. This suggested a relatively higher substitution possibility of energy for capital. In small firms, the MES of energy for labour was higher than that of energy for capital. This suggested a relatively higher substitution of labour for energy.

MES estimates of labour and capital showed no consistent pattern in the capital-labour ratio. Large firms had the highest capital-labour ratios (MES_{kl}= 0.980) followed by small firms (MES_{kl}= 0.756) and medium firms (MES_{kl}= 0.738) in that order. There was also no consistent pattern in the labour-capital ratio. Large firms had the highest energy-labour ratio (MES_{lk}= 0.983) followed by small firms (MES_{lk}= 0.943) and medium firms (MES_{lk}= 0.921) in that order. The results indicated that the labour-capital ratio was more sensitive to variations in capital prices than the capital-labour ratio was to changes in labour prices.

4.5 Summary, Conclusion, Policy Implication and Areas for Further Research

Summary and Conclusion

The global concern over the implications of energy use in industrial production on competitiveness and environmental quality resulting from the process brings out the issue of whether energy and non-energy inputs are substitutes or complements. The relationship has implications on capital investment and formation, employment and environmental quality. While the conventional view holds that natural resources such as energy and materials limit growth in the long run because they are exhaustible, neoclassical economists argue that the limitation could be overcome through technical change and the substitution of factor inputs.

Some studies have set to establish the energy and non-energy substitution in the manufacturing sector. However, they do not reach a consensus on energy and non-energy input substitution possibility. For example, in the case of energy-capital substitution, Onuonga, et al. (2011), Smyth et al. (2011), Krishnapillai and Thompson (2012), Haller and Hyland (2014), Zha and Ding (2014), Deigner et al. (2018) and Wang et al. (2019) have found capital to be a substitute for energy. On the other hand, Fiorito and van den Bergh (2015) have found capital to be a complement for energy. In energy-labour substitution, Onuonga, et al. (2011), Smyth et al. (2011), Krishnapillai and Thompson (2012), Deininger et al (2018) and Haller and Hyland (2014) have found labour to be a substitute for energy while Dahl and Erdogan (2000), Wang et al. (2019) have found labour to be a complement for energy.

Due to a lack of consensus on the issue, discussions on how a rise in energy price could affect demand for a non-energy input cannot be overemphasized. This calls for more empirical research on the subject, particularly in the case of developing countries. In sub-Saharan Africa, there is a dearth of evidence in this regard, yet these countries heavily rely on energy in production. In Kenya and using time series data at the macro level, Onuonga, et al. (2011) find capital and labour to be substitutes for energy. But macro-level data has been criticized for the purpose since it yields estimates that suffer from aggregation bias. Micro-level data is recommended instead as it is free from such bias.

Secondly, Onuonga, et al. (2011) does not provide current substitution potential between energy and non-energy inputs, yet production relationships adjust over time given the varying preferences or tastes and technological change. Furthermore, the study does not provide an analysis of sub-sector and firm size differences in the substitution of non-energy inputs for energy. Yet this information is useful in isolating firms that are flexible in responding to energy price changes from those that are rigid. This study sought to fill the gaps by assessing the substitution prospects between energy and capital and energy and labour in the Kenyan manufacturing sector using the most recent available firm-level data. The study assessed sub-sector and firm size differences in the substitution of energy and non-energy inputs. The sub-sectors of concern were: chemicals, plastics and pharmaceuticals, food, textile and garments and paper and other manufacturing sub-sector. For robustness check, the study further analysed the situation at the aggregate manufacturing sector level. The firm sizes considered were small, medium and large.

The analysis was performed in two stages. In the first stage, a translog cost function with controls for firm heterogeneity was jointly estimated with cost-share equations by applying the iterated seeming unrelated regression (iSUR) technique with the adding up, homogeneity and symmetry conditions imposed. In the second stage, elasticities were calculated right from the estimated parameters of the translog cost function and predicted cost shares. An unbalanced panel data of 1265 observations obtained from the World Bank Enterprise Survey (WBES) for the most recent years (2007, 2013 and 2018) was employed. Additionally, data on energy prices for respective years was drawn from EPRA. The findings showed that capital had the highest cost share (57.3 percent) followed by labour (31.5 percent) while energy had the least share (11.2 percent).

At the sub-sector level, the estimates of the translog cost functions showed that the coefficients on input prices and output had economically plausible signs. The coefficients on input prices revealed the contribution of capital, labour and energy, evaluated at the sample mean, on the total cost. This varied across inputs and sub-sectors. The coefficient on output showed the cost elasticity of output. A positive sign on this variable revealed that a 1 percent increase in output led to an increase in total cost. The increase was highest in the food sub-sector (35.5 percent) and lowest in the paper and other manufacturing sub-sector (28.9 percent).

The translog cost functions passed the monotonicity and quasi-concavity tests. Own-price elasticities of capital, labour and energy were negative. Energy was the most sensitive input to own-price change across the sub-sectors as well as the overall sector, except in the textile and garments sub-sector where capital was most sensitive. Capital was the second most sensitive to own price change across the sub-sectors as well as the overall sector, except in the textile and garments sub-sector where energy was second most sensitive. Labour was the least sensitive factor to own-price change across the sub-sectors and the overall sector.

The estimated cross-price elasticities were positive with absolute values of less than unity. That indicated the existence of substitution possibilities between the factors. A change in one factor's input price led to a less than proportionate change in demand for a second input. Factor substitution possibilities varied in degree among the various factors and across sub-sectors. The elasticities of substitution were asymmetric in general.

The textile and garments sub-sector had the highest cross-price elasticity of substitution of capital for energy (ϵ_{ke} = 0.271) while the chemicals, plastics and pharmaceuticals sub-sector had the least (ϵ_{ke} = 0.030). The corresponding elasticities in the food and paper and other manufacturing sub-sectors were (ϵ_{ke} = 0.248), and (ϵ_{ke} = 0.160), respectively. In the overall sector, the cross-price elasticity of capital for energy was (ϵ_{ke} = 0.454). The findings implied that energy price changes could see the highest substitution of capital for energy in the textile and garments sub-sector and the least in the chemicals, plastics and pharmaceuticals sub-sector. Even though the elasticity of substitution in the chemicals, plastics and pharmaceuticals sub-sector was small and positive implying that a rise in energy price would not cause a reduction in capital investment, the findings reflected that the complexity in adjusting capital in this sub-sector could result in a large increase in the cost of production. The cross-price elasticity of energy for capital showed that estimates ranged from ϵ_{ek} = 0.091 in the chemicals, plastics and pharmaceuticals sub-sector to ϵ_{ek}= 0.364 in the food. Estimate for the overall sector ϵ_{ek} = 0.611.

The estimates of substitution of labour for energy showed minimal variation across the sub-sectors. They ranged from $\epsilon_{le} = 0.202$ in the food sub-sector to ϵ_{le}= 0.269 in the textile and garments sub-sector. In the chemicals, plastics and pharmaceuticals sub-sector, the elasticity was $\epsilon_{le} = 0.215$ while in the paper and other manufacturing sub-sector, it was $\epsilon_{le} = 0.214$. The overall sector had ϵ_{le}= 0.210. The findings implied that an energy price policy could be successful in reducing energy consumption and in expanding labour employment. Such a policy would be most effective in the food sub-sector and least effective in the textile and garments sub-sector. Elasticities of substitution of energy for labour were higher than those of substitution of labour for energy. They ranged from ϵ_{el}= 0.286 in the textile and garments sub-sector to ϵ_{el}= 0.383 in the chemicals, plastics and pharmaceuticals sub-sector. In the overall sector, this elasticity was ϵ_{el}= 0.350. The estimates of capital-labour substitution showed that both factor inputs could substitute each other across all the sub-sectors and the overall sector. There was a greater substitution of labour for capital than of capital for labour.

MES estimates confirmed the substitution possibilities between the factor inputs. The degree of substitution, however, varied across factors and sub-sectors. The MES estimates were also asymmetric but higher than those of cross-price elasticities. The capital-energy MES estimates ranged from 0.752 in the chemicals, plastics and pharmaceuticals sub-sector to 0.913 in the food sub-sector. The corresponding estimate in the textile and garments and the paper and other manufacturing sub-sectors were 0.848 and 0.808, respectively. In the overall sector, the MES estimate was 1.119. The findings confirmed that besides energy price variations affecting energy consumption, they could also affect capital investment in Kenya's manufacturing sector. Except in the paper and other manufacturing sub-sector, findings showed that the energy-capital ratio was more sensitive to variation in capital price than the capital-energy ratio was sensitive to variation in energy price.

The labour-energy estimates exhibited minimal variation across the sub-sectors except in the chemicals, plastics and pharmaceuticals sub-sector. They ranged from 0.846 in the textile and garments sub-sector to 0.936 in the chemicals, plastics and pharmaceuticals sub-sector. The MES estimates in the food and paper and other manufacturing sub-sectors were 0.866 and 0.862, respectively. The estimate for the overall sector was 0.874. Intuitively, estimates implied that energy price changes could affect employment across the Kenyan manufacturing sector. On capital-labour substitution, demand for labour was more sensitive to changes in capital price than demand for capital was with respect to changes in labour price across all sub-sectors except the paper and other manufacturing sub-sector where demand for capital was more sensitive to changes in labour price than demand for labour was with respect to change in capital price.

Firm size level analysis considered three size categories: small firms (5-19 employees), medium firms (20-99, employees) and large firms (over 100 employees). The estimates of the translog cost function showed that input prices and output had economically plausible signs. The translog cost functions passed the monotonicity and quasi-concavity tests, implying that the functions were well-behaved and elasticities of substitution could be calculated from their estimates. The estimated own-price elasticities were negative with absolute values less than one. Energy was the most sensitive input to own-price change across firms of all sizes, apart from the small firms where capital was the most sensitive input to own-price change. There was a clear consistent pattern in labour and energy own-price elasticities, but no consistent pattern in capital own-price elasticities. Labour and energy own-price elasticities increased with firm size and there was minimal variation in energy own-price elasticities across firm sizes. Small firms had the highest own-price elasticities of capital followed by large firms and medium firms had the least own-price elasticities of capital.

The cross-price elasticity of substitution of capital for energy in medium firms was 0.339 and 0.582 in large firms. The estimates were positive and with absolute values of less than unity. They indicated the substitution possibility of capital for energy. The possibility increased from medium to large firms. Large firms could be well endowed financially to replace old equipment with energy-efficient technologies than smaller firms. It is also probable that large establishments had more investments in R&D than smaller establishments. Nonetheless, in small firms, the cross-price elasticity of capital for energy was negative with a small absolute value of -0.080. This implied that capital was at best a weak complement for energy. This means that a rise in energy prices in small firms could lead to a high cost of production. Cross-price elasticities of substitution of energy for capital were found to be positive with absolute values less than one. These elasticities increased with the size of firms.

The cross-price elasticities of substitution of labour for energy were positive with absolute values less than one. This implied that a change in energy price could lead to expansion of employment across the firms, but the increase in demand for labour was less than proportionate. No clear consistent pattern of these elasticities was observed across firm sizes. Labour was most sensitive to changes in energy prices in Large firms (ϵ_{le}= 0.386) followed by small firms (ϵ_{le}= 0.193) and medium firms (ϵ_{le}= 0.196) There was also no clear consistent pattern in elasticities of energy with respect to variations in labour price. Large firms had the highest response to changes in labour price followed by small firms. Medium firms had the least response.

The cross-price elasticities of substitution between capital and labour were positive with absolute values less than one across firms of all sizes. No consistent patterns were found in these elasticities and they displayed asymmetric behaviour. Except in the medium firms, the cross-price elasticities of labour with respect to change in capital price were higher than cross-price elasticities of capital with respect to change in the price of labour. This implied that in small and large firms, labour price changes could attract more capital formation than an expansion of labour arising from a change in capital price. In medium firms, capital price changes could lead to more labour employment than capital formation resulting from a change in labour price.

In the MES, all estimates were positive, indicating that there existed substitution possibilities between factor inputs across firms of all sizes. The estimated values were higher than those of respective cross-price elasticities. On capital-energy substitution, MES estimates showed that the capital-energy ratio increased with firm size. This implies that large firms were relatively more flexible in substituting capital for energy than smaller firms. Large firms had the highest ratio capital-energy ratio ($\mathrm{MES_{ke}}$= 1.237) followed by medium firms ($\mathrm{MES_{ke}}$= 0.987) and small firms had the least ratio ($\mathrm{MES_{ke}}$= 0.555). The MES estimates in small firms contrasted the cross-price elasticities which had displayed a weak complementarity between capital and energy. MES estimates are theoretically superior as they provide a measure of technical substitution among inputs. MES estimates of the energy-capital ratio were also found to increase with firm size.

The MES estimates of the labour-energy ratio were highest in large firms ($\mathrm{MES_{le}}$= 1.042) followed by small firms ($\mathrm{MES_{le}}$= 0.828) and medium firms had the least ratio ($\mathrm{MES_{le}}$= 0.811). This result implied that a rise in energy price could lead not only to a cut in energy use but also to an expansion in the employment of labour. The energy-labour ratio increased with firm size. The Labour-energy ratio was more responsive to variations in energy price than the energy-labour ratio was sensitive to changes in labour price. The labour-capital ratio was more responsive to changes in capital price than the capital-labour ratio was to changes in labour prices.

Policy Implication

Capital and labour were observed to be substitutes for energy in Kenya's manufacturing sector. Energy price movements could therefore have important implications on energy use, environmental quality, capital investment and labour employment. Energy price policies that lead to an increase in energy prices, such as carbon tax or environmental tax are likely to boost capital investment and employment. They may also stimulate investment in energy-efficient equipment. Further, they could also promote the competitiveness of the manufacturing sector. This is because a reduction in energy use resulting from substituting capital and labour for energy could save firms some energy costs that increase the total cost of production. Ultimately manufactured products could become cheaper. Given that energy prices in Kenya are prescribed by the government through EPRA, the energy pricing system needs to reflect the environmental cost of fossil fuels.

Limitations of the Study

In the analysis of factor substitution possibilities, the price of capital defined as the user cost of capital is one of the useful information needed, yet the WBES did not have firm data on this variable. The total replacement cost of capital was employed as a proxy for the price of capital.

Future Research

Further research in this area could be on the analysis of regional and firm age differences in the substitution possibilities between energy and non-energy inputs in the Kenyan manufacturing sector. This is because firms in different regions and firm ages use different product mixes. This implies that the firms could be having different cost functions at the regional levels or firm ages. Moreover, this research can be extended to other high-consuming sectors of the economy, such as the transport sector.

CHAPTER FIVE: SUMMARY, CONCLUSIONS AND POLICY IMPLICATIONS

5.1 Introduction

This chapter concludes the thesis by providing a summary of the study, highlighting key findings and policy implications. Limitations of the study and areas for further research are also discussed in this chapter.

5.2 Summary and Conclusions

The research sought to analyse energy efficiency, productivity and energy and non-energy substitution potential in Kenya's manufacturing sector. Specifically, the main objective of the study was to analyze energy efficiency in Kenya's manufacturing sector; assess the effect of energy efficiency on productivity in Kenya's manufacturing sector and; investigate the energy and non-energy input substitution possibilities in Kenya's manufacturing sector. The first chapter presented a background of energy consumption and the economic performance of Kenya's manufacturing sector and a basis for the three essays in the thesis.

The first objective of the study sought to analyze sub-sector energy efficiency differences, determine the extent of energy efficiency change and establish energy efficiency drivers in Kenya's manufacturing sector. Sub-sectors of concern were: chemicals, pharmaceuticals and plastics, food, textiles and garments and paper and other manufacturing sub-sector. Energy efficiency and its drivers were assessed by the use of SFA. More precisely, an input distance function with the assumption of a translog production function was estimated in a pooled regression model covering the years 2007, 2013 and 2018 in the assessment of electricity efficiency and 2013 and 2018 in the assessment of fuel efficiency. Data was obtained from WBES.

Findings revealed that there existed significant potential to improve electricity and fuel efficiency in the Kenyan manufacturing sector. The mean electricity efficiency levels in the chemicals, pharmaceuticals and plastics, food, textiles and garments and paper and other manufacturing sub-sectors and the overall sector were 80.5, 64.8, 78.6, 67.8 and 64.5 percent, respectively. Average fuel efficiency scores for respective sub-sectors and the overall sector were 73.9, 72.3, 71.5, 68.8 and 69.4 percent. The Malmquist index revealed that electricity efficiency improved in the chemicals, pharmaceuticals and plastics and textile and garments sub-sectors but had a decline in the food and paper and other manufacturing sub-sectors as well as in the overall sector. An increase in fuel efficiency was recorded in the food and paper and other manufacturing sub-sectors and overall sector and a decline in fuel efficiency was recorded in the chemicals, pharmaceuticals and plastics and textiles and garments sub-sectors.

Analysis of drivers of energy efficiency revealed that determinants of energy efficiency varied across sub-sectors and between electricity and fuel. Labour productivity influenced fuel efficiency negatively in all sub-sectors and the overall sector. It influenced electricity efficiency negatively in all sub-sectors, except the food sub-sector, and the overall sector. This suggests that measures to improve labour productivity do not provide further emphasis to ensure a significant level of skill improvement required to increase energy efficiency. Firm age negatively influenced electricity efficiency in the food sub-sector and fuel efficiency in the chemicals, pharmaceuticals and plastics sub-sector. This suggests that old firms could be employing old technologies whilst young firms employ current technologies. It had a positive effect on electricity efficiency in the chemicals, pharmaceuticals and plastics and textiles and garments sub-sectors. This outcome could be due to the benefits of learning-by-doing. Firm age squared positively influenced electricity efficiency in the food and textiles and garments sub-sectors and fuel efficiency in the paper and other manufacturing sub-sector and the overall sector. Benefits linked to learning-by-doing could be responsible for this outcome. Firm age squared negatively influenced fuel efficiency in the textiles and garments sub-sector. This suggests that huge sunk costs could be a barrier to the replacement of old technologies in this sub-sector.

Top manager's experience was found to promote electricity efficiency in the food and paper and other manufacturing sub-sectors. This suggests that experienced managers could have improved electricity efficiency using skills and abilities gained over time. Firm size had a positive effect on electricity efficiency in the paper and other manufacturing sub-sector and fuel efficiency in the textiles and garments sub-sector and the overall sector. This indicates that large firms could have employed a highly skilled workforce and had the financial ability to purchase recent technologies. Firm size had a negative effect on electricity efficiency in the chemicals, pharmaceuticals and plastics and food sub-sectors. This suggests that complications in the inner structure of large firms could have led to more energy use.

Foreign ownership positively influenced fuel efficiency in the food sub-sector. This indicates that foreign-owned firms attract technical support from host countries. Female firm-ownership was found to have a positive influence on electricity efficiency in the food sub-sector and overall sector and fuel efficiency in the chemicals, pharmaceuticals and plastics and food sub-sectors. This suggests that female members enhance firm performance by providing cooperation, solutions to problems, inventiveness and ingenuity and honesty.

Exporting had a positive influence on electricity efficiency in the chemicals, pharmaceuticals and plastics, food and textiles and garments sub-sectors and the overall sector. In a similar way, exporting had a positive influence on fuel efficiency in chemicals, pharmaceuticals and plastics and paper and other manufacturing sub-sectors. This suggests that there were benefits associated with learning-by-exporting. R&D had a positive effect on both electricity and fuel efficiency in the chemicals, pharmaceuticals and plastics sub-sector. This suggests that R&D activities could have exposed firms to innovations in electricity and fuel efficiency.

In the second objective, the study sought to investigate how energy efficiency influenced TFP in the Kenyan manufacturing sector TFP. Energy intensity measured as the ratio of expenditure on energy to the value of output was used to indicate energy efficiency. TFP was estimated using Levinsohn-Petrin (LP) algorithm. To achieve the objective, a dynamic panel model and an instrumental variable GMM estimator were adopted. This was suitable in dealing with the potential endogeneity of energy efficiency resulting from unobserved heterogeneity and reverse causality. An unbalanced panel for the years 2007, 2013 and 2018 drawn from WBES was used in this objective.

Findings show that energy intensity was highest in the food sub-sector at 0.413 followed by paper and other manufacturing at 0.225, chemicals, pharmaceuticals and plastics at 0.120 and textiles and garments at 0.064. Energy intensity was found to have a positive correlation with capital intensity. This indicates that widening capital investment did not necessarily result in efficient energy use. Energy intensity had a negative correlation with the value of output. This suggests that a large amount of output was produced at high energy efficiency.

TFP levels for the chemicals, pharmaceuticals and plastics, food, paper and other manufacturing and textiles and garments sub-sectors were 3.071, 2.925, 2.722 and 2.079 respectively. The paper and other manufacturing and chemicals, pharmaceuticals and plastics sub-sectors had tightly dispersed distribution plots. This suggests minimal heterogeneity in productivity. The food sub-sector had tight dispersion but lower than that in the paper and other manufacturing and chemicals, pharmaceuticals and plastics sub-sectors. This also suggests minimal heterogeneity in productivity. The textile and garments sub-sector had widely dispersed distribution plots with a relatively large density below the mean. This suggests sizable heterogeneity in productivity and signals the existence of rigidities or other distortions that pose a barrier to the efficient allocation of resources within the sector.

Energy efficiency was found to positively affect TFP in the Kenyan manufacturing sector, a finding that was in line with the Porter Hypothesis. This implies that the enhancement of energy efficiency is key to realizing higher TFP in this sector. Capital intensity had a positive influence on TFP. This indicates that firms with high capital investment realize high TFP. Firm age positively influenced TFP. This suggests that there were TFP premiums of learning-by-doing. Firm size positively influenced TFP. This implies that large firms had highly skilled staff and better access to financial resources which helped them acquire recent technologies, thereby enhancing productivity. Top manager's experience was found to positively influence TFP. This suggests that learning-by-doing effects linked to managers with high experience promoted productivity.

Separate regressions by sub-sectors and firm sizes were also performed to account for heterogeneity. Sub-sectors of concern were: food, textiles and garments and paper and other manufacturing sub-sector. The chemicals, pharmaceuticals and plastics sub-sector was dropped because the analysis failed convergence tests. Energy efficiency was found to positively influence TFP across all sub-sectors. This was in agreement with the Porter Hypothesis. Capital intensity was found to positively influence TFP in the food and textile and garments sub-sectors. This suggests that high capital investment was linked to high TFP. Nevertheless, capital intensity negatively influenced TFP in the paper and other manufacturing sub-sector.

Firm age had a positive influence on TFP in the food and paper and other manufacturing sub-sectors. This implies that TFP premiums were arising from learning-by-doing effects. Firm size positively influenced TFP in the same sub-sectors. This indicates that large firms had access to highly skilled staff and better technologies which boosted their productivity. Foreign ownership positively influenced TFP in the textiles and garments sub-sector. This suggests that foreign-owned firms had some cost advantage over domestic firms. Exporting status positively influenced TFP in the textile and garments sub-sector. This indicates that exporting firms learned better production techniques from foreign markets. R&D positively influenced TFP in the textile and garments sub-sector. This suggests that R&D activities led to process and product innovation besides improving the absorptive capability of firms, thereby promoting productivity.

On firm size analysis, firm sizes of interest were: small, medium and large. Energy efficiency was observed to have a positive influence on TFP in small and medium firms. The finding supported the Porter Hypothesis. Capital intensity had a positive influence on TFP across all firm sizes. This suggests that firms with more capital investments had higher TFP. Firm age had a positive influence on TFP in small and large firms. This indicates that there were TFP premiums associated with learning-by-doing effects. Firm age had a negative influence on TFP in medium firms. Probably, old firms in this size category had old technologies. Foreign ownership positively influenced TFP in medium-sized firms. This signals that foreign-owned firms had some features that gave them a cost edge over local firms, which boosted productivity. Exporting influenced TFP positively in small firms. This suggests that exporting firms learned new production technologies from the export market.

The third objective sought to analyse energy and non-energy input substitution possibilities in addition to establishing whether these substitution possibilities varied with firm size in the Kenyan manufacturing sector. Iterated seeming unrelated regression (iSUR) was applied on a pooled model and unbalanced panel data for the years 2007, 2013 and 2018 drawn from WBES. Additional data on energy prices for respective years was obtained from EPRA. The empirical analysis was conducted in two steps. First, a translog cost function was jointly estimated with cost-share equations using iSUR with the adding up, homogeneity and symmetry conditions imposed. In the second step, estimated parameters of the translog cost function and cost shares were directly applied to compute elasticities.

Empirical results revealed that the translog cost function met monotonicity and quasi-concavity conditions. Elasticities of substitution could therefore be drawn from them. Factor substitution was found to vary in degree among various factors across sub-sectors. The cross-price elasticities of substitution of capital for energy in the textile and garments, food, paper and other manufacturing and chemicals, pharmaceuticals and plastics sub-sectors and the overall sector were 0.271, 0.248, 0.160 and 0.030 and 0.454 respectively. These elasticities indicate that capital was a substitute for energy. The cross-price elasticities of labour for energy across sub-sectors had minimal variation. They ranged from 0.202 in the food sub-sector to 0.269 in the textiles and garments sub-sector. In the chemicals, pharmaceuticals and plastics and paper and other manufacturing sub-sectors and the overall sector, the elasticities were 0.215, 0.214 and 0.210 respectively. These elasticities indicate that labour was a substitute for energy.

MES estimates confirmed substitution possibilities between factor inputs. The capital-energy MES estimates in the food, textile and garments, paper and other manufacturing and chemicals, pharmaceuticals and plastics sub-sectors and the overall sector were 0.913, 0.848, 0.808, 0.752 and 1.119 respectively. These estimates suggest that capital was a substitute for energy. Energy price policies could thus cut energy consumption and carbon emissions and promote capital investments in the Kenyan manufacturing sector. The labour-energy MES estimates in the chemicals, pharmaceuticals and plastics, food, paper and other manufacturing and textile and garments sub-sectors and the overall sector were 0.936, 0.866, 0.862, 0.846 and 0.874 respectively. The estimates indicate that labour was a substitute for energy. Therefore, energy price policies could be suitable in reducing energy consumption, cutting carbon emissions and boosting employment in the Kenyan manufacturing sector.

Finally, on analysis at the firm level, cross-price elasticities of substitution of capital for energy showed that capital was a substitute for energy in the medium (0.339) and large (0.582) firms. These estimates indicate that the substitution possibility of capital for energy increased from medium to large firms. However, in small firms (-0.080), cross-price elasticities showed that capital was at best a weak complement for energy. Cross-price elasticities of labour for energy showed that labour was a substitute for energy. However, estimates did not show a consistent pattern across firm sizes. Elasticities in small, medium and large firms were 0.193, 0.163 and 0.386 respectively.

MES estimates at the firm size level confirmed that capital was a substitute for energy and substitution increased with firm size. Small firms had the lowest estimates at 0.555 followed by medium firms at 0.987 and large firms at 1.237. No consistent pattern was observed in the labour-energy MES estimates across firm sizes. MES estimates for small, medium and large firms were 0.828, 0.811 and 1.042 respectively. Findings at the firm size level also implied that energy price policies could be useful in reducing energy consumption, cutting carbon emissions and expanding capital investments and employment in the Kenyan manufacturing sector.

5.3 Policy Implications

The employment of new technologies is the basis for energy efficiency. There is a need to strengthen technological innovation in the manufacturing sector. An increase in R&D funds is important in enabling the discovery of recent technologies and the development of new equipment. Available data shows that R&D funding in 2018 only stood at 0.48 percent of GDP, which was below the 2 percent level recommended in the NRF Science, Technology and Innovation Act 2013. In addition, there is a need for The National Treasury and Planning to provide R&D subsidies and low-interest loans or tax incentives to firms engaging in R&D activities. Supporting technological innovation will be instrumental in supporting the government's effort to enhance energy efficiency and conservation as indicated in the Least Cost Power Development Plan.

Exporting status had a positive influence on electricity efficiency in all the sub-sectors except the paper and other manufacturing sub-sector. It promoted fuel efficiency in the chemicals, pharmaceuticals and plastics and the paper and other manufacturing sub-sectors. There is a need for the Ministry of Industrialization, Trade and Enterprise Development to promote exports beyond the establishment of export processing zones. Finding foreign markets is especially important in this regard. It is also important to offer specialized counselling and training to exporters on how to capitalize on business opportunities abroad. Additionally, the ministry needs to offer training to exporters on ways to access specialized foreign markets such as those requiring products to meet certain environmental quality standards.

Firm size had a positive effect on electricity efficiency in the chemicals, pharmaceuticals and plastics sub-sectors and fuel efficiency in the textiles and garments sub-sector. This finding supports the argument that large firms are potentially more energy-efficient than small firms because of their better access to financial resources, particularly from third parties. Small-sized firms are limited by such factors as the inability to provide collateral. They also face lenders who require high interest on loans given that the economic risk is greater. For instance, small firms have less diversification in their product portfolio which exposes them to hurting economic shocks. Therefore, there is a need for The National Treasury and Planning to offer financial incentives such as tax exemptions, low-interest loans and subsidies to small firms that to help them make energy efficiency investments.

Top manager’s experience positively influenced electricity efficiency in the food and paper and other manufacturing sub-sectors. There is a need for manufacturing firms to constantly provide staff with formal training to refine their energy efficiency skills. Female firm-ownership had a positive effect on electricity efficiency in the food sub-sector and fuel efficiency in the chemicals, pharmaceuticals and plastics and food sub-sectors. There is a need for the Ministry of Public Service, Gender, Senior Citizens Affairs and Special Programmes to design policies that increase the visibility of female entrepreneurs. Such policies include sustained education and training programmes on business skills. It is also important to publicize the success stories of female entrepreneurs through mainstream media and other facilities. This could be useful in encouraging and expanding the confidence of other potential women entrepreneurs. One of the main barriers to women entrepreneurship is the failure to access capital because of stringent requirements by lending institutions. For instance, women are required to offer collateral for them to access loans, which in most instances they do not own. Therefore, there is a need for finance lending institutions to rethink the requirements to advance credit to female entrepreneurs to increase access to this facility.

Other policies to enhance energy efficiency include policies to promote foreign ownership, especially in the chemicals, pharmaceuticals and plastics and food sub-sectors where this variable positively affected fuel efficiency. The management in foreign-owned firms could also capitalize on present foreign direct policies such as tax incentives encouraging the importation of modern technologies from host countries. There is also a need for the Ministries of Energy and Petroleum and Mining to promote awareness of energy efficiency benefits in manufacturing firms. This could be through conferences and leadership forums. Such an initiative may increase the uptake of energy efficiency measures particularly after producers learn the benefits linked to such measures.

Energy efficiency was found to be positively associated with higher TFP. This finding has important implications for energy efficiency and productivity policies. Policies to enhance energy efficiency need to be paired with policies to promote growth. Policies to promote energy efficiency should incorporate increased total factor productivity to make them, even more, cost-effective. Policies to enhance TFP could also be drawn from other covariates. The findings of the study show that there cannot be a one-size-fits-all solution to TFP due to the existence of strong heterogeneity by sub-sectors and firm sizes. Capital intensity was found to promote TFP in the overall sector, food and textile and garments sub-sector and in all firm sizes. There is a need for The National

Treasury and Planning to put up measures to strengthen the uptake of capital, and in particular, capital associated with modern and advanced technologies.

Firm age was found to positively promote TFP in the overall sector, food and paper and other manufacturing sub-sectors and small and large firms. Productivity premium in old firms could be a result of learning-by-doing effects or the ability of old firms to easily acquire better production technologies. Nevertheless, firm age had a negative influence on TFP in medium firms, implying that young firms could be enjoying the advantages of new and advanced technologies and flexible internal structures. There is a need for the Ministry of Industrialization, Trade and Enterprise Development and the business community to promote startups through measures such as mentorship of young manufacturers and the opening of manufacturing innovation hubs across the country. Firm size was found to influence TFP positively in the overall sector and paper and other manufacturing sub-sector. There is a need for the Ministry of Industrialization, Trade and Enterprise Development to provide a favourable business environment to enable the growth of firms. For instance, the government could support efforts that expose small firms to international markets from which they can expand their sales and earn more profits.

Top manager's experience had a positive effect on TFP in the overall sector. There is a need for manufacturing firms to constantly furnish staff with formal training to hone their expertise. Foreign ownership was found to promote TFP in the textiles and garments sub-sector and medium firms. This means that these sub-sector and size categories benefitted from superior technologies and management and access to distribution and marketing channels and networks that come with foreign ownership. As highlighted earlier, there is a need for the government to continue supporting foreign direct investments through measures such as corporate tax incentives. Top managers of foreign-owned firms should continue leveraging existing tax incentives to import superior technology from host countries. Exporting was found to positively influence TFP in small firms. This implies that small firms enjoyed productivity gains resulting from learning-by-exporting. As discussed earlier, there is a need for the Ministry of Industrialization, Trade and Enterprise Development to go beyond creating export promotion zones to exploring new foreign markets. Specialized counselling and training on approaches to exploit prevailing business openings abroad and how to access particular markets such as those requiring certain conditions and quality standards to be met need to be offered to exporters.

Capital and labour were found to be substitutes for energy in the Kenyan manufacturing sector. The findings implied that energy policies could not only have useful implications on energy consumption and environmental quality but also capital investments and employment. Given that energy prices in Kenya are set by the government through EPRA, there is a need for the energy pricing system to reflect the environmental cost of fossil fuels. Such a policy could boost capital investment and employment and may also enhance the uptake of energy-efficient equipment. Further, the policy could be useful in promoting the competitiveness of the manufacturing sector by reducing energy costs.

5.4 Limitations of the Study

In the analysis of energy efficiency, the 2018 WBES did not have data on fuel expenditure. Therefore, the analysis of fuel efficiency change was limited to the period 2007-2013. In the evaluation of the effect of energy efficiency on TFP, the chemicals, pharmaceuticals and plastics sub-sector had a low sample size and thus the analysis failed the converge tests. Consequently, this sub-sector was dropped from the analysis. In the assessment of energy and non-energy input substitution possibilities, the WBES did not have firm-level data on the price of capital, yet this variable is important in the analysis of factor substitution. The study used the total replacement cost of capital as a proxy for the price of capital.

5.5 Areas for Further Research

This study acknowledged that energy efficiency could be varying across sub-sectors because of varying production technologies. Consequently, analysis was at the sub-sector level. Future studies should consider analysis at the regional level. This is because different regions have unique characteristics such as energy prices and access to electricity which may influence demand for energy among firms and thus lead to regional differences in energy efficiency. Upon the availability of more data, more periods may be included in the panel data to allow more observations on each firm. More information is important in developing more discerning conclusions on energy efficiency. Analysis may also be extended to separate regressions based on years to provide an understanding of changes in energy efficiency over time. Further, a more comprehensive study could be done on gender and energy efficiency relation. Although this study found female firm ownership to positively influence energy efficiency, the issue of gender and energy efficiency is wide and this study might have failed to study it exhaustively. Findings from the proposed study are likely to offer important policies to address climate change.

Energy efficiency policies could be a win-win solution in terms of environment and productivity. Thus, there is a need to investigate why the uptake of energy efficiency measures is low yet such measures are linked to higher TFP. An investigation of the effect of energy efficiency on the productivity of the Kenyan manufacturing sector can also be complemented by an investigation of the energy efficiency and profitability relation in the manufacturing sector. Such an assessment is important by itself because of the high cost incurred in adopting energy-efficient technologies.

Research on energy and non-energy substitution possibilities can be extended to investigating regional and firm age differences in substitution possibilities. This is because different regions and firm age categories could be using varying product mixes and thus they could be operating on different cost functions leading to regional and firm age differences in energy and non-energy substitution possibilities. Research could also be extended to other high-energy consumers such as the transport sector.

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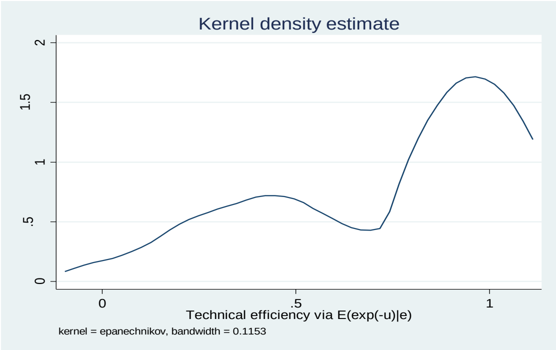
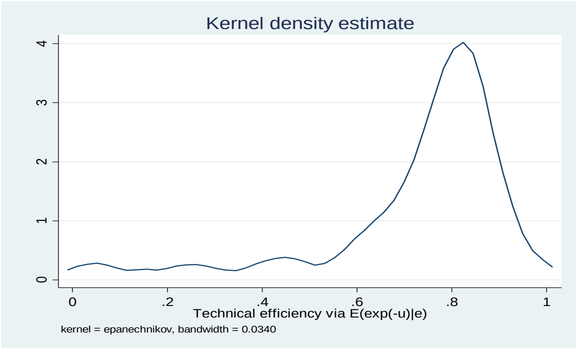
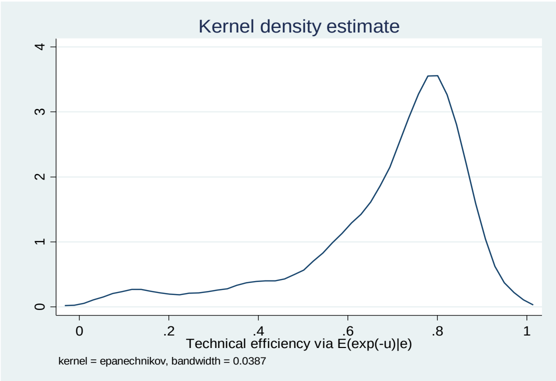
APPENDICES

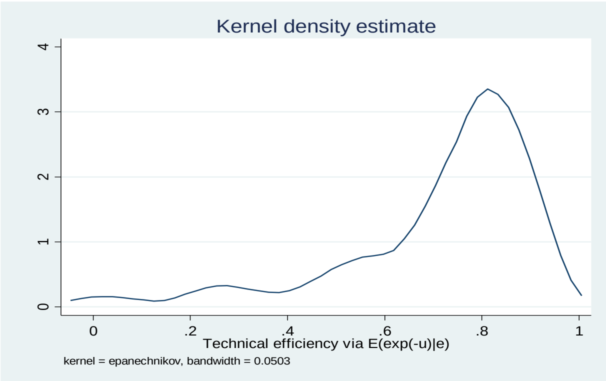
APPENDIX 1: Kernel Density Function of Energy Efficiency



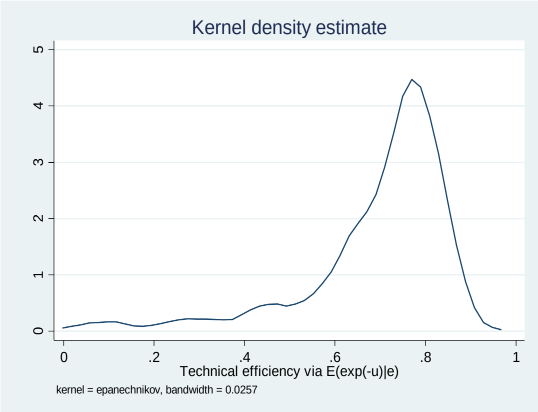


Chemicals, Pharmaceuticals and plastics sub-sector   Food sub-sector



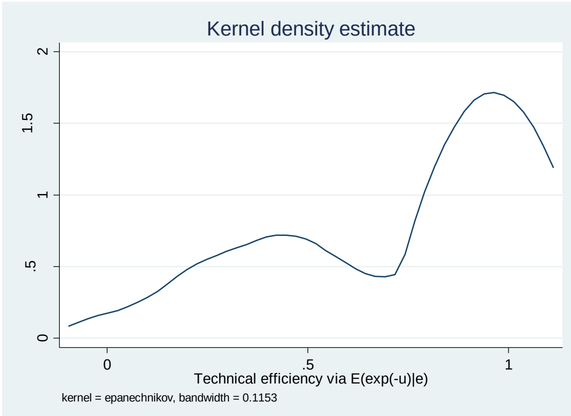


Paper and other manufacturing sub-sector   Textiles and Garments sub-sector

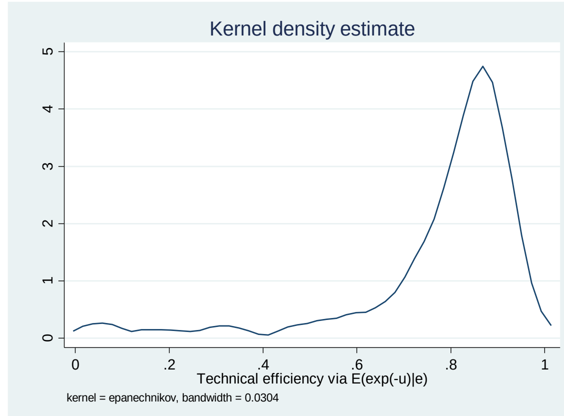


Overall sector

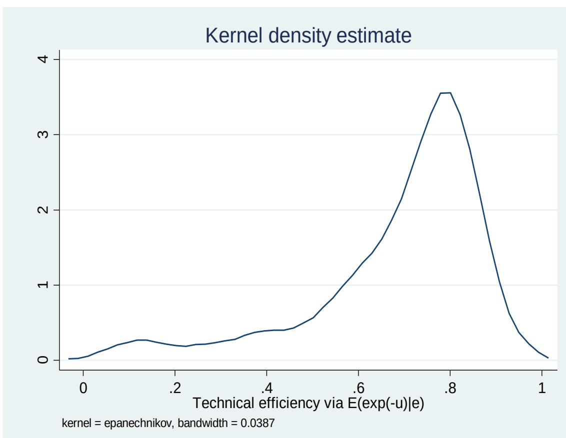
Figure A.1.1:Kernel Density function of electricity efficiency



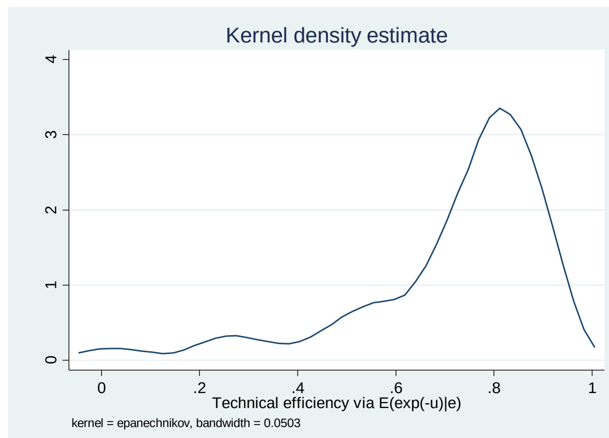
Chemicals, pharmaceuticals and plastics sub-sector



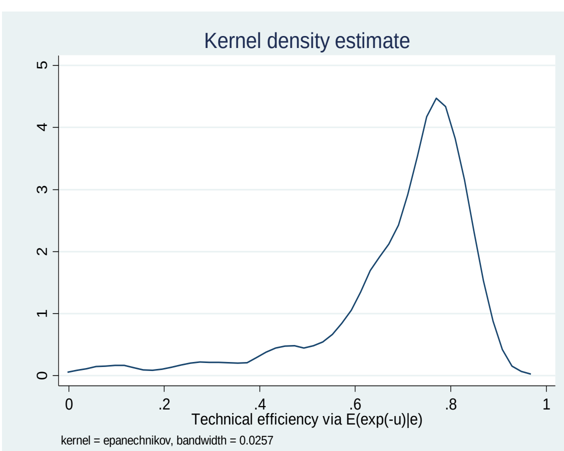
Food sub-sector



Paper and other manufacturing sub-sector



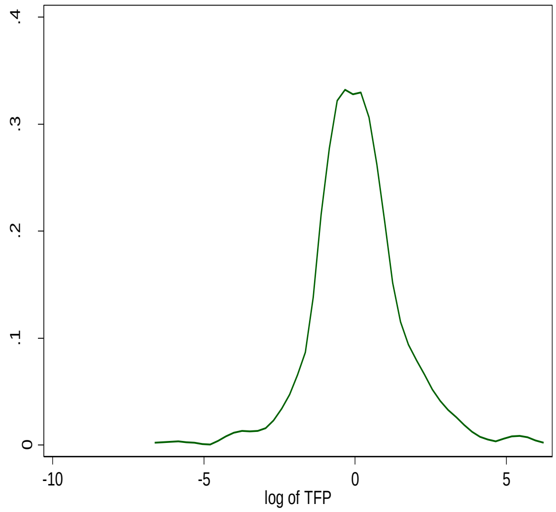
Textiles and garments sub-sector



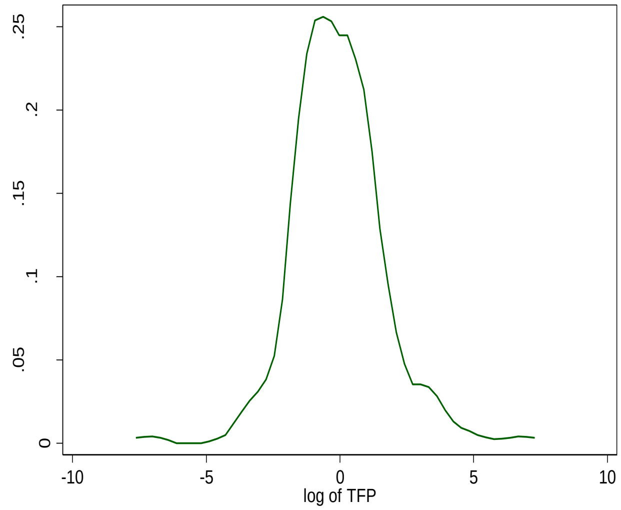
Overall sector

Figure A.1.2:Kernel Density Function of fuel efficiency

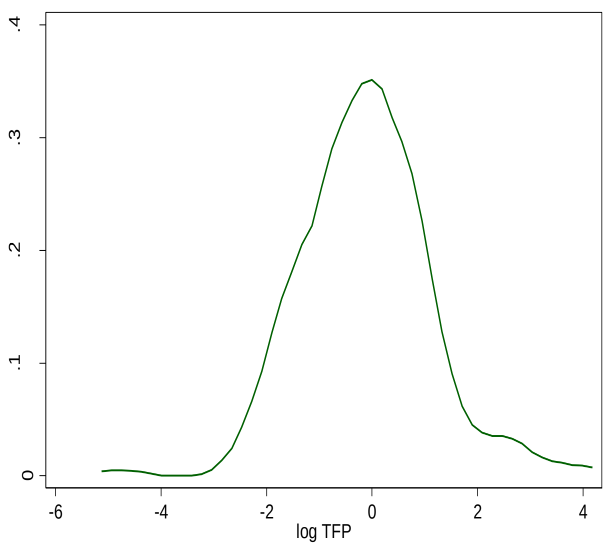
APPENDIX 2: Distribution of TFP by sub-section



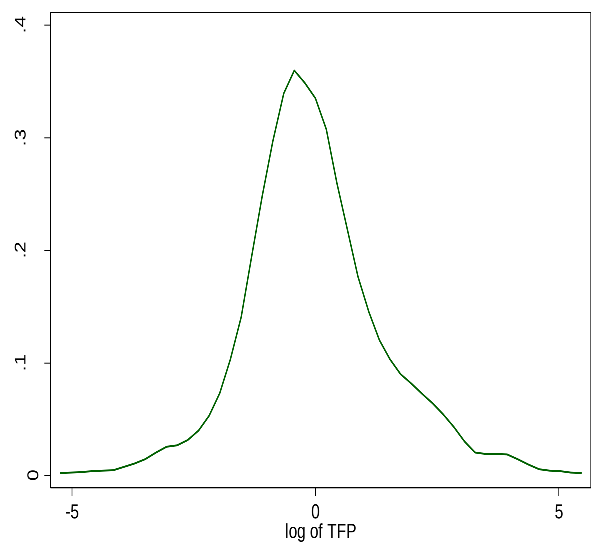
Paper and other manufacturing sub-sector



Chemicals, pharmaceutical and plastics sub-sector



Textile and garments sub-sector



Food sub-sector

Figure A.2.1:TFP distribution by manufacturing sub-sector