The Factors Influencing Energy Intensity in the South African Manufacturing Industry

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Dedication

I dedicate this study to my late grandfather Mr Joseph Dlamini who has always encouraged me to further my studies. I would also like to dedicate this study to my beautiful daughter Melokuhle Zanengcebo Mdluli, I hope when you are old enough to understand, you will take up space and become all that you are meant to be.

Abstract

The study investigates the determinants of energy intensity in the manufacturing industry. The objectives are to analyse trends, to determine the drivers of manufacturing energy intensity and make policy recommendations. The study investigates the effects of manufacturing value added, foreign direct investments, energy prices and trade openness on manufacturing energy intensity. The study employs the Vector Error Correction Model on time series data for the period of 1980 to 2017.

The findings of the study depict that manufacturing value added, foreign direct investment and energy prices are the most important determinants in explaining manufacturing energy intensity over the reviewed period. Manufacturing value added is found to be statistically significant both in the short and long run. Foreign direct investment is found to be statistically significant in the long run whereas, energy price is significant in the short run.

In light of this, the study makes policy recommendations. With regards to total manufacturing value added, the study recommends that the industry be closely monitored. Government should subsidize energy efficient machinery and equipment and the use of old outdated technology should be banned. With regards to foreign direct investment, the study recommends that the FDI policy be reviewed such that it attracts foreign investors. The recommendation regarding energy prices is that government should encourage energy price reform and use subsidies to encourage energy saving enterprises.

Key words: Energy Intensity, Manufacturing industry, Manufacturing Value Added, Foreign Direct Investment, Energy Prices, Trade Openness, Vector Error Correction Model

List of Abbreviations

ADF	Augmented Dickey Fuller
ADRL	Autoregressive Distributed Lag
AEEFM	Assessment of Energy Efficiency Financing Mechanism
AIC	Akaike Information Criterion
AR	Autoregressive
AMG	Augmented Mean Group estimator
CAICA	Chartered Alternative Investment Analyst
CCE	Common Correlated Effects
CTL	Secunda coal-to-liquids
DSMP	Demand Side Management Programme
DTI	Department of Trade and Industry
EI	Energy Intensity
EO	Economic Openness
EP	Energy Prices
EU	European Union
EMAK	Energy Management Action Network for Industrial Efficiency
ESKOM	Electricity Supply Commission
FAIST	Fixed Assets Investment Structure
FDI	Foreign Direct Investment
GDP	Gross Domestic Product
Gwh	Gigawatt hour
GSEP	Global Superior Energy Performance Partnership
GTL	Gas-to–liquids
HQC	Hannan-Quinn criterion

IDC	Industrial Development Corporation
IEA	International Energy Agency
IEO	International Energy Outlook
IIEC	International Institute for Energy Conservation
IEP	Integrated Energy Plan
IPEEI	Improving Policies through Energy Efficiency Indicators
IPAP	Industrial Policy Action Plan
IVA	Industrial Value added
JB	Jarque-Bera
LDPE	Low-density polyethylene
LL	Linear-low
LMDI	Log-mean Divisia Index Method
MBI	Market Based Instruments
MCEP	Manufacturing Competitiveness Enhancement Programme
MEPS	Minimum Energy Performance Standards
MJ	Mega Jules
NEES	National Energy Efficiency Strategy
NERSA	National Energy Regulator
OECD	Economic Co-operation and Development Countries
OPEC	Organization of the Petroleum Exporting Countries
OLS	Ordinary Least Squares
PAMSA	Paper Manufacturers of South Africa
PEI	Primary Energy Intensity
PP	Philip Peron
PVC	Polyvinyl chloride

UN	United Nations
R&D	Research and Development
SARB	South African Reserve Bank
SBN	Sustainable Building Network
SEDA	Small Enterprise Development Agency
SEAD	Super-efficient Equipment and Appliance Deployment Initiative
SIC	Standard Industrial Classification System
SIC	Schwarz Information Criterion
StatsSA	Statistics South Africa
UN	United Nations
US	United States of America
TECP	Technological Progress
TOP	Trade Openness
TMVA	Total Manufacturing Value added
VAR	Vector Auto Regressive
VECM	Vector Error Correction Model

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Chapter One

Introduction

1.1. Background of the study

Energy is a vital commodity for economic growth and development. This means that an inefficient use of the commodity would have detrimental effects on the economy. Thus, the concept of energy intensity defined as the ratio of energy consumption to output, comes as a special focus. Energy intensity is closely linked to the inefficient use of energy and higher carbon dioxide emissions (Kwakwa and Adusah-Poku, 2019). The International Energy Agency report (2019) records that in 2018, primary energy intensity an important indicator of how much energy is used by the global economy, improved by just 1.2%, the slowest rate since 2010. This was significantly slower than the 1.7% improvement in 2017.

Despite this improvement, the value of energy intensity remains far from the 3.5% per year decrease required to achieve the 2^{o}C scenario (Global Energy Statistical Yearbook, 2020). This is an indication that there are national priorities and policy ambitions that still need to be strengthened in order to ensure that the world meets its energy efficiency target for 2030 under the sustainable development goals (International Energy Agency, 2018).

Variations in energy intensity levels and trends in the different regions of the world are a reflection of the differences in economic structure and energy efficiency achievements (Global Energy Statistical Yearbook, 2020). High energy intensity in some regions, especially the developing world, is influenced by the dominance of energy-intensive industries and low costs of energy. The US Energy Information Administration (2016), estimates that globally the manufacturing industry consumes approximately 54% of the energy produced. The International Energy Outlook (IEO) (2018) also estimates that energy consumption by the manufacturing industry will increase by an average of 1.2% per year until 2040 (International Energy Outlook, 2018).

In South Africa manufacturing energy intensity stands at 4 MJ/$, a figure which is still high when compared to other BRICS member states (National Efficiency Strategy Report, 2019). The high level of energy intensity is perpetuated by the industry's inefficient

consumption of energy. According to the Energy Sector Report (2019) the manufacturing industry consumes about 52% of the country's energy. The report also reveals that the industry relies heavily on coal as a source of primary energy, making it the biggest emitter of greenhouse gases. In 2015, energy use of the manufacturing industry contributed about 20% of the total emissions (Kan *et al,* 2020). This, in addition to recent struggles in finding sustainable energy sources leading to electricity blackouts brings forth the need to study and understand the key drivers of energy intensity in the industry.

The South African manufacturing industry has been trying to find ways of reducing its energy intensity. These include, the industry's energy efficiency strategy which was initiated by government and South African industries in 2005 with the aim of improving energy efficiency at 12% by 2015. The National Strategy Energy Efficiency report (2019) established that within the most intensive industries in the private sector, the most easily achieved energy savings have been met. However, with regards to the more challenging ones there are additional costs associated to them which are detrimental to investment.

The government of South Africa has also initiated a number of programs and policies to improve energy efficiency levels and these include the White paper policy on renewable energy of 2013, aimed at ensuring that the contribution of renewable energy to final energy consumption in the economy reached a target of 10 000 Gwh by 2013. Also, as part of its National Development Plan 2030 the government of South Africa drafted its Post- 2015 National Energy Efficiency Strategy which targets a 16% improvement in energy efficiency by 2030, it is aimed at increasing the adoption of energy management systems by companies (IEA, 2018).

Moreover, there are studies that have looked at manufacturing energy consumption, energy efficiency and energy intensity, these include; Thiel (2016) who investigated energy intensity in the South African foundry in Western Cape; Cargill (2015) investigated the effects of market based instruments in promoting industrial energy efficiency; Kohler (2012) analysed energy efficiency in South Africa; Olanrewaju (2017) assessed the energy consumption pattern in the South African industry; Adom (2014) investigated the determinants of energy intensity taking into account the effects of structural shifts; and Kan *et al*,(2020) analysed energy use in the South African manufacturing industry placing more focus on the intensity effects.

Despite all these there is still a gap with regards to literature on the drivers of energy intensity in the manufacturing industry. According to the National Strategy on Energy Efficiency, there is a great opportunity for further research and development which can improve the industry's energy saving by at least 24.5%.

1.2. Problem statement

South Africa's primary energy intensity is high when compared to other BRICS member states, currently standing at 8.5MJ/$. The country's primary energy intensity levels are mainly influenced by manufacturing energy intensity which remains high, currently at 4 MJ/$ (Energy Efficiency Report, 2019). Empirical literature has also revealed that manufacturing activity is one of the determinants that increases the country's energy intensities (Kan, *et al,* 2020, Kwakwa, 2014 and Kwakwa and Adusah-Poku, 2019).

The manufacturing industry is energy intensive when compared to the other sectors of the economy. According to the Energy Sector Report (2019), industry consumes approximately 52% of the primary energy produced in the country. Estimates from Eskom also revealed that in 2017 the industry's electricity consumption was about 60% of the total electricity produced in the South Africa. According to Kan *et al* (2020) about 80% of manufacturing energy consumption is dominated by the manufacture of basic iron and steel, refined petroleum products as well as chemical and chemicals products.

The country's high energy intensity which is mainly influenced by the manufacturing industry has had a big toll on the growth and development of the economy. Firms and households have suffered a great deal because of electricity blackouts that have been introduced by Eskom in an attempt to manage energy supply. Also, due to the industry's heavy reliance on coal as a primary source of energy, the country has been labelled as a major emitter of carbon dioxide gases in the African continent.

South Africa like many other countries is determined to achieve both sustainable and efficient energy use. After the financial crisis of 2008, the government introduced renewable energies of a large scale and further enhanced the promotion of energy efficiency in all sectors in order to meet energy demand (Bergh, 2012). These include investment in renewable technologies such as photovoltaic system, concentrated solar power plants and wind turbines. The government has also put in place several policies and programs aimed at reducing energy demand and increasing energy efficiency. These

include amongst others the Energy Efficiency Strategy for South Africa whereby, industry players in mining and manufacturing as well as the government voluntarily committed to a target of an energy demand decrease of 15% by the year 2015 (Department of Energy Report, 2015). Furthermore, there are a number of studies that have attempted to identify the means with which the country can improve its energy intensity levels.

These policies however, have done little work in ensuring that energy intensity for the industry is reduced to an appreciable extent. The National Strategy Energy Efficiency Draft (2019) reported that through consultations with the private sectors' most energy intensive industries, the easily achieved energy savings have been implemented. The challenge however, was with regard to the more challenging ones which were regarded as an additional cost to the investors. The argument was that there are costs related to energy efficiency implementation which are considered to be an impediment. Such costs include the costs of energy audit and time spent conducting research and holding discussions. Also, due to financial constraints certain policies which were aimed at improving energy intensity are currently put on hold.

Furthermore, previous studies on energy intensity have not paid much attention to the possible effect of the manufacturing sector. This suggests that there is still a gap in understanding the main drivers on energy intensity in the industry. In light of this, the study investigates the effects of manufacturing value added, foreign direct investment, trade openness and energy prices on manufacturing energy intensity. The findings of the study will help industry players, academics and policy makers to make informed decisions when it comes to energy use in the industry.

1.3. Research Questions

(i) What are the drivers of energy intensity in the manufacturing industry?

(ii) Does energy price, foreign direct investment and manufacturing value added reduce or increase manufacturing energy intensity?

(iii) To what extent do the factors identified have an effect on manufacturing energy intensity?

1.4. Research aim and objectives

1.4.1. Research aim

The purpose of the study is to examine the factors/determinants influencing energy intensity in the South African manufacturing industry.

1.4.2. Research objectives

(i) To analyse trends of the determinants of energy intensity.

(ii) To identify determinants of energy intensity.

(iii) To make policy recommendations.

1.5. Hypothesis

The null hypothesis is as follows:

$H0$: Manufacturing value added, energy prices and foreign direct investment do not influence manufacturing energy intensity.

1.6. Significance/Justification of the Study

Energy security is important in ensuring economic growth and development for the country. A keen interest on the drivers on energy intensity in the economy has developed for many researchers and policymakers. However, for South Africa little attention has been placed on the manufacturing industry which is considered to be the biggest consumer of energy (52%) and a major contributor of greenhouse gases (20%).

The study is important because industry objectives are deeply rooted in energy planning processes. As such, it would be counterproductive for a developing country like South Africa to divorce discussions on energy intensity. Also, promoting small businesses, improving competitiveness, creating employment have been an integral component of industrial policy over the years. This implies that energy related decisions are notably significant for the success of other national policies.

Furthermore, in order for the country to meet its energy saving targets research related to energy intensity such as this one provides a clear roadmap. In addition to energy security, the environment is at the forefront of energy policy debates in the world. This means that choice of energy input is very important in ensuring that greenhouse gases are reduced.

In light of this, the study seeks to investigate the main drivers of energy intensity in the industry with particular focus on manufacturing value added, foreign direct investment, energy prices as well as trade openness. It also aims to ascertain if the implementation of certain energy efficiency policies has brought about the desired outcomes. The findings of the study are intended to highlight certain energy efficiency gaps, energy efficiency

potentials and make recommendations with which the industry can improve its energy intensity.

1.7. Ethical considerations

The study employs secondary data which is readily available from the South African Reserve Bank, Statistics South Africa, Quantec and World Bank databases hence; there is minimal interaction with industry players. It should be noted however, that should a need arise for the researcher to request for information from industry players, an ethical consent form which is endorsed by the scientific committee will be provided and confidential information will be marked and kept as such within the North West University. Furthermore, the study adheres to all ethical considerations (code of ethics) pertaining to research of the North West University.

1.8. Organisation of the Study

The rest of the study is organised as follows: chapter one presents the background of the study; chapter two presents an overview of the manufacturing industry, the energy sector in South Africa and trends on the determinants of energy intensity; chapter three present theoretical and empirical literature review for the study; chapter four presents the methodology to be followed in the study; chapter five presents results and analysis; and chapter six presents summary, conclusions and recommendations.

Chapter Two

An Overview of the Manufacturing Industry, Energy Sector and Determinants of Manufacturing Energy Intensity in South Africa

2.1. Introduction

The purpose of this chapter is to discuss the overview of the manufacturing industry, energy sector and the determinants of energy intensity in the manufacturing sector. Under the overview of the manufacturing industry, the chapter will discuss the international experience, industry structure, industry legislation as well as energy consumption patterns within the industry. Under this overview of the South African energy sector, the structure of the sector will also be discussed, energy demand and supply, energy sector legislation as well as energy intensity, a global experience and a South African experience. Furthermore, the determinants of manufacturing energy intensity to be discussed in the chapter are; total manufacturing value added, energy prices foreign direct investment and trade openness.

2.2. Manufacturing International experience

The Small Agency Development Enterprise (SEDA) defines manufacturing as a process that involves tools and labour to produce goods for use or sale as intermediaries or final goods. This includes a range of activities (innovation, labour and entrepreneurship). The manufacturing sector is recognised as one of the important industries in any economy as it provides great opportunities for poverty reduction, sustainable growth and employment (McCamel, 2017). The industry is also responsible for ensuring sustenance in the other sectors of the economy, through guided technological developments and innovation. According to SEDA (2012) the most leading economies in terms of manufacturing output, account for about 61.65% of the world's manufacturing. These include China (28.7%), United States of America (16.65%), Japan (7.23%), Germany (5.78%) and South Korea (3.29%) (West, 2018).

2.3. Overview of the South African manufacturing industry

The history of manufacturing in South Africa is traced back in the 1920s. During that time the main contributors to the economy were mining and agriculture (South African Market

Insights, 2018). In that period, the mining industry expanded and the need for processed foods and textiles increased. The government of the country began providing cheap electricity and steel for industrial use and imposed tariffs to assist and support local manufacturers. The manufacturing industry in South African became developed with most businesses owners dominating the industry. Government offered support to the manufacturing industry and state owned corporations helped to launch the paper, textile, fertiliser, chemical, and oil and armament industries (South African Market Insights, 2020).

In previous years the manufacturing industry was a major contributor into the local economy, with manufacturing value added of above 20% (World Bank Data, 2019). As time went by the industry faced numerous challenges which led to it facing a downward decline in performance and its overall output. Data from the Industrial Development Corporation (2018) shows a steady decline in the industry's contribution to the overall economy in the last two decades. For instance, the industry's contribution to GDP between 1994 and 2012 declined from 20.9% in 1994 to 12.4% in 2012, with the industry currently holding the 4th position in terms of its contribution to GDP contributing about 13.53% (Statistics South Africa, 2018).

2.4. Structure of the South African economy and Manufacturing industry

2.4.1. Structural shifts of the economy

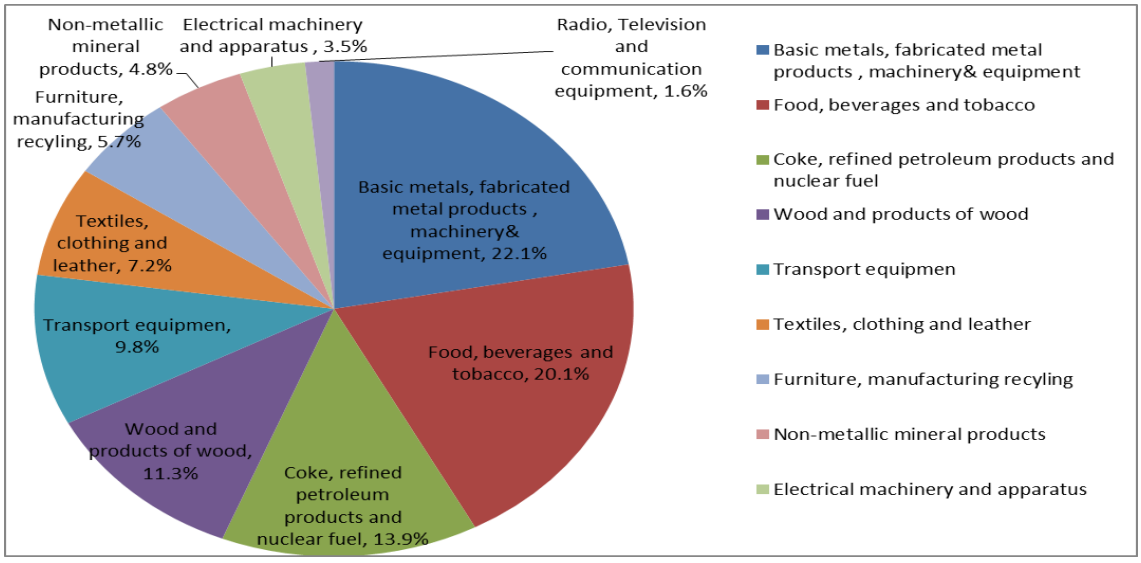
Before discussing the structure of the manufacturing industry, it is imperative that structural shifts of the economy be briefly discussed as this will give a clear understanding of the current picture of the manufacturing industry. According to Adom (2015) the structure of the economy of South Africa shifted from the primary and secondary sector-led economy in the mid-twentieth to a tertiary sector–led economy, with the contribution of the tertiary sectors currently standing as 65% of GDP. Industry value added continues to decline since the 1980, refer to figure 2.4 for trends on industry value added. The implication of this is that the economic reform which began in 1994 has caused de-industrialisation in the South African economy. The structural shift from energy intensive sectors to less energy intensive sectors could imply a reduction in energy intensity for the country. It is also worth mentioning that the structural shifts on trade liberalisation has caused more penetration of imports with a decline in exports. However, the recovery of the economy has boosted business confidence with increasing foreign direct inflows.

2.4.2. Structure of the South African Manufacturing industry

The country's manufacturing activity is mostly concentrated in the Gauteng province with a 40% contribution to South Africa's manufacturing industry, followed by KwaZulu Natal with 15.3%, Western Cape with 15.3%, Eastern Cape with 7.5%, Mpumalanga with 7.1%, Free State with 4%, North West with 2%, Limpopo with 1.5% and Northern Cape with 0.5% respectively (Statistics South Africa, 2016).

Based on Standard International Trade Classification (SITC), the South African manufacturing industry is categorised into 9 sub sectors namely: chemicals and petrochemicals, food and beverages, metals and machinery, textiles and clothing, wood/pulp and paper, plastic, automotive, electric machinery and apparatus, furniture and other manufacturing (Statistics South Africa, 2018). The most dominant sub-sectors are metals and machinery (22.1%), food and beverages (20.1%) and chemicals and petrochemicals (13.9%) as shown in figure 2.2 below. These three (3) sub-sectors contribute approximately 60% of the entire manufacturing industry of South Africa.

Figure 2.1: Contribution into the overall manufacturing industry by each sector



Source: Statistics South Africa (2019)

2.4.3. Different sub-sectors in the Manufacturing industry

2.4.3.1. Chemicals and petrochemicals sector

The South African chemicals and petrochemical sector is well developed, extremely complex and diversified and is considered as one of the largest in Africa (MacCamel,

2017). Its set of experiences follows back to the 1950s when the first oil from coal was extracted in Sasolburg (SEDA, 2012). The chemical sector was predominantly evolved by the gasification of South Africa's plentiful coal reserves since the country lacks sufficient upstream oil reserves, and hence the launch of two large oil from coal plants by Sasol at Secunda in the 1980s (Chartered Alternative Investment Analyst (CAIA), 2010).

With regards to performance, the sector has been experiencing a slow growth over the years, this is evidenced by the recent statistics released by Statistic South Africa and Quantec which shows that the gross value added in the sub-sector followed the commodity boom of 2002. According to the databases the sector increased by 4.7% in the period of 2002 to 2008; dropped by 1.5% from the period of 2008 to 2010; from 2010 to 2012 it recovered by 12.5%; in 2012 to 2016 it slowed to a growth of 1% a year.

2.4.3.2. Metals, metals products, machinery and equipment sector

South Africa's metals sector is advanced and forms part of the main sectors of the economy of South Africa (Brand South Africa, 2017). In 2001 the country was ranked 19th the largest producer of steel and in Africa the steel industry accounted for approximately 60% of Africa's total production in 2010 (SEDA, 2012). The country's metal sector comprises of basic iron ore and steel which involves the manufacture of primary iron and steel products from smelting to semi-finished stages.

The sector has been experiencing a downward decline which started during the 2008/9 financial crisis. In that period the production of heavy industry machinery, especially metal refining and metal products declined sharply with a 6% fall in metals and metal products (Trade and Industry Strategies, 2017). It was also affected by the doubling of electricity prices from 2008 to 2016. As a result of these trends the sector's share in total manufacturing production declined from 17% in 2006 to 11% a decade later.

2.4.3.3. Food, beverages and tobacco

South Africa is a food self-sufficient country as majority of the populace's food is produced locally from raw materials (SEDA, 2012). The South African food and beverages sector is one of the sectors that play a significant role in improving the economy of the country as it is crucial for the health of the people and life sustenance (McCamel, 2017). The country's food and beverages sector is considered as well developed and as such has become a global player. Data from Statistics South Africa shows that the sector has

remained steady even when the manufacturing's contribution to GDP declined (period of 2002 to 2016).

The sector is categorised into 11 agricultural sub-sectors which include the processing of meat, fruit preservation, dairy products, canning and preservation of fish (SEDA, 2012). Moreover, according to the information acquired from the Trade and Industry Strategies, the performance of the sector has been improving ever since the 2000 boom, as it grew at 6% per year from the period of 2000 to 2008 becoming the most important sector in the industry. From 2008 to 2016 its contribution to total manufacturing rose from 11% to 18% respectively.

2.4.3.4. Textile, clothing and leather sector

The South African clothing and textile sector is well established and highly diversified, with a crucial part of employer in the country to enact. According to DTI (2014) the sector is one of the most labour-intensive sectors in the manufacturing industry, with approximately hundred (300) manufacturers concentrated in Gauteng, Kwazulu Natal, Eastern Cape as well as the Western Cape. The manufacturers vary in size, composition, and in manufacturing processes.

This sector is important in the lives of South Africans and the various sectors in the economy such as the health, transport and construction sectors amongst others (SEDA, 2012). When it comes to performance, the sector saw a sharp decline between the periods of 1994 to 2001, with its contribution to GDP dropping over 1% per year (Quantec database). It only grew at over 4% per year from 2001 to 2010, and then it levelled out. However, from 2014 it showed a decline of about 1% a year. These trends according to Quantec database meant that the share of the sector into manufacturing value added dropped for most of the past 20 years, falling from 7% in 1994 to 3% from 2011 to 2016.

2.4.3.5. Pulp, paper, publishing and printing sector

South Africa is ranked the 15th largest producer of pulp in the world and 24th in paper production (Paper manufacturers of South Africa, 2016). This according to PAMSA is an investment in local resources, innovation and people power. The value chain of the sector begins in the plantation of forests, to pulp and milling and lastly to beneficiation. Products made from paper and paper products include boxes, tissues, posters, newspapers, books and magazines amongst others.

According to the PAMSA website the sector plays a significant role in both the local and international markets. Locally the sector has contributed about R28 billion to the economy. Furthermore, according to Statistics South Africa the sector's performance grew by 2.3% from 2000 to 2008 but it dropped 4.5% during the 2008/9 global financial crisis. It again rose steadily at 2.5% a year from 2009 to 2017. These trends meant that the total manufacturing value added fell from just over 7% in 2003 to 5% in 2010, and then rose sharply to 8% in 2016.

2.4.3.6. Plastic and other chemicals

The country's plastic sector is well established and mostly dependent on feedstock from Sasol (SEDA, 2012). This sub-sector is separated into different divisions according to plastic type. According to SEDA, all the commodity polymer is manufactured locally, save for polystyrene which is completely imported from other countries. The plastics sector in global terms is small, especially when compared with European member states, the United States of America and the United Kingdom. Moreover, Plastics South Africa cited the sector to be worth R35 billion annually and an employer of approximately 40 000 people in plastic supply chain.

The sector's performance according to Quantec database grew by 2% per year in the period of 2000 to 2008 and after the financial crisis the sector struggled to regain its power. The share of the sector dropped in 2008 and has not recovered since. From 2008 to 2016 it declined from 18% to 13% of value added in manufacturing as a whole.

2.4.3.7. Automotive, transport equipment sector

The automotive sector is an important sector in the manufacturing industry and its history is traced back in 1995 (McCamel, 2017). According to the ASSCC website (2019) the sector is one of the largest in the manufacturing industry contributing approximately 6.9% to the country's GDP and employs about 110 000 people. The Sector comprises 7 vehicle assemblers, 13 assemblers of heavy and medium commercial vehicles and approximately 360 component manufacturers (ASCCI, 2018). According to the ASSCC website the sector's manufacturing activities is concentrated in Gauteng, largest manufacturer with approximately 40% of the automotive components sector and home for BMW, Ford and Nissan. Followed by Port Elizabeth with approximately 30%, and home for Isuzu and Volkswagen. Then KZN (Durban and Pietermaritzburg to be specific) the largest producer of vehicles with approximately 20% of the automotive components

sector. KZN is home for Toyota. The last one is East London, home of Mercedes Benz, with approximately 6% of the automotive components sector.

With regards to performance the sector grew rapidly before 2008, fell rapidly by 10% during the 2008/9 global financial crisis, then recovered in 2010. Data from Quantec and Statistics South Africa databases show a 5% annual growth from 2000 to 2008, a recovery of 5.6% a year in 2009 to 2012 and a contraction after 2008/9. The share of transport equipment value added in manufacturing as a whole dropped from 11% in 2008 to 7% in 2015.

2.4.3.8. Electrical machinery and apparatus sector

The Electrical machinery and apparatus sector a large and growing sector in the industry (SEDA, 2012). It is recognised for its world-class innovation and production. Within the sector there are different sub-sectors which relate to distinct electric components. The big companies in the sector specialise in professional electronics whereas, the small and medium ones specialise in security electronics and pre-payment meters.

The value added for this sector grew more rapidly and with greater stability than the rest of the economy until 2014 (Quantec database, 2019). It expanded by 5% a year before 2008, dropped by 5% during the 2008/9 crisis but again recovered to grow at 6% a year through to 2014. The share of value added in manufacturing fluctuated around 1.5% a year from 2008 to 2016 according to the Quantic and Statistics South Africa databases.

2.4.3.9. Furniture, manufacturing recycling and other manufacturing sector

The South African furniture and solid manufacturing sector is considered as an old sector in the industry (SEDA, 2012). It is a traditional sector accounting for a substantial amount of employment in the South African economy.

According to Quantec estimates, furniture production rose by 2% a year from the period of 2002 to 2008. In contrast, other manufacturing expanded by 4% a year in the same period, and between 2008 and 2016 there was no growth in the sector. Based on Quantec estimates the share of furniture in total manufacturing added fell from 2% in 1994 to 1% in 2008, then it stabilised. Whereas, for other manufacturing it dropped from 8.5% in 1994 to 6.5% in 2009, then it fluctuated around 7% ever since.

2.5. Manufacturing and energy policies and programmes in South Africa

The manufacturing industry, just like any other sector is governed by different policies and programmes which are aimed at ensuring growth and a competitive environment for incumbent firms and these are industrial policy action plan and manufacturing incentive schemes.

2.5.1. Industrial Policy Action II (IPAP2)

The Industrial Policy Action was adopted in 2007 and it recognises the manufacturing industry as a significant contributor to economic growth and development. The purpose of the policy is to address the country's unsustainable growth path. The policy aims to direct finances to more labour absorbing and high value add sectors.

The national industrial policy framework guides the industrial policy with the aim to apply government's approach to industrialisation through promoting diversification beyond current traditional commodities; intensifying long-term industrialisation processes in the country; promoting a broader–based industrialisation path and; contributing to industrial development in Africa (Department of Trade and Industry, 2018).

2.5.2. Incentive Schemes

According to the DTI documents there are various incentive schemes which are designed to support the broadening of economic participation, inclusive growth as well as job creation. The schemes include the Manufacturing Competitiveness Enhancement Programme (MCEP), which was launched in 2012, through this initiative local manufacturers were able to discard obsolete and antiquated machinery and equipment for investments valued at about R30 billion in both production assets and competitiveness improvements measures;The Automotive Incentive Scheme which helped secure investment commitments of over R45 billion by auto assemblers and component suppliers, retaining 38 267 jobs; and The Business Process Services (BPS) Incentive implemented in 2014 with the aim of creating about 43 657 jobs.

The government of South Africa in an attempt to encourage end-use energy efficiency has adopted the following policies, according to the South African Energy Sector Report (2018). The White Paper on the Energy policy, 1998; the National energy efficiency strategy (2005); White Paper on Renewable Energy, 2003; and the Integrated Energy Plan (IEP).

2.5.3. White Paper on the Energy policy,1998

The White Paper on the Energy Policy recognises the relationship between energy, social and economic development. It was developed for purposes of clarifying government policy regarding the supply and consumption of energy for the next decade. It also recognises that sustainability is important and that efficiency should be considered.

2.5.4. National energy efficiency strategy (2005)

The National Energy Efficiency Strategy derived its mandate from the White Paper on Energy Policy (1998). It is aimed at responding to the increasing demand for energy alongside a growing commitment to improving resource use and reducing South Africa's national environmental footprint. The National Energy Efficiency Strategy set an overall reduction target in energy intensity of 12% by 2015 and sectorial intensity improvements as follows; industry and mining (15%), power generation (10%), transport (9), commercial and public building sector (15%) and residential (15%).

2.5.5. White Paper on Renewable Energy,2003

The White Paper on renewable energy sets out Government's vision, policy principles, strategic goals and objectives for promoting and implementing renewable energy in South Africa.

2.5.6. Integrated Energy Plan (IEP)

The Integrated Energy Plan is described as a long-term energy framework which takes into account the crucial role that energy plays in the entire economy. It is undertaken in order to determine the best way to meet current and future energy service need in the most efficient and socially beneficial manner

2.5.7. Nuclear Energy Policy, 2008

The Nuclear Energy Policy outlines the government's vision for the development of an extensive nuclear energy programme by ensuring that Government's objective on the prospecting and mining of uranium ore and the use of uranium as a primary resource of energy must be regulated and managed in a manner that will be for peaceful purposes. The Nuclear Energy Policy's objectives include:

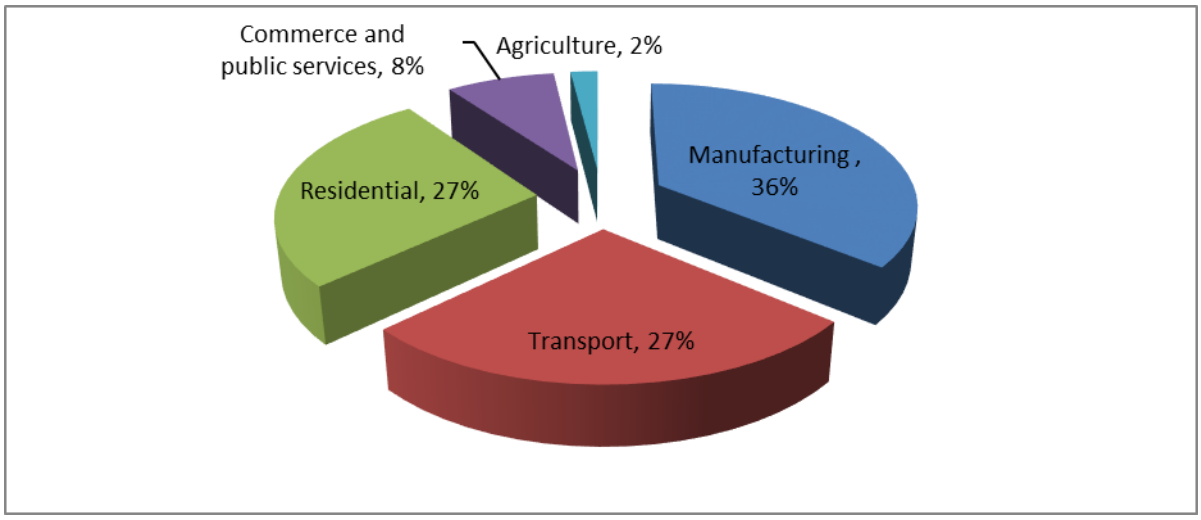
2.6 Overview of the South African energy sector

South Africa's energy sector is reliant on the extensive energy intensive coal mining industry (Energy Overview Report, 2017). The country has limited oil and gas reserves, and most of its large coal deposits are used to fulfil its energy needs, especially the electricity sector. South Africa uses oil imported from producers in the Middle East and West Africa in the Organization of the Petroleum Exporting Countries (OPEC) and is locally refined. Also, the country has fuel industries which produce gasoline and diesel fuels from Secunda coal-to-liquids (CTL) and Mossel Bay gas-to-liquids (GTL) plants.

2.6.1. Energy Demand in South Africa

Energy is one of the vital forces that enhance the growth of the economy. Energy demand has been increasing over the years with certain sectors consuming more energy than others (Energy Sector Policy Report, 2018). In 2015 the manufacturing industry including mining consumed more energy (36%) as compared to the other sectors of the economy, followed by the transport and residential each consuming (27%), then commerce and public services (8%) and agriculture with (2%) as shown in the figure below.

Figure 2.2: Energy Demand by Sector



Source: Department of Energy South Africa

2.6.2. Energy Supply in South Africa

South Africa's energy supply is dominated by coal with 59% of primary energy supply, followed by renewables and waste 20%, natural gas 3%, nuclear 2% (Statistics South

Africa, 2017). The different types of energy supplied in South Africa are further discussed below:

2.6.2.1. Coal

South Africa is considered as one of the top 10 producers of coal worldwide. The country is the second largest exporter of steam coal after Australia. In 2014, the share of coal in its primary energy consumption was 70% (Energy Security, 2015). Currently, South Africa has proven reserves of 4Gt, representing about 5.7% of total global reserves (Maleka *et al,* 2010). In 2013, the largest proportion of coal was produced from the Witbank (61.9%) coalfield followed by Highveld (20.2%), then Waterberg (7.33%) and Sasol-Vereeniging (7.29%) coal fields (Statistics South Africa, 2014). The key players are Anglo coal; Eyesiszwe coal; BHP Billton Energy South African Limited; Exxaro Resources and Glencore Xstrata Coal South Africa.

2.6.2.2. Petroleum Gas

The country imports most of its oil and natural gas. It has a few reserves for gas and oil (Statistics South Africa, 2006). In 2006, South Africa produced about 12157 barrels of oil per day, 482000 million cubic feet and had four production fields respectively. The country has about seven (7) oil companies namely; Chevron, Engen, PetroSA, Sasol Shell, BP and Total and the bigger one is BP Southern Africa (Maleka *et al,* 2010).

2.6.2.3. Crude Oil refining industry

There are four (4) oil refineries in South Africa. Three (3) are located on the coast and one (1) inland. The coastal refineries are Calref in Cape Town owned by Chevron, Enref in Durban owned by Engen and Sapref in Durban owned by BP and Shell. The inland refinery is Natrief in Sasolburg owned by Sasol and Total.

2.6.2.4. Renewable energy

According to the Department of Energy the country's sources of renewable energy are:

(i) Biomass which is used in the rural areas as wood;
(ii) Bagasse which is produced from sugarcane production and waste from pulp and paper, this is mainly used in industry;
(iii) Hydropower which is energy produced from water, this kind of energy is limited in the country because of the country's large flooding areas;
(iv) Wind energy which is also limited but a potential source of energy in some part of the country; and

(v) Solar energy which is also limited.

2.6.2.5. Electricity

The electricity produced in the country is from coal. The biggest producer and generator of electricity is Eskom (National electricity utility). Eskom supplies over 94% of electricity in South Africa and the rest is supplied by the municipality and auto-generation from the industry (Maleka *et al,* 2010). There are about 25 operational stations for each energy source owned by Eskom: Coal fired stations (14), Nuclear (1), Hydro pumped storage (3), wind (2) gas turbines (4). The biggest consumers of electricity are industry (66%) and residential areas (17.4%).

2.6.3. Energy sector Legislation

The South African energy sector is regulated by the National Energy Regulator (NERSA) which was established as a justice person in terms of section 3 of the National Energy Regulator Act No 40 of 2004.

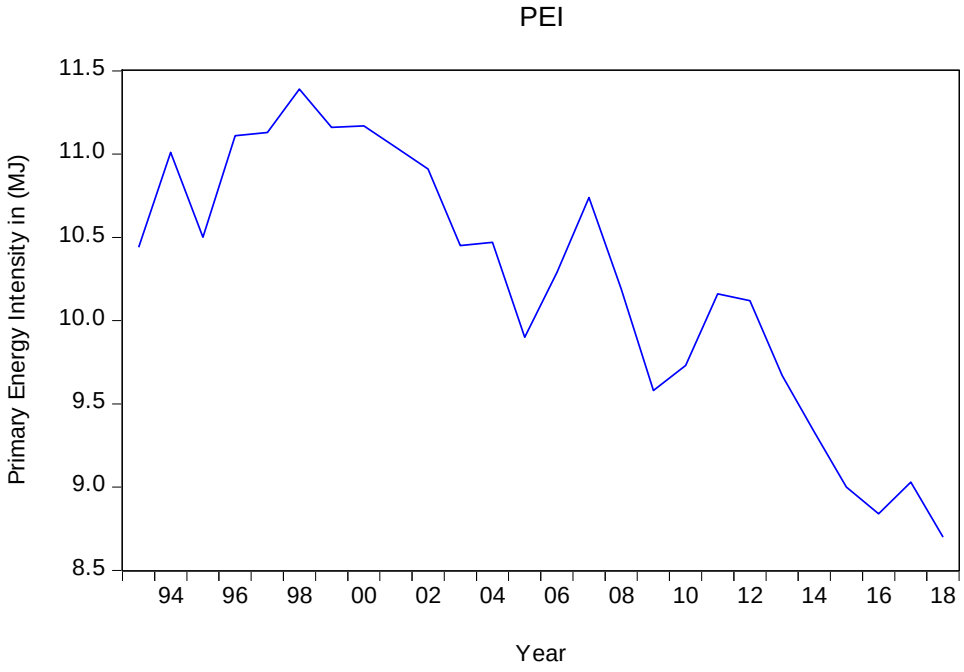
2.7 Energy Consumption patterns in the South African manufacturing industry

The manufacturing industry as already discussed consumes the highest percentage of energy in South Africa (Statistics South Africa, 2017). The main products consumed by the industry are coal and electricity. The industry uses coal as raw material for the production of secondary energy products and it uses electricity for lighting and other industry needs (Winkler, 2007). In 2015 the industry's final consumption of coal increased from 60.5% in 2006 to 74% in 2015. With regard to electricity consumption, a historical trend from the Department of Energy reveals the manufacturing industry as a dominant consumer of electricity with its share of total national consumption varying between 52% and 63% over a 20-year period (1993-2013). Furthermore, in 2017 the industry consumed about two-thirds (2/3) of total electricity consumption with the iron and steel (10%), non-ferrous metals (9%) and chemicals (6%) as the most electricity intensive sectors (Eco Overview Electricity SA report, 2017). These sectors use energy for various activities which include process and assembly, process heating and cooling, lighting and air conditioning (Parker, 2016).

2.8. Energy Efficiency Overview in South Africa

As part of the International Energy Agency commitment to pursue energy efficiency programmes, South Africa implemented the National Energy Efficiency Strategy (NEES) (The Department of Energy, 2013). It outlined an overall reduction in energy intensity target of about 12% by the year 2015. Following the approval of the Energy Efficiency Strategy in 2005 the country's aggregate energy intensities have been decreasing over the years; the decline however, does not imply a reduction in energy consumption (Kohler, 2013). Between the periods of 1990 to 2009 total energy intensity decreased at a slower rate of 0.4% per year. Since 2000 the country's total intensity has been decreasing more rapidly at around 1% per year (Energy Efficiency report, 2011). On average, the reduction in the country's final energy intensity was faster between the period of 1990 and 2008 respectively. The different trends are explained by the increasing losses in power generation due to that electricity consumption has been increasing more rapidly. In 2015 the country's energy intensity stood at about 9 Mega Jules (MJ) per dollar of GDP measured at purchasing power parity basis (Statistics South Africa, 2018). Despite the fact that it fluctuated in recent years, it tended to decrease through the period of 1996 to 2018.

Figure 2.3 Primary Energy Intensity in South Africa



Source: world bank data (2020)

From Figure.2.3 it shows that primary energy intensity in South African has been declining over the last decade. In 2018 primary energy intensity stood at 8.5 MJ, from 9 MJ in the previous 3 years.

2.9. International overview

The efficient use of energy has become one of the important topics to be discussed in meetings and other gatherings of the world. Different countries are actively looking for techniques to reduce energy intensity. They formulated and implemented several policies which are designed to ensure the efficient use of energy resources.

Japan has implemented several energy intensity and energy conservation policies which have led to the country achieving a decline in energy intensity. Such policies include, the Law Concerning the Rational Use of Energy in 1979 which was amended in 1983, 1993, 1999, 2003, 2005 and 2009 with the sole purpose of ensuring that firms in various economic activities reduce energy consumption and energy intensity. In an effort to improve energy efficiency the U.S. government through the Department of Energy's Office of Energy Efficiency and Renewable Energy (EERE) has effected various federal laws, established financial incentives, educational efforts, set efficiency standards and budgetary provisions for energy efficiency R&D and grants. In China, the goal to reduce energy intensity is the most talked about issue in the country's government documents (Tan and Lin, 2017). For instance, there is a 12^{th} five-year plan which is aimed at reducing energy intensity by 16%. There is also a Made in China 2025 plan which proposes to reduce energy intensity in the manufacturing industry by 18% in 2020 and 34% in 2025.

There are several international organisations and programs that are put in place in an effort to improve energy efficiency. The international organisations include, the International Institute for Energy Conservation, the International Partnership for Energy Efficiency Cooperation as well as the International Energy Agency (Vandermerwe, 2012). In Southern Africa some of the organisations include the Southern Africa Association for Energy Efficiency and the Department of Minerals and Energy. At local level Eskom the country's power utility has also come up with programmes designed to improve energy efficiency and these include the Energy Efficiency and Demand Side Management Program (Department of Energy South Africa, 2010).

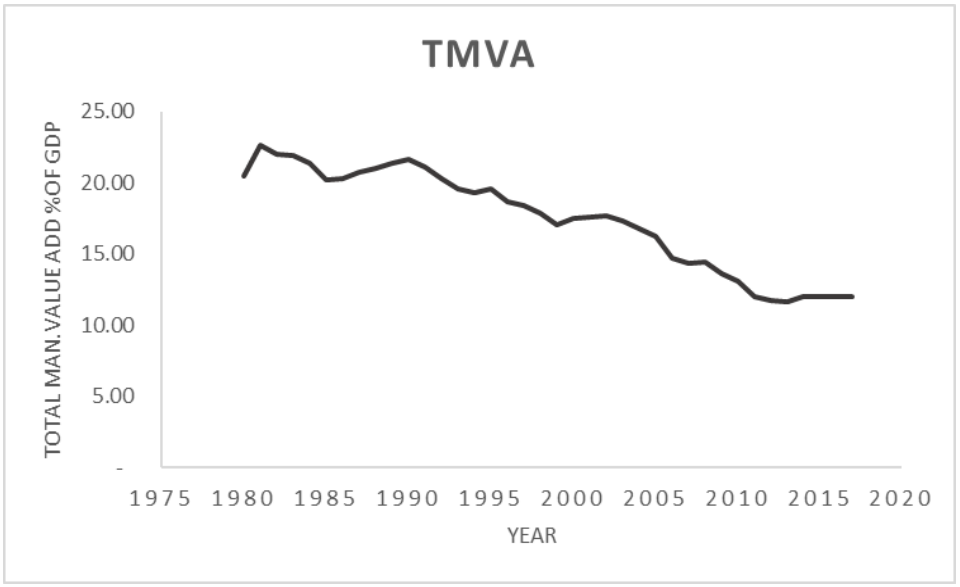
2.9.1. Determinants of manufacturing energy intensity in South Africa

The determinants of manufacturing energy intensity are discussed below.

2.9.1.1. Total manufacturing value added

Manufacturing activities are more energy intensive. As such, as the industrial base increases, it increases the energy requirements which causes energy intensity to increase (Adom, 2015). Previous studies such as Adom and Kwakwa (2014) and Kwakwa and Adusah-Poku (2019) have found a positive link between manufacturing energy intensity and industrial value added in South Africa. Over the years manufacturing value added has been declining as shown in figure 2.4.

Figure 2.4 Total manufacturing value added



Source: World Bank Data (2020)

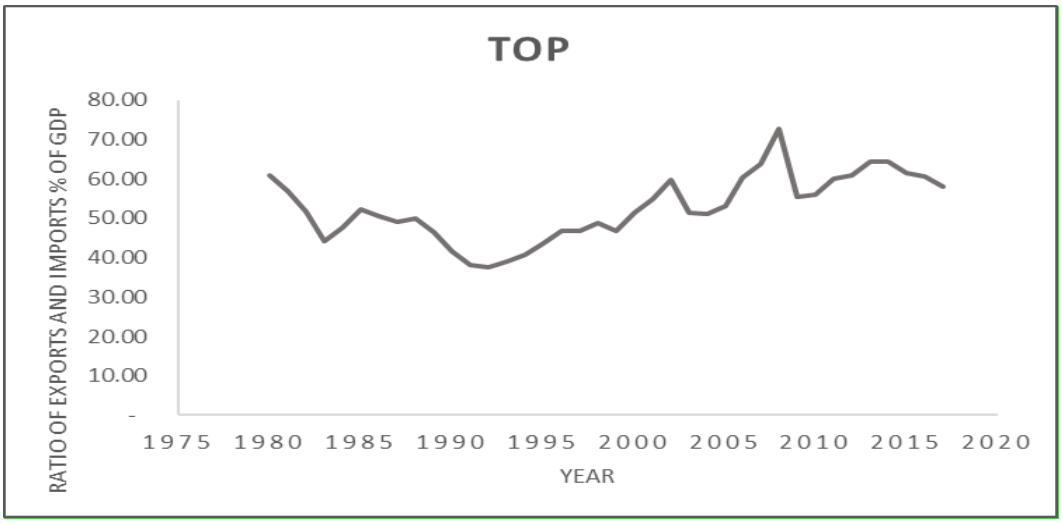
From figure 2.4 it shows that the South African total manufacturing value added has been declining gradually from the period in the last two decades.

2.9.3.2. Trade openness

The relationship between manufacturing energy intensity and trade openness is on one hand because firms in an open economy are confronted by fierce competition from local and international firms. Thus, they are forced to increase their productivity and improve their energy efficiency. On the other hand, it is the impact of technology transfers through the import of modern capital and equipment (Petrovića *et al,* 2018). Trade openness according Fisher-Vanden *et al* (2016) is a significant variable in explaining differences in

firm level energy intensity. It tests how the export orientation of firms affects their intensity, with the assumption that greater openness to foreign markets and world prices induces greater energy efficiency. Trade liberalisation in South Africa has changed the structure of the trade with growing penetration of the import and falling shares of exports. Data collected from the World Bank (2020) revealed that the average value for South Africa's trade openness was 37.49 percent in 1992 and a maximum of 72.87 percent in 2008. Figure 2.5 shows the value of trade openness from the period of 1980 to 2017.

Figure 2.5 Trade Openness



Source: World Bank Data (2020)

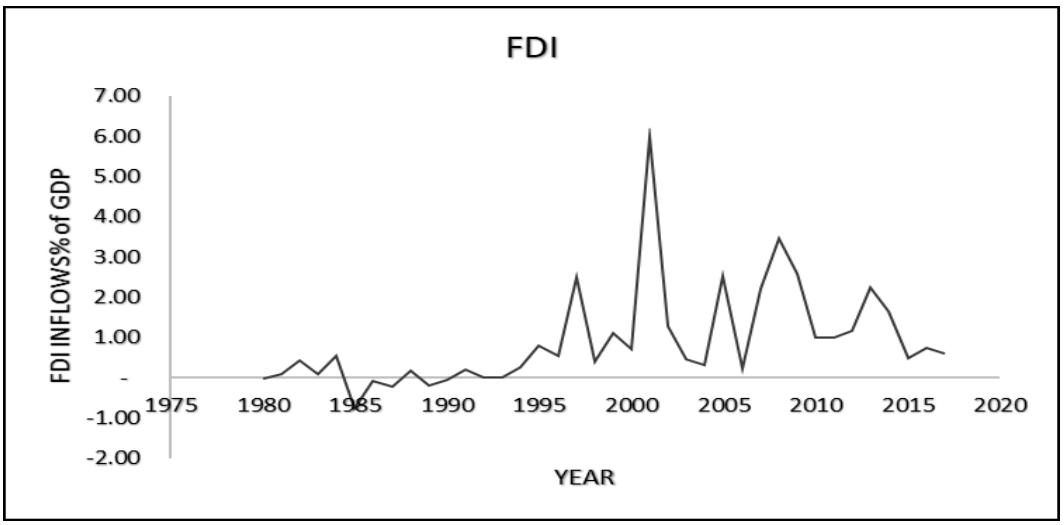
Based on Figure 2.5 trade openness has been fluctuating from 1980 to 2018. In 2008 it rose sharply and declined in 2009. From 2010 it started to increase slowly until 2014 where it began to decline slowly again till 2017.

2.9.3.3. Foreign direct investment FDI

FDI is an important determinant of manufacturing energy intensity, as it is associated with the technique effect (Fisher-Vanden *et al,* 2016). The impact of FDI on energy intensity can be decomposed into scale and technique effects developed by Grossman and Krueger (1993). By technique effect the assumption is that FDI supposedly introduces new advance technology and managerial skills to the host country resulting to improved energy efficiency (Petrovića *et al,* 2018). Also, firms with higher technological development activity have larger adaptive capacities and they may have access to foreign technology. In South Africa the impact of FDI inflows has increased the country's business

confidence leading to a decline in energy intensity levels (Adom,2019). FDI inflows trends are shown in figure 2.6.

Figure 2.6: Foreign Direct Investment



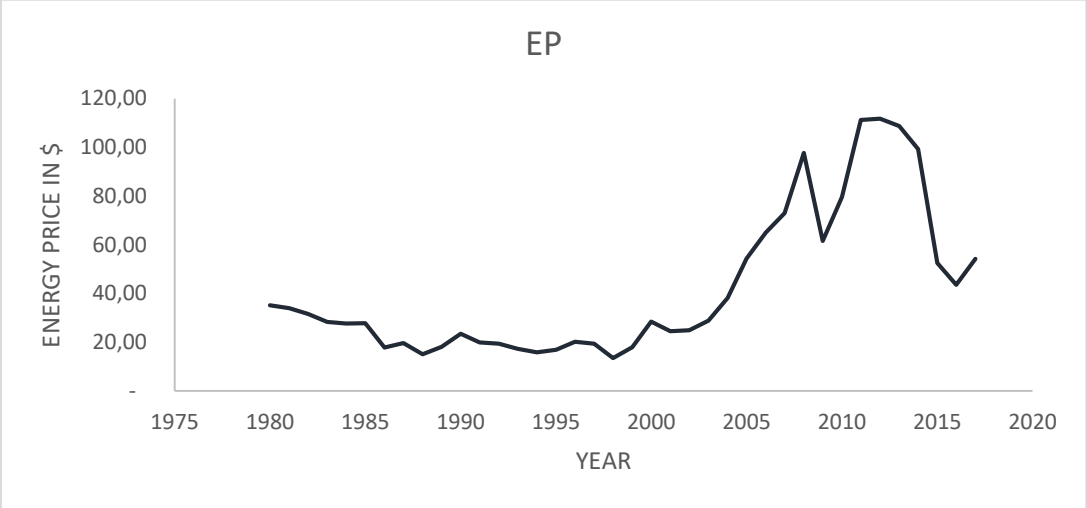
Source: World Bank Data (2020)

FDI inflows has been fluctuating from 1980 to 2017. From 1985 to 1989 the value of FDI was negative, from 1991 it started to increase positively then it began to fluctuate positively until year 2017.

2.9.3.4. Energy prices

Energy prices are the cost of energy consumed by the manufacturing industry in a year (Adom, 2020). Energy is assumed to be one of the basic input elements of enterprises, and as such energy price directly affects production. So, when energy rises, production costs rise (Li *et al,* 2017). The higher costs of energy will inspire companies to save energy through raising awareness, banning of old outdated technology and equipment and by strengthening enterprise management. The consumption of energy in the economy of South Africa has increased due to rising energy needs of the country. The manufacturing industry is the biggest consumer of energy. It consumes approximately 36% of the primary energy consumed in the country (StatsSA, 2018). The price of energy in Dollars over the reviewed period is shown in figure 2.7.

Figure 2.7 Energy Prices



Source: World Bank Data (2020)

From Figure 2.7, energy price over the reviewed period has been fluctuating. In 2008 it increased sharply and dropped sharply in 2009, again it increased in 2011 and declined gradually from 2013 to 2016. It began to increase from 2017 with a value of $54.25 per barrel.

2.10 Conclusion

Chapter two discussed the overview of the manufacturing industry as well as the energy sector. During the analysis, the study found the manufacturing industry is still one of the important industries in the economy of South Africa as it contributes to the overall GDP and employment. The most dominant sectors of the industry are metals and machinery (22.1%), food and beverages (20.1%) and chemicals and petrochemicals (13.9%). These three (3) sub-sectors alone compose approximately 60% of the total manufacturing industry of South Africa. Despite this, the industry's contribution to GDP over the years has declined. For instance, the industry's contribution to GDP between 1994 and 2012 declined from 20.9% in 1994 to 12.4% in 2012, with the industry currently holding the 4th position in terms of its contribution to GDP contributing about 13.53%. With regards energy consumption patterns, the study found that the manufacturing industry consumes more energy as compared to the other sectors of the economy with coal and electricity as the most consumed energies.

The chapter also discussed the overview of the energy sector, taking into account energy demand and supply, energy sector legislation as well as energy intensity in the world and

in South Africa. During the analysis it was found that the country's energy supply is dominated by coal which is used as primary energy and for producing electricity. With regards to energy legislation, the chapter discussed the different Acts and policies governing the energy sector under the National Energy Regulator (NERSA). Furthermore, under energy intensity and efficiency it was found that different economies have implemented several policies with the aim of improving energy efficiency. With these policies the different economies have recorded a decline in overall energy intensity. When it comes to South Africa, the country's energy intensity has been fluctuating over the years and currently standing at 8.5MJ per dollar of GDP measured at purchasing power parity basis. With regards to the determinants of manufacturing energy intensity, manufacturing value added has been declining steadily over the reviewed period. Whilst the other determinants have been fluctuating some gradually, others sharply. For instance, FDI has been fluctuating sharply whereas, energy prices and trade openness has been fluctuating gradually.

Chapter Three

Literature Review

3.0. Introduction

Chapter 3 discusses the literature review taking into account theoretical and empirical literature relating to energy intensity and the manufacturing industry. Section 3.1 discusses the theoretical literature; section 3.2 discusses the empirical literature; and section 3.3 concludes the chapter.

3.1. Theoretical literature

The different theories that are discussed in this section include the energy demand theory, decomposition theory and the endogenous growth theory.

3.1.1. The energy demand theory

The energy demand theory was developed by Beenstock and Dalziel (1989). It is based on the assumption that the demand for energy occurs for several reasons. For industries, energy is seen as an input which maximises production and hence, aims to minimise production costs. It assumes that in the production process the producer will try to combine various inputs to help minimize production costs. For instance:

$$Q = K, E \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots \; 3.1.$$

Where, Q is output, K is units of capital and E represent units of energy. The production function shows that the producer uses capital and energy to produce output and as such the total production costs would be $K + E$ respectively.

Further, the energy demand theory suggests that in the long and short run the demand for energy is decomposed by many factors (Evans and Hunt, 2009). These factors include economic structure, the technological change, the effect of energy prices on the structure, efficiency and utilization of deployed capital and the influence of policy. Based on this theory each of these factors influence energy intensity. With regards to economic structure, the theory suggests that the progression of an economy implies it will become focused on service and will require less amount of energy, leading to a decline in energy intensity. With regards to technological development the assumption is that the deployment of energy efficient capital will lead to a decline in energy requirement for a

particular level of output, thus allowing for expansion in economic activity without increasing energy demand. This means that as industrialisation grows energy efficiency can be achieved by the development of new technologies.

The influence of structural changes on energy intensity can be illustrated as follows:

Suppose there is a three sector economy (A, I and S) where total consumption is given by the sum of energy across all sectors, $E = E_A + E_I + E_S$. The energy intensity in each sector i is given by ${E_I}/{Y_i}$. Where Y_i is the output of sector i. Total output is given as $Y = Y_A + Y_I + Y_S$. Thus, total energy intensity can be illustrated as

$$\frac{E}{Y} = \frac{E_A + E_I + E_S}{Y} \dots\dots\dots\dots\dots\dots .3.2.$$

$$= \frac{E_A}{Y_A}.\frac{Y_A}{Y} + \frac{E_I}{Y_I}.\frac{Y_I}{Y} + \frac{Y_I}{Y_S}.\frac{Y_S}{Y} \dots\dots\dots .3.2$$

$$= \frac{E_A}{Y_A}.\theta_A + \frac{E_I}{Y_I}.\theta_I + \frac{E_S}{Y_S}.\theta_S \dots\dots\dots\dots\dots 3.3$$

Where

θ_i is the sector i share of capital output. Thus, energy intensity is the share-weighted sum of energy intensity of each sector. By definition $\theta_A + \theta_I + \theta_S = 1$

Suppose that energy intensity of each sector is given as follows:

$$\frac{E_A}{Y_A} < \frac{E_S}{Y_S} < \frac{E_I}{Y_I} \dots\dots\dots\dots\dots .3.4$$

It follows that if sector I grows faster than sector A, holding the output share of sector S constant, energy intensity will increase. The increase in energy intensity can be shown as

$$\frac{d(E/Y)}{d\theta_I} = -\left(\frac{d\theta_A}{d\theta_I}.\frac{E_S}{Y_S} + \frac{E_S}{Y_S}.\frac{d\theta_S}{d\theta_I}\right) + \frac{E_I}{Y_I} > 0 \dots\dots\dots\dots 3.5$$

Equation 3.5 is positive because

$$\left|\frac{E_A}{Y_A}.\frac{d\theta_A}{d\theta_I} + \frac{E_S}{Y_S}.\frac{d\theta_S}{d\theta_I}\right| < \frac{E_I}{Y_I} \dots\dots .3.6$$

Which follows from the fact that $E_A/Y_A < E_S/Y_S < E_I/Y_I$ and $\Delta\theta_A + \Delta\theta_S + \Delta\theta_I = 0$

In this case the impact on energy intensity on the aggregate shift to industry is positive. It can also be shown in a similar manner that growth in less energy intensive sectors results in decreasing energy intensity.

With regards to technology, the equation can be shown as follows,

$$\frac{E}{Y} = \frac{u_A/\varepsilon_A . K_A}{Y_A} . \theta_A + \frac{u_I/\varepsilon_I . K_I}{Y_I} . \theta_I + \frac{u_S/\varepsilon_S . K_S}{Y_S} . \theta_S \ldots\ldots\ldots\ldots\ldots 3.7$$

Equation 3.7 shows that an upsurge in energy efficiency in any sector i through the adoption of new technology result in a decline in energy intensity of sector i. This is apparent by differentiating equation 3.7 with respect to energy efficiency in sector i.

$$\frac{d(E/Y)}{d\varepsilon_I} = -\frac{u_A/\varepsilon_A . K_I}{Y_I} . \theta_I < 0 \ldots\ldots\ldots\ldots\ldots 3.8$$

In this case, the impact of technological change will have a great impact if it occurs in the sector with the largest total output.

Worth noting, is that the decline in energy intensity does not mean that the demand for energy declines, rather it implies that energy growth is slower than that of output. The shortcoming with this theory is that it does not explain anything about structural breaks and location shifts which can play a considerable role in explaining a given process. Also, the theory takes into account the cost of capital as an explanatory variable of energy demand. One disadvantage of this is that it is almost difficult to find the exact cost of capital data for non-oil manufacturing even if a proxy is used it can result in biased results.

Another challenge with this theory is that technological change which is captured by the technique effect is influenced by other factors which are not directly related to energy intensity. As such, it would be difficult to control technological progress implicit in energy efficiency. It would also be difficult to control technological progress which is above and beyond normal trend related to economic development (Benthen and Romani, 2009). In this context, if technology is linked to income growth, then the estimated income elasticity would include the associated technological change. Also, there is a challenge when it comes to explicit technology data availability, especially with models that rely on long time series data for many countries.

3.1.2. The decomposition theory

The decomposition approach was developed by Grossman and Krueger (1993) and was backed up into a formal theory by Antwieler *et al* (2001) and further elaborated by Copeland and Tylor (2003). It is based on the assumption that changes in energy demand arises from different factors such as economics changes, structural changes and technological changes (Bhattacharyya, 2011). The decomposition model determines the contribution of these effects to changes in energy consumption i.e. to separate the effects of improvements in energy use from structural shifts of the economy. It can distribute variables between industries in an aggregate indicator to predefined factors also known as decomposition results. According to Bhattacharyya (2011) structural changes in the economy reduce energy consumption. Such that, the intensity effect captures the role of changing intensities in the sectors. The major determinants of energy intensity are explained by technical energy efficiencies, product mix of certain industries and changes in the use of fuel as a result of different levels of efficiencies involved in conversion. From the theory of Antwieler *et al* (2001) fluctuations in such factors can be interpreted as scale effects i.e. the impact of an increasing or decreasing economic activity, technique effects i.e. implementation of a more energy-efficient technology and composition effects i.e. impact of producing relatively more energy-intensive products due to sectoral changes.

Different decomposition techniques include the index decomposition analysis; the structural decomposition analysis and the production theoretical-decomposition. (Chontanawat *et al,* 2014). All of these have different theoretical foundation, methodological and application features. In the context of energy, index decomposition models the impacts of energy emission intensity, structural intensity and total activity intensity. Structural decomposition models analyse regional/ emissions disparities from an economic systems perspective whereas production theoretical decomposition models reveal the impacts of production efficiency and technology on energy/emissions. The model is expressed as follows:

$$D_{tot} = D_{str} \times D_{int} = \frac{I_t}{I_0}$$

$$D_{str} = Exp \sum_{i}^{n} \left[\frac{L\left[w_{i,t}, w_{i,0}\right]}{\sum_{i}^{n} L\left[w_{i,t}, w_{i,0}\right]} ln \left[\frac{S_{i,t}}{S_{i,0}} \right] \right] \ldots\ldots\ldots\ldots 3.9 \text{ (a)}$$

$$D_{int} = Exp \sum_{i}^{n} \left[\frac{L[w_{i,t}, w_{i,0}]}{\sum_{i}^{n} L[w_{i,t}, w_{i,0}]} ln \left[\frac{I_{i,t}}{I_{i,0}} \right] \right] \ldots\ldots\ldots 3.9(b)$$

$$L[w_{i,t}\ w_{i,0}] = \frac{w_{i,0} - w_{i,t}}{ln \left[\frac{w_{i.0}}{w_{i,t}} \right]} = \frac{\frac{E_{i,0}}{E_0} - \frac{E_{i,t}}{E_t}}{\left[\frac{\frac{E_{i,0}}{E_0}}{\frac{E_{i,t}}{E_i}} \right]} \ldots\ldots\ldots 3.9(c)$$

$$S_i = \frac{y_i}{y}$$

Where:

D_{tot} = total change of energy intensity in year t relative to the reference year

D_{str} = change of total energy intensity due to structural change effect

D_{int} = change of total energy intensity due to the change of energy intensity of individual sub-sectors

S_i = ratio of output of sub-sector i to the aggregate output

Decomposition theory has several strengths; one of them is that it provides aggregate measures that capture energy efficiency trends (Liu and Ang, 2001). Another strength is that it is noticed for its contribution to the development of energy efficiency indicators, such as those appropriate for sustainable development. The theory also allows the researcher to further relate the overall trends with policy measures that have been taken whereby, the success of these measures can be evaluated.

Despite the fact that vast amount of literature has employed this approach there are shortcomings related to it. Energy economists argue that countries differ when it comes to their energy use of factors such as different technologies, different energy prices, and different factor endowments. As such ignoring these may lead to bias estimates (Medlock III *et al*, 2001).

3.1.3. The New endogenous growth theory

The new growth theory is incorporated in the study because it is believed that for the manufacturing industry to be energy efficient it needs to invest more in new technologies and research and development (Romer, 2012). The new growth theory or endogenous theory was set forth by Paul Romer in 1986 and Robert Lucas in 1998. It involves four

variables namely labour (L), capital (K), technology(A) and output (Y) and is set in continuous time. It incorporates technological progress and advances in knowledge as endogenous factors within the growth model because it is believed that technological innovations are the result of conscious investment decisions taken by entrepreneurs and individual firms. The theory is based on the assumption that there are two sectors, a goods-producing sector where output is produced and an R&D sector where additions to stock of knowledge are made. The quantity of output produced at time t is therefore:

$$Y(t) = [(1 - a_k)K(t)] \propto [A(t)(1 - a_L)L(t)] \propto -1, \qquad 0 <\propto< 1 \ldots\ldots\ldots 3.10$$

Equation 3.10 entails that constant returns to capital and labour; with given technology, doubling the inputs doubles the amount that can be produced. As discussed above the endogenous theory includes technological progress and improvements in knowledge in addition to capital and labour as endogenous factors within the growth model. This implies that investment in technology, capital and knowledge can stimulate long–term growth in per capita income. Also, increasing returns to scale and positive investment economies leads to improved growth rate especially in sectors with advanced technology. Moreover, the theory views technology as an endogenous factor that is associated with energy, because technology is dependent on whether energy is available or not (Odularu and Okonkwo, 2009). The technology referred to here is plants and machinery amongst others. An inadequate supply of energy will mean that these technologies are useless. Also, the technology is used to convert energy from its raw state into usable state and this process is technological oriented. This implies that energy at whatever level it is being utilized, it is important.

One of the greatest strengths of the Endogenous theory over the Neoclassical theory is that it includes technological innovation and improvements in knowledge as endogenous within the growth model (Gilpin and Gilpin, 2001). While the neoclassical model builds on only two factors of production namely capital and labour without technology. Another strength is that it views the economy as oligopolistic because of increasing returns to scale, cumulative processes, or some other market imperfections.

Despite its strengths, the New growth theory has been criticized by economists (Gilpin and Gilpin, 2001). One of the biggest criticisms of the endogenous growth theory is that it cannot be validated with empirical evidence. There are arguments that the theory makes

contentious assumptions without robust evidence. Also, as argued by Rosenberg (1998) technology is not a simple commodity that can be easily measured.

3.2. Empirical literature

Previous studies on energy intensity and the manufacturing industry have emphasised the significant relationship between structural effects of the industry, energy policies, technological advancements or improvements, capital intensity and energy intensity. Empirical literature in the study is categorised as follows; (i) grouped countries; (ii) developed countries; (iii) developing countries; and (iv) literature on South Africa.

3.2.1. Literature from grouped countries

Miketa (2012) employed the fixed effects model on ten manufacturing industries in thirty-nine countries for the period of 1971 and 1996 they found gross fixed capital formation to have the most effect on aggregate energy intensity when compared to sector economic activity and industrial energy prices and the effect according to the author was stronger where sectoral output was larger. Miketa (2012) also argued that the size of an industry in some way affects energy intensity change. In the EU, the growth of gross domestic consumption and final energy consumption per capita were found to positively affect energy intensity. Also, the price of electricity had the biggest impact on energy intensity implying that there is a need to consider the structure of this determinants.

Similarly, Petrovića *et al* (2017) conducted a study using panel data samples for the period of 1995 to 2015 in the European Union. During their analysis they found that gross fixed capital formation and industrial value added were found to be positive and statistically significant in all thirty-six estimated baseline regressions. On the other hand, real per capita GDP and oil retail prices were found to have a negative and statistically impact on energy intensity in all 36 estimated empirical model.

Gerstlberger *et al* (2016) found that the most technologically innovative firms in the European manufacturing sector were more energy efficient. This according to the authors was because energy efficient technologies were closely related or linked to product innovation. As a result, firms who invested more on technology were most likely to experience a decline in production costs, green-house gases and energy use. The study employed the logistic regression model for time series data from the period of 2006 to 2008 for 2573 firms.

Kepplinger *et al*, (2013) conducted a study on cross country analysis, for 163 countries employing panel data from the period of 1963 to 2009 using the mixed-effect model. The model included fixed effects for the intercept, gross domestic product, population and for time given developmental status. Uncorrelated random effects i.e. country specific effects were included for the intercept, gross domestic product, population and time. They found that energy intensities of industrial sectors decreased around the world. In particular, industrialized countries with higher value of GDP (gross domestic product) per capita had lower energy intensity indicating that efficiency in energy use is achieved along with the technological advancement. Countries with higher GDP and smaller population had lower energy intensity values and a lower energy intensity index. In leading developing economies including Brazil, China and India industrial growth was not always achieved in energy efficient manner. Industrial expansion was often made with increasing energy intensity. China stood out from these other countries as it drastically reduced energy intensity by a very steep increase in manufacturing value added.

In a similar way Parker (2015) maintained that technological efficiency effect was a main driver for the reduction in manufacturing energy intensity in the OECD whereas, structural effects were found to be generally complementing efficiency improvements. Parker (2015) also pointed out that rising energy prices in the OECD manufacturing sector led to improved efficiency with the effects varying across countries and sectors of the manufacturing. The methodology employed by the author is the augmented mean group estimator (AMG) on panel data from the period of 1980 to 2009.

Using the combination of index number decomposition and convergence analysis techniques Mulder (2015) conducted a study for 19 OECD countries on how and to what extent aggregate manufacturing energy intensity trends during the period 1980 to 2005. The study found that structural changes influence a significant and increasing part of manufacturing energy intensity dynamics across countries. According to the authors, manufacturing energy intensity levels were completely driven by efficiency improvements in lagging countries. However, they were weakened by a rise in international differences in sectoral structure.

Employing the decomposition analysis for panel data from the period of 1980 to 2010 Zhao *et al* (2014) found that energy intensity in the Japanese and Chinese industries declined significantly. The reduction in manufacturing energy intensity in both countries

was due to the efficient effect which showed an exponential decay. Structural effects influenced energy intensity in the Japanese manufacturing industry with little influence on the Chinese manufacturing industry. Based on their findings, the authors suggested that energy policies can have a substantial impact in reducing industrial energy intensity (Zhao *et al* 2014).

Furthermore, Pardo Martinez (2009) employed a decomposition analysis on panel data from 1998 to 2005 on a study based on Colombia and Germany manufacturing industries. Their findings revealed that aggregate energy intensity in the two countries depended on the changes by the industries that consumed more energy. The trend according to the authors was producing more while consuming less energy. Also, energy intensity during the reviewed period decreased by 12% and 6%. Further, the findings of their study revealed that organizational and intensity effects contributed to improvements in energy efficiency in Germany whilst in Colombia intensity effects had more influence over organizational effects. Energy costs and capital intensity was found to have influence on the changes in aggregate energy intensity in both countries.

Differently, Rennkamp *et al* (2017) employed the classical qualitative text-analytical method on competition coalitions with regards to politics on renewable energy and fossil fuels in Mexico, South Africa and Thailand. The database used in the study included 560 coded statements in the independent media, policy documents, and parliamentary notes in combination with 75 interviews in the period 2008 to 2015. During their analysis they found that programs and policies on renewable energy were well executed. According to the authors the way in which renewable energy technologies and incentive structure work is important in realizing energy efficiency.

Choi *et al*, (2017) investigated the association of energy intensity and the growth of a firm. They found that increased profitability of firms due to improvements on energy efficiency. Their findings revealed that energy intensity and real energy intensity affects the growth of a firm in term of profits and capital accumulation differently. This implies that firm profits in the industry club with lower real energy intensity grew faster than the six country average. Comparing the six countries, Choi *et al* (2017) found that the efficient use of energy inputs made smaller changes to firm growth in Korea. Their study employed panel regression for the period of 1991 in 21 manufacturing industries for 6 countries.

3.2.2. Literature from developed countries

In the developed countries Karimu *et al* (2016) conducted a study based on Swedish manufacturing industry using a panel nonparametric regression analysis and composition analysis. Their paper analysed the influencers of the ratio of energy to output in fourteen Swedish industrial sectors using panel data from the period of 1990 to 2008. Their findings revealed that the costs of inputs inclusive of energy prices have had substantial role in explaining energy intensity. According to the authors this can be attributed to that as the price of energy increased firms were able to use energy efficiently thus resulting to reduced energy intensity.

According to Metcalf (2008) the decline in energy intensity in the United States manufacturing sector has been attributable to mostly advances in energy efficiency as compared to shifts from industries that consume more energy to industries that consume less energy. Employing the Fisher Ideal Index decomposition and regression analysis on time series data from the period of 1970 to 2001 the author found that higher energy prices raised energy efficiency; this is through implementing efforts which may reduce the adverse effect of price on their profits by lowering the use of the now costly input.

Furthermore, Gamtessa and Olani (2018) found that the key mechanism for energy efficiency improvements in Canada was as a result of the careful employment of the most energy efficient capital from the existing vintages and investments in new energy-efficient capital. Using panel vector autoregression, cointegration and error correction techniques on times series data for the period of 1961 to 2007 the authors found that a positive shock to energy prices decreased energy capital and energy-output ratios. They also found that the elasticity of energy intensity in relation to real energy price was negative and statistically significant in the overall industries including the energy intensive and non-energy intensive industries. This according to Gamtessa and Olani (2018) was due to both adjustments in utilization and induced investment in new capital which improves capital productivity.

Employing the decomposition analysis Norman (2017) conducted a study measuring improvements in industrial energy efficiency in the United Kingdom for panel data from the period of 1997 to 2012, the author uncovered that reduced energy demand in the UK industries was due to the intensity effect which means there were improvements in energy efficiency. In the same way Song & Oh (2015) found that innovation or the introduction

of newly improved technologies in the Korean manufacturing industry was one of the factors that could be used to enhance energy efficiency in the short run. The introduction of new technologies as suggested by the authors could boost energy efficiency at production process and manufacturing facilities.

In the same way, Song & Oh (2015) found that innovation or the introduction of newly improved technologies in the Korean manufacturing industry was one of the factors that could be used to enhance energy efficiency in the short run. The introduction of new technologies as suggested by the authors could boost energy efficiency at production process and manufacturing facilities. The Probit model was adopted to estimate the effects of 8 determinants in the Korea Innovation Survey of 2008 data.

Chontanawat *et al*, (2014) found that the decline in energy intensity in the manufacturing industry in Thailand was as a result of changes in structure where, the production shares of the most energy intensive sub-sectors such as non-metallic mineral products, basic metal products, paper and paper products and food and beverages were declining and the share of the low energy intensity machinery and equipment industry increasing. Chontanawat et al (2014) used the mean divisia index decomposition analysis to compute the source of the changes of energy intensity on panel data of 9 manufacturing industries in Thailand from the period of 1991 to 2011.

Employing the Extended Divisia index decomposition on panel data Chi & Oh (2013) examined energy efficiency in 10 sub-manufacturing sectors in Korea. Their analysis was based on real energy intensity and organizational change. They found that there were improvements in real energy intensity from the period of 1981 to 2010. Also, real energy intensity was found to have had a huge impact on aggregate energy intensity when compared to structural change. The implication of this is that real energy intensity plays an important role in the short run whilst restructuring industries takes a longer time.

Ali *et al,* (2018) investigated the factors affecting energy intensity change in the manufacturing industry in Malaysia. Employing the structural decomposition for panel data from the period of 1971 to 2015, they investigated five factors contributing to energy intensity change; these are energy mix, sectorial energy efficiency, production structure, final demand structure and final demand components. Their analysis established that the demand structure factor was the most prominent factor which resulted in changes of energy intensities in the industry.

Differently, an analysis by Torrie *et al* (2015) established that the decline in total energy intensity in Canada between 1995 and 2010 was as result of inter-sector structural change in the economy i.e. the increase in contribution to total GDP of low energy-using commercial and institutional sector when compared to high energy-using manufacturing and heavy industry sectors. They also, found that the decline was associated with an overall reduction in business energy intensity and the country's GDP which grew much faster than the population. A logarithmic mean divisia index (LMD-I) method was used to decompose the annual time series data for the period of 1995 to 2010.

Moreover, according to Akbostance *et al* (2010) the changes in carbon dioxide emission in the Turkish manufacturing industry from the period of 1995 to 2001 were as a results of changes in energy intensity and economic activity. These changes vary with different periods for instance, in 1995 to 1996 energy intensity was the driving force whereas from 1999 to 2001 economic activity was the main driving force. According to the authors, these developments revealed the changes in internal production structure of the manufacturing industry, the macroeconomic conditions of the local economy as well as the changes in international energy prices.

3.2.2. Literature from developing countries

In China, Li *et al* (2017) investigated the factors influencing manufacturing energy intensity for the period of 1980 to 2014 using the VAR technique. Their findings revealed that in the short term manufacturing energy intensity is reduced by improvements in technology, GDP per capita, enterprises owned by the governments. Whereas, the rise in energy prices, result in the reduction in energy consumption in the manufacturing industry. Based on their results, the authors recommended that the energy consumption structure be optimized, energy prices be controlled and technological progress be promoted in order to reduce manufacturing energy intensity.

Tan and Lin (2018) found that the decline in energy intensity in the Chinese manufacturing sector was as a result of technological improvements and technical efficiency effect. Technological levels according to the authors were gradually improving in all the provinces of China. The technical efficiency effect was negative in some provinces of China. The study employed the index decomposition analysis together with the production decomposition analysis for time series data between 2000 to 2013 for China's most energy intensive industries.

On the other hand, Zheng *et al*, (2017) argued that even though the structure of the industry has significant impacts on energy efficiency the impact varies in the different regions of China. They however, agree with other scholars on a significant relationship between firm size and energy efficiency in the industry. This according to the authors implies that industrial structuring measures. The authors employed the panel regression model for the paper industry in 29 provinces of China for the period of 1999 to 2013.

When investigating the uneven effects of the determinants of energy intensity in Nigeria, Adom (2015) found that a positive relationship existed between the country's industry structure and energy intensity. Implying that organizational shifts towards more energy intensive sectors increases energy intensity levels. The authors also found that industry value added reduced energy intensity by 0.18. This was due to progresses in technical characteristics of the sector and change in output composition as well as intra-sectoral structural shifts.

In India Sahu & Narayanan (2010; 2011) found a positive link between industry performance and energy intensity. The authors argued that energy prices and markets somehow affect firms' decisions on how much to invest in energy saving products, equipment as well as processes. Following Porters' theory, Sahu and Narayanan (2010) made assumptions that two industries have the same input purchasing patterns, in this case the two firms consume the same source of energy as their input. As such, the performance of firms is linked to the choice of energy source used by the firm. Employing panel regression for the period of 2000 to 2008 Sahu and Narayanan (2011) analysed the drivers of profitability of companies based in three clusters of energy namely; natural gas, petroleum and coal of thirty-six Indian manufacturing industries. Moreover, based on the Porter's theory Sahu and Narayanan (2011) are of the view that firms in the industry consume different sources of energy based on the technologies that they adopt for production, implying that firms consume efficient energy sources given that they are technologically stronger than the others.

Furthermore, Sahu and Narayanan (2015) when assessing the relationship between energy use patterns and firm performance in the Indian manufacturing industry found that the relationships between profitability and energy intensity vary across groups. Industries adopting natural gas were found to be more profitable when compared to those adopting coal and petroleum gas. They also found that firms with high research and development

and capital intensive were more profitable. The study by Sahu and Narayanan (2015) employed an econometric analysis for a sample 23434 firms from 2005 to 2013. The sample was divided into three categories based on the primary energy demand namely natural gas, petroleum and coal.

Soni *et al*, (2017) found that the reduction in energy intensity in the Indian manufacturing sector was attainable through concentrating on contributing factors such as labour intensity, plant and machinery intensity, raw material intensity, outsourcing intensity, software intensity, repair intensity and technology development intensity. Of all the factors discussed it was found that labour intensity was significant for the different sectors studied in the manufacturing industry. Data sample for the study was collected from five different Indian manufacturing industries and the linear regression by stepwise method was used for analysis.

A study conducted by Sterner (2010) found that reduced energy intensity in the Mexican cement industry resulted from capital embodied technical progress, implying that developments in plan efficiency are linked to investment in new pieces of specific equipment. A short run production function was used to analyse data based on survey for 1976, 1970, 1960 and 1950. Sharing similar thoughts, Lin and Du (2014) found that change in technology and advanced capital were the main drivers of energy intensity across China's provinces in period of 2005 and 2010.

Contrariwise, Sheinbaum-Pardo *et al* (2009) argued that reduced energy intensity in the industry is not always a reflection of energy efficiency concerning changes in technology changes or material changes but was also a reflecting of changes in product production. According to the authors real energy intensity change in the Mexican manufacturing industry was as a result of product mix, implying that there was a need to re-design the products in the industry. The methodology employed by Sheinbaum-Pardo *et* al (2009) is the decomposition analysis on panel data for 15 manufacturing industries from the period of 1990 to 2008.

On another note, Adom and Kwakwa (2014) conducted a study to analyse the change in structure and characteristics of the manufacturing industry in Ghana. They employed the Engle-Granger and Philip-Quliaris cointegration test on times series data for the period 1975 to 2011. Their findings revealed that product mix changes and technical characteristics in the industries that consume less energy improved energy intensity.

They however, found that the exportation of energy intensive energy products increases energy intensity. They further, recommended that the government should formulate policies that will encourage the production of less energy intensive products.

Locmelis *et al,* (2018) used the decomposition analysis on time series data from 1990 to 2012 and found that energy efficiency in the Latvian manufacturing industry was as result of certain obligations which were adopted in the country. These obligations according to the authors required that companies perform energy audits or implement energy management systems. These management systems or energy audits were viewed as successful and cost-effective ways in which energy efficiency can be improved.

3.2.3. Literature review based on South Africa

Kwakwa and Adusah-Poku (2019) investigated the determinants of electricity consumption and energy intensity in South Africa using the ADRL for the period of 1975 to 2014. Using the determinants of income, urbanization, domestic credit and manufacturing, findings were that manufacturing activity increased energy intensity in the country. The results led to the recommendation that policymakers should pay closer attention to the manufacturing industry, by subsidizing energy efficient machines that will enable the sector to consume less energy. Stricter enforcement on the ban of importation of outdated and energy inefficient machines was encouraged by the authors.

Using the decomposition LMDI approach Olanrewaju (2017) found that the effects of activities in the in the country influenced energy dynamics leading to effect organisational structure and energy consumption by the country. Thus, increasing the country's industrial energy consumption. Similarly, a study conducted by Adom (2014) using the decomposition analysis approach revealed that industry value added and FDI inflows were the main determinants of energy intensity in the long-term. Implying that continuous structural shifts are most likely to reduce energy intensity in the future. FDI inflows reduced energy intensity when taking into account industry characteristics and structural breaks.

Employing the Fisher Ideal Index approach when conducting a study on the empirical analysis of energy efficiency in South Africa Kohler (2012) found that developments in South Africa's energy intensity were mainly driven by the efficiency channels rather than the activity channel. This means that shifts away from industries that consume more

energy to industries that consume lesser energy. Their findings also suggested that the cost of energy resulted in lower energy intensities.

A study conducted by Theil (2016) on the energy intensity in the South African foundry in the Western Cape using energy audits on qualitative data found that the current used technologies or measures in the foundry were only able to reduce energy usage by 5% resulting in energy intensity of about 1.493ZAR/ ton. On the analysed measures they found that lighting, load shifting and demand management measures were the most cost effective solutions.

On another note, Cargill (2015) studied the role played by market based instruments in promoting energy efficiency in the South African industry. The study employed market based instruments (MBIs) to measure the drivers of environmental improvements in South Africa. They found that MBIs are a powerful tool to promote domestic industrial energy efficiency. The evaluated MBIs currently used in South Africa the s12I and S12L of the Income Tax Act 58 of 1962, Demand Side Management Programme by ESKOM and the Cogeneration Feed-in Tariff program by NERSA. However, the main shortcomings about these MBIs according to Cargill (2015) are that they fail to cover energy products such as coal and fuel oil as their main focus has been on electricity. The author also argued that the currently used MBIs although they present positive incentive to industry to implement energy efficiency projects, they are perceived as complicated, high risk of energy efficiency projects by investors and they bring about high administration costs and they contribute to higher electricity prices. The study further recommended that South Africa, adopts the MBIs used in other developed countries such as the Europe. Such MBIs include; the Restructuring the Community Framework for the Taxation of Energy Products and Electricity programme as well as the Reducing Greenhouse Gas Emissions: The Carbon Tax Option.

3.3. Conclusion

This section presented the literature reviewed in the study, it takes into account the theoretical and empirical literature. With regards to the theoretical literature the different theories discussed include the energy demand theory, decomposition theory and the new growth endogenous theory. The energy demand theory is based on the assumption that demand for energy arises for different reasons, for instance households demand energy

to meet certain needs whilst industries demand energy as an input of production (Medlock III, 2009).

The Decomposition theory identifies changes in energy demand which arises from a number of factors such as economics changes, structural changes and technological changes (Bhattacharyya, 2011). The decomposition model determines the contribution of these effects to changes in energy consumption i.e. to separate the effects of improvements in the use of energy from the structural shifts of the economy. It can distribute variables between industries in a comprehensive indicator to predefined factors also known as decomposition results.

The new growth theory by Paul Romar (1986) and Robert Lucas (1998) is included in the study because it is believed that for manufacturing industries to be energy efficient they need to invest more in new technologies as well as research and development (Romer, 2012). It takes into account four (4) variables namely capital, labour, technology and output and is set in continuous time.

The empirical literature discussed in the study is categorised as follows; (i) grouped countries; (ii) developed countries; (iii) developing countries; and (iv) literature on South Africa. Previous studies on energy intensity and the manufacturing industry have emphasised the significant relationship between structural effects of the industry, energy policies, technological advancements or improvements, capital intensity and energy intensity.

Literature from grouped countries found that technological development and structural shifts in the economy were the main reason for the decline in manufacturing energy intensity in most countries. The change was mostly visible in the industrialised countries of the world. They also, found that energy prices had a biggest impact on energy intensity implying that manufacturing firms will try by all means to save energy in order to minimise costs.

Literature from developed countries established that innovation or the introduction of newly improved technologies improved manufacturing energy intensity. Structural and sectoral shifts from more energy intensive industries to less energy-intensive industries improved energy intensity in the long term. Energy price was found to decrease energy intensity in the short term.

Literature from developing countries found that firms with high research and development, and capital embodied technical progress were found to be more energy efficient. Also, the improvements in energy intensity in these countries were as a result of production and product mix. Further, certain obligations such as energy audits or energy management system reduced energy intensity in the manufacturing industry.

In South Africa, the studies reviewed advocated for new technologies to be adopted by the different manufacturing industries. The introduction of foreign technology through FDI was found to reduce manufacturing energy intensity. Also, continuous structural shifts in the economy reduced energy intensity in the long run.

Chapter Four

Research Methodology

4.0. Introduction

Chapter 4 discusses the methodology adopted in the study. The chapter is divided into the following sections; section 4.1 presents the philosophy being followed; section 4.2 discusses the theoretical framework; section 4.3 specifies the model; section 4.4 defines the variables to be used in the study; section 4.5 discusses the expected signs of the variables; section 4.6 presents the data sources; section 4.7. discusses the estimation technique and 4.8 presents the conclusion of the chapter.

4.1. Research Philosophy (The Positivism paradigm)

A research paradigm provides guidance to the researcher in relation to philosophical assumptions about the research and in selecting the appropriate tools, instruments and methods to use in the study (Ponterotto, 2005). There are various paradigms used to guide research however, for this study the positivism (logic) philosophical paradigm is followed. This paradigm was developed in the 19th century when Auguste Comte (1798–1857) disputed that true reality was revealed by scientific knowledge thus rejecting the metaphysics philosophy (Kaboub, 2008). Positivism asserts that real events can be observed empirically and explained with logical analysis. It holds that the methods, techniques and procedures used in the natural sciences offer the best framework for investigating the social world (Chilisa & Kawulich, 2001). In the mind of the positivist the purpose of research is to predict results, test theory, find strength in relationships between variables, cause and effect relationship. Positivism emphasises that quantitative research begins with defined ideas and theories or concepts. The general methodologies used by the positivist include experiments, association, and causal comparison, quantitative and randomized control trials research (Kivunja & Kuyini, 2017). The positivism paradigm is in line with the objectives of this particular research because the purpose of this study is to test theories relating to manufacturing energy intensity for a period of 1980 to 2017. In doing this the study employs econometric techniques which helps determine the cause and effects of the variables used in the study.

4.2. Theoretical framework

The times series model is derived from the new growth endogenous theory which specifies that the growth of the economy is a result of endogenous influences (Choga, 2014). The endogenous theory includes technology and advances in knowledge, as endogenous factors within the model. The inclusion of these variables in the model is based on the assumption that firms and entrepreneurs make informed decisions to invest in modern technology (Gilpin, 2001). These firms invest in research and development in the same way that they invest in other factors of production such as energy. Based on this theory the study treats energy as one of the important inputs for the production of manufacturing output.

Following Liu *et al*, (2018) the study assumes that the cost function of the manufacturing industry is as follows:

$$Y_t = AK^{\propto}E^{1-\propto}, 0 < A < 1 \dots\dots\dots\dots\dots 4.1$$

Where E is energy input; K is capital input (both human and non-human capital); and A productivity factor. The value of A reflects the state of technology as well as the skill and education level of the workforce, which is expected to gradually increase over time. The functional form exhibits a diminishing returns to K and E that is, production is linked to reduced returns that are associated with capital if the input of energy does not increase in a parallel manner. The role of energy in production is considered as an essential input that cannot be replaced (Young-Seok and Yang-Hoon, 1996).

4.3. Model Specification

This study follows Petrovića *et al* (2018) in using the standard regression model to investigate the determinants of manufacturing energy intensity. The variables used by Petrovića *et al,* (2018) are energy intensity as the dependent variable and the explanatory variables are energy price, economic openness, industry value added, fixed asset investment structure, foreign direct investment, and technological progress. Their model is expressed as follows:

$$EI = EP + EO + IVA + FAIST + FDI + TECP + \mu \dots\dots\dots 4.2$$

Where:

$EI =$ Energy Intensity

$EP =$ Energy Price

$EO =$ Economies Openness

$IVA =$ Industrial Value added

$FAIST =$ Fixed Assets Investment Structure

$FDI =$ Foreign Direct Investment

$TECP =$ Technological Progress

$\mu =$ Captures the error term

The model employed by Petrovića *et al* (2018) involved the use of panel data for selected manufacturing firms in the European Union. This study however, employs annual times series for the period of 1980 to 2017 covering the nine sub-sectors of manufacturing in South Africa and has added trade openness in the model. Trade openness is an important variable in explaining the differences in firm level energy intensity (Fisher-Vanden *et al,* 2016). It tests how the orientation of exports in local firms affect their intensity levels. Trade openness falls under the composition effect which capture structural activity (Stern, 2004). The study assumes that improvements in energy consumption are due to reduction in inputs for a certain level of output. This implies that if energy efficiency increases, the dependent variable in this case manufacturing energy intensity is reduced. In order to capture the determinants of energy intensity in the manufacturing industry the study uses the following explanatory variables; total manufacturing value added, trade openness, foreign direct investment and energy prices.

The model is therefore specified as follows:

$$LEI_t = \beta_0 + +\beta_1 LTMVA_t + \beta_2 LTOP_t + \beta_3 LFDI_t + \beta_4 LEP_t + \mu \dots \dots \dots .4.3.$$

Where:

LEI – Logarithm of Energy intensity

$LTMAVA$- Logarithm of total manufacturing value added

$LTOP$ - Logarithm of trade openness

$LFDI$- Logarithm of foreign direct investment

LEP - Logarithm of energy prices

$\beta_{0,}\beta_1\beta_2, \beta_3, \beta_4, \beta_5$ – Coefficients

μ - Captures the error term

4.4. Definition of variables

(i) Energy intensity is the ratio between the supply of energy and gross domestic product (GDP). To calculate energy intensity, the study employs energy uses per kilogram of oil equivalent per capita, multiplied by total population divided by manufacturing value added at constant values. Energy intensity indicates the amount of energy used to produce one unit of economic output. Lower levels of energy intensity imply that less energy input is used to produce one unit of output (World Bank Database, 2020). Energy intensity is the dependent variable which is explained in the model and data for this variable was obtained from the World Bank Database in 2020.

$$EI = \frac{(EU * TP)}{MAN.VAL.AD} \dots\dots\dots\dots\dots\dots 4.4$$

Where:

EI =energy intensity

EU = Energy use per kilogram of oil equivalent per capita

TP = total population

$MAN.VAL.AD$ =manufacturing value added at constant values

(ii) Total Manufacturing value added is defined as the industry output measured after adding up all output and subtracting intermediary inputs expressed as a percentage of GDP (World Bank, 2019). It is calculated without making deductions for depreciation of fabricated assets or depletion and degradation of natural resources. Data for this variable was collected from the World Bank Database in 2019.

(iii) Trade openness (TOP) refers to the ratio of imports and exports of goods and services expressed as a percentage of GDP (World Bank, 2020). The effect of trade openness on manufacturing energy intensity emanates from the fact that enterprises in more open economies are exposed to fierce competition locally and internationally. This encourages productivity and improved energy efficiency. Also, the import of capital equipment improves technology in the local economy (Petrovića *et al,* 2018). Data for trade openness was obtained from the World Bank Database in 2020.

(iv) Foreign Direct Investment (FDI) is the net inflows of investment used to secure long-term investment interest in enterprises that operate in an economy besides that of the investor. Foreign direct investment includes all equity capital, re-investments on earnings, long term and short-term capital (World Bank, 2020). It is an important determinant of manufacturing energy intensity, as it is associated with the technique effect (Fisher-Vanden *et al,* 2016). The study employs data on foreign direct investment which was obtained from the World Bank Database in 2020.

(v) Energy price refers to the cost of energy consumed by the manufacturing industry in a year. Energy price is included in the model because it is assumed that the cost of energy will motivate industry players to implement more energy saving programmes in an attempt to avoid high costs (Li *et al,* 2017). For this variable the study uses the price of Brent crude oil expressed in dollar terms. Data on energy price was obtained from the South African Reserve Bank Database in 2020.

4.5. Expected Signs

The study hypothesises that a positive association between manufacturing energy intensity and the independent variables indicates an increase manufacturing energy intensity whereas a negative relationship indicates a decline in manufacturing energy intensity, reflecting an improvement in energy efficiency.

The study assumes that the coefficient of total manufacturing value added is positive. In theory, structural shifts in the economy are measured by changes in the share of industrial value added in GDP, which capture the composition effect and technique effects (Petrivic *et al,* 2017). Hence, the increasing share in GDP of this variable indicates above-average growth on the production of manufacturing products, including energy intensive products (Kumar and Kumar, 2013).

The influence of trade openness on manufacturing energy intensity is expected to be negative. Trade openness according to Fisher-Vanden *et al* (2016) is a significant variable in explaining differences in firm level energy intensity. It tests how the orientation of exports in local firms affect their energy intensity levels. The assumption is that improved openness to international markets and world prices improves energy efficiency for the local firms. Theoretically, trade openness falls under the composition effect (Stern, 2004). The composition effect covers changes in structural activities such as movements from

more energy intensive sectors to lesser energy intensive sectors (Hübler and Keller, 2010).

The coefficient of foreign direct investment is expected to be negative. In theory the impact of FDI on energy intensity can be decomposed into scale and technique effects developed by Grossman and Krueger (1993). By scale effect it is assumed that for constant returns to scale of production, an increase in output leads to a comparative rise in inputs of energy implying that energy intensity remains constant. Also, the impact of FDI on economic growth is expected to be positive and since economic growth is closely linked to the use of energy, the scale impact from FDI inflows is expected to be positive and its impact is dependent on the extent of the influence of FDI on GDP (Hubler and Keller, 2010). By technique effect the assumption is that FDI is expected to bring new advance technology and managerial skills to the host country resulting in improvements in firm efficiency (Petrovića *et al,* 2018). Also, it is thought that firms advanced in technology activity have greater adaptive capacities and hence may be exposed to foreign technologies. Therefore, the link between FDI and technology is expected to reduce manufacturing energy intensity.

Energy is assumed to be one of the basic input element of enterprises, and as such energy price directly affect production, implying that the rise in energy prices will increase production costs (Li *et al,* 2017). The higher costs of energy will inspire companies to save energy through raising awareness on energy saving, improve their technology and do away with old outdated technologies and reduce energy consumption by strengthening enterprise management. Hang and Tu (2007) found that the rising costs of energy throughout China have helped to induce energy savings in that country. In light of this, a negative coefficient of energy price is expected, implying that higher costs of energy are likely to reduce manufacturing energy intensity.

4.6. Data Sources

The study employs annual time series data for the period of 1980 to 2017. Data is obtained from World Bank, South African Reserve Bank and Statistics South Africa databases.

4.7. Estimation Technique

The technique chosen for the study is the Vector Error Correction model (VECM) which combines both levels and differences. The VECM is a restricted Vector Auto Regressive

(VAR) for variables that become stationary after differencing (Greene, 2012). The advantages of employing the VECM technique is that it allows for any cointegrating relationship among the variables and there are no restrictions in the short run dynamics of the empirical model (Hyndman and Athanasopoulos, 2018). This implies that there won't be constraints in the effects of structural disturbances on the variables in the short run. It also establishes both short and long run causality and the resulting VAR from VECM representation has more efficient coefficient estimates. The use of this technique is not unique to this study as it was previously employed by Li *et al* (2017) when conducting a study on factors influencing change of manufacturing energy intensity in China. The steps involved when running the VECM are discussed in the next section.

4.7.1. Step 1: Descriptive statistics

Descriptive statistics is a term used in data analysis. It describes, shows and summarises data in a more meaningful way such that patterns emerge from the data (Leard Statistics, 2020). According to Fabozzi *et al* (2010) descriptive statistics uses visuals and computers to transform data into quantities that show the essentials of interest. To allow for easy grasp of information visual support in a form of tables, graphs and statistics is used. The centre and location in descriptive statistics is expressed using three different measures namely; the mean, mode and median (Trochim and Donnelly, 2011). Of these measures, the commonly used in descriptive statistics are the mean and median.

Descriptive statistics also uses measures of variation and these are used to capture the way in which data is spread in absolute terms and relative terms Fabozzi *et al* (2010). The commonly used measures are absolute deviation, standard deviation (variance) and skewness. Absolute deviation is the average deviation of all data from some reference value. In this case the deviation is measured from the mean. Similar to the absolute deviation, the standard deviation measures the deviations from the mean. The only difference is that it averages both the absolute and squared deviations. The standard deviation can be defined using an equation as follows:

$$s = \sqrt{\frac{1}{n-1}\sum_{i-1}^{n}(x_i - x^{-})^2} \ldots\ldots\ldots\ldots\ldots\ldots\ldots 4.5$$

The unit of the standard deviation correspond to the original units of data and is defined to be a positive square root of the variance.

Skewness is the last measure of variation and the most commonly used is the Pearson skewness. The Pearson skewness is computed as follows;

$$Sp = \frac{3(m_d - \bar{x})}{s} \ldots\ldots\ldots\ldots\ldots\ldots 4.6$$

Where m denotes the median. The skewness is different from the other measures in that it can obtain both positive and negative values. For data whose mean is different from the median hence, located either to the right or left, the data are skewed.

4.7.2. Step 2: Pairwise Correlation Analysis

Correlation according to Gujarati and Porter (2010) measures the strength of a true relationship in the variables. The variables are treated symmetrically such that there is no discrepancy between the explained and explanatory variables as the variables are expected to be random. Brooks (2014) puts it this way, if it is stated that y and x are correlated, it implies that y and x are being treated in a similar way. Suggesting that changes in y do not cause change in x. Rather it means that there is evidence for linear relationship between the two variables and that movements in the variables are on average related to an extent given by the correlation coefficient.

Pair wise correlation can be measured using the correlation coefficient which can be computed as follows:

$$r = \sqrt[\pm]{r^2} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 4.7$$

$$r = \frac{\sum x_i y_i}{\sqrt{(\sum x_i^2)(\sum y_i^2)}}$$

$$= \frac{n\sum X_i Y_i - (\sum X_i)(\sum Y_i)}{\sqrt{[n\sum X_i^2 - (\sum X_i)][n\sum Y_i^2 - (\sum Y_I)]}} \ldots\ldots\ldots\ldots 4.8$$

With the properties of r discussed as follows:

(i) it can be positive or negative

(ii) it lies between $-1$and $+1$, that is,$-1 \leq r \leq 1$

(iii) it is symmetrical nature; that is, the coefficient of correlation between X and Y (rXY) is the same as that between Y and $X(rYX)$

(iv) it is independent of the origin and scale

(v) if X and Y are statistically independent, the correlation coefficient between them is zero

(vi) it is a measure linear association or dependence only and it does not imply any cause and effect relationship.

A high pair-wise correlation among regressors may suggest that a multicollinearity problem exists. Pairwise correlation can be presented in a correlation matrix table as will be shown in the next chapter.

4.7.3. Step 3: Testing for unit root/ Stationarity

According to Gujarati and Porter (2010), a stationary times series has a mean, variance and auto-variance that does not change over time. The properties of the series are not dependent on the time under observation. In other words, shocks in a stationary series will slowly fade away, implying that a shock in time t , will have a minimal effect in time $t+1$, a smaller effect in time $t+2$ and the next periods. Thus, times series whose properties have trends are considered to be non-stationary since the trend and seasonality will affect the value of the times series at different times.

If two independent variables are regressed with each other, then the *t*-ratio on the slope coefficient would not be significantly different from zero. Also, the R^2 value would be very low. However, if two random variables trend over time, the regression of one variable on the other would result in a high R^2 even if there is no relation in the variables (Brooks, 2014). Further, if the variables used in a regression model are not stationary then the standard assumption for asymptotic analysis would be invalid (spurious regression) implying that the usual *t*-distribution and the *F*-statistic will not follow an *F*-distribution.

There are informal methods that provide useful guidance about whether a times series stationarity or not (weak dependence). The autoregressive average AR (1) model, suggests that if $|\rho_1| < 1$, then the process is $I(0)$, but if $\rho_1 = 1$ then it is $I(1)$. A week stationary series according to Hyndman and Athanasopoulos (2018) is integrated of order zero or $I(0)$ which means nothing needs to be done to such series before using them in regression analysis. One the other hand, random walk (unit root) with or without a drift are said to be integrated of order one or $I(1)$ and such a series is often said to be a difference-stationary process.

Most macro-economic variables face problems of non-stationarity and as such, differencing the series until stationary is advised as a possible solution by most

econometricians (Nissan, 2009). Differencing the series helps to stabilise the mean by eliminating the changes in the level of the time series and removing the trend (Hyndman and Athanasopoulos, 2018). Simply put, if a non-stationary series y_t is differenced (d) times before it becomes stationary then it is said to be integrated of order (d). Applying the difference operator more than d times with $I(d)$ variable will result in a stationary series.

Testing for unit root implies that the null and alternative hypothesis need to be specified appropriately in order to characterise the trend properties of the data in use. If the data under observation does not show an increasing or decreasing trend, then the appropriate null or alternative hypotheses should indicate this. The basic objective of the test is to examine the null hypothesis that $\phi = 1$ against the one sided alternative $\phi < 1$. The study presents the hypothesis for unit root testing as follows:

$H0$: series contains a unit root

$H1$: series is stationary

Unit root tests are given by the following equation:

$$Y_t = \rho Y_{t-1} + u_t \dots\dots\dots\dots\dots\dots\dots\dots\dots\ 4.9$$

Where:

$-1 \leq \rho \leq 1$

u_t - White noise error term.

If $\rho = 1$ then the series is not stationary and the null hypothesis cannot be rejected (Gujarati and Porter 2010). However, if $\rho < 1,$ then the time series under observation is considered to be stationary and the null hypothesis will rejected respectively.

To test for unit root the study employs the formal Augmented Dickey Fuller and the Phillip Peron unit root tests. However, before employing these formal tests, informal graphical analysis will be plotted first. This provides for a preliminary analysis which gives an idea of structural breaks, trends and stationary data set (Choga, 2014).

4.7.3.1. Augmented Dickey Fuller test

As discussed above one way of testing for unit root is by employing the Augmented Dickey Fuller Test named after its discoverers Dickey and Wayne Fuller (1979). The standard DF test is based on the following model:

$$Y_t = \beta_0 + \beta_1 Y_{t-1} + y_t + u_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 4.10$$

Rewritten as

$$\Delta Y_t = \beta_0 + (\beta_1 - 1) Y_{t-1} + y_t + u_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 4.11$$

Where: $\Delta Y_t = y_t - y_{t-1}$

Y_t – is the relevant time series

Δ -represents the first difference operator

t –is the trend variable which takes the values of 1, 2 and 3

$\beta_1 Y_{t-1}$ –represents the one period lagged value of the variables *Y* respectively.

According to Gujarati and Porter (2010) if the coefficient of $Yt - 1$ is zero then, the time series is not-stationary. This implies that it becomes stationary after differencing and as such is called difference stationary. One property of the Dickey-Fuller test is that the disturbance term is not auto-correlated Nilsson (2009). If the error term is auto-correlated then more lagged values of yt need to be included on the right hand side of the equation.

Rewriting equation 4.11 brings about the Augmented Dickey Fuller (ADF) model as follows:

$$\Delta Y_t = \beta_0 + (\beta_1 + \beta_2 - 1) Y_{t-1} + y_t + u_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 4.12$$

The ADF model is used to test whether a time series is affected by transitory or permanent shocks, it tests the null hypothesis that $(\beta_1 + \beta_2 - 1) = 0$, implying that the series exhibit unit root or it is non-stationary. The null hypothesis is tested against the alternative hypothesis that $(\beta_1 + \beta_2 - 1) < 0$, implying that the series is stationary and in this case the Δ denotes the first difference of time series y_t (Milsson, 2009). The null hypothesis is rejected if the p-value is below 5% indicating that the series is stationary.

4.7.3.2. Phillip Peron Unit Root test

The Phillip- Peron test similar to the ADF test estimates the null hypothesis of first order integration. It was named after its discoverers Phillips (1987) and Peron (1988). The PP includes an automatic correction to the DF procedure to allow for auto-correlated residuals (Brooks, 2014). According to Hoque and Banerjee (2014) the PP test takes into account heteroscedasticity and autocorrelation using the non-parametric method. Thus,

they argue that the PP carries more weight when compared to the ADF test under a range of circumstances.

The Philip-Peron test can be illustrated as follows:

$$\Delta Y_t = \rho Y_{t-1} + u_t \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots 4.13$$

Where:

Δ = first difference operator

Y_t = higher order

Y_{t-1} = endogenous

The PP test is conducted under the following hypothesis

$H0$:series contains unit root

$H1$:series is stationary

The null hypothesis is rejected if the p −value is less than 5% which indicates that the series is stationary.

4.7.4. Step 4: Lag length selection criteria

The VECM test entails that the proper lag length be determined and this can be achieved in different ways. For instance, E-views offers different values information criterion and other methods for determining the lag order (Brooks,2014). These include the Akaike information(AIC), Schwartz (SIC) and the Hannan-Quinn criterion as discussed below.

4.7.4.1. Akaike Information Criterion

The AIC is defined by Gujarati and Porter (2010) using an equation as follows

$$AIC = e^{2\frac{k}{n}} \frac{\sum \hat{u_i^2}}{n} = e^{2\frac{k}{n}} \frac{RSS}{n} \dots\dots\dots\dots\dots\dots 4.14$$

Where k is the number of regressors which include the intercept and n is the number of observations. Equation 4.14 can be rewritten as follows

$$lnAIC = \frac{2k}{n} + ln\frac{RSS}{n} \dots\dots\dots\dots\dots\dots\dots 4.15$$

Where $AIC =$ natural log of AIC and $2k/n$ = penalty factor. The AIC imposes a harsher penalty when compared to the R^2. In other words, when making comparisons for two or more models, the one with the lowest value of AIC is preferred. The advantages of using

the AIC when compared to other criterion is that it can be used in-sample and out-of-sample forecasting.

4.7.4.2. The Schwarz Information Criterion (SIC)

Similar to the AIK the SIC can defined using an equation as follows

$$SIC = e^{2\frac{k}{n}} \frac{\sum \hat{u_i}^2}{n} = e^{2\frac{k}{n}} \frac{RSS}{n} \dots\dots\dots\dots\dots\dots 4.16$$

or in log form as

$$lnSIC = \frac{2k}{n} \ln n + ln\frac{RSS}{n} \dots\dots\dots\dots\dots\dots .4.17$$

Where $[(k/n)ln\,\mathrm{n}]$ is the penalty factor. The SIC imposes a harsher penalty when compared to the AIC. Similar to the AIC the lower the value of the SIC the better the model.

4.7.4.3. The Hannan-Quinn

The Hannan-Quinn information criterion (HQC) is defined by Enders (2014) as a measure of goodness of fit of a statistical model. The HQC is related to the AIC criterion and it presents a penalty term for the number of parameters in the model like the AIC. The penalty of the HQC is larger than the AIC one. It can be illustrated using an equation as follows

$$HQC = n * \ln\frac{RSS}{n} + 2 * k * \ln(\ln n) \dots\dots\dots\dots\dots 4.18$$

Where n is the number of observations; k is the number of model parameters and; RSS is the residual sum of squares. A lower value of the HQC is preferred over other models and the lower value implies that there is either fewer explanatory, better fit or both.

4.7.5. Step 5: Cointegration Test

Step 3 discussed the different types of unit root tests. This implies that if the variables under study are found to be stationary or to have no unit root even after differencing, the study will then proceed to test for cointegration. Cointegration is detected if two variables have a long run or equilibrium relationship amongst them i.e. the manner in which the variables move together (Gujarati and porter,2010).

Cointegration can be shown as follows:

$$Y_t = \alpha + \beta X + \mu \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 4.19$$

Implying that;

- If both Y and X are stationary, the classical or OLS is valid and there is no need for cointegration test.
- If Y and X are integrated of different orders, the regression is said to be nonsensical.
- If Y and X are integrated of order one $I(1)$ and the residuals are non-stationary, then there exists spurious regression
- If Y and X are integrated of order one or $I(1)$ and residuals are stationary, then there is cointegration.

Several techniques are proposed in literature and these amongst others include the Engle-Granger (1987) or Augmented Engle-Granger test which is used to assess whether a single-equation estimates of the equilibrium errors seem to be stationary (Greene, 2012). However, for the purpose of this study the Johansen cointegration test is employed. The Johansen was introduced by Johansen test (1988, 1991) and is based on the VAR approach (Greene, 2012).The advantages of using the Johansen technique as compared to other techniques is that it tests the hypothesis about one or more coefficients in the cointegrating relationship by observing the hypothesis as a restriction on the Π matrix (Brooks, 2014). It also allows for the estimation of an error correction and is able to eliminate simultaneous equation bias as opposed to single equation methods (Mpatane, 2015). The Johansen cointegration test requires that the variables under study be stationary at the same level, that is, at first difference. In other words, if the variables are stationary at levels then the Johansen is not the appropriate technique to be used (Brooks, 2014).

4.7.5.1. Deterministic components in cointegration model based on the Pantula Principle Test

Before determining the cointegrating vectors, we first need to determine the deterministic elements of the model i.e. whether the deterministic components are a constant term or time trend (Hubana, 2013). In order to determine the trends components, the Pantula Principle test proposes by Johansen (1992) is used in the study. Based on the Pantula principle test, there are five (5) different assumptions when applying the Johansen cointegration model, in accordance with E-views software package.

Option one assumes that there is no deterministic trend in the data or in the cointegrating relations; option two is based on the assumption that a linear trend exists in data but only in intercept; option three allows for linear trend in data and intercept in cointegrating relation; option four assumes that there is a linear trend in data while intercept and trend exist in cointegrating equations; option five (5) assumes that linear trends are present in both the cointegrating relation and in the model. In practice option 1 and 5 are not used hence option 2 to 4 is considered, with option 2 considered as the most restrictive and option 4 the less restrictive. The Pantula principle test estimates all 3 options from the most restrictive hypothesis that is option 2 to the least restrictive one being option 4. The rank statistic is compared with its critical value and the model is estimated until the null hypothesis is not rejected.

4.7.5.2 Johansen Cointegration test

The Johansen cointegration test is based on the likelihood estimation of the VAR system and it gives estimates of all cointegrating relationships that may exist in a vector of non-stationary variables. It is centred around investigating the Π matrix which can be deduced as a long run coefficient matrix since in equilibrium all the Δy_{t-i} will be zero (Brooks, 2014).The Johansen methodology takes its starting point in the vector auto-regression (VAR) of order p given by

$$y_t = \beta_1 y_{t-1} + \beta_2 y_{t-2} + \cdots + \beta_k y_{t-k} + u_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 4.20$$

Where $y_t$is an $nx1$ vector of variables that are integrated of order one commonly denoted $I(1)$ and ε_t is an $nx1$ vector of innovations.

The Johansen cointegration test requires that the VAR equation 4.20 be turned into a vector error correction model (VECM) as follows:

$$\Delta y_t = \Pi y_{t-k} + \Gamma_1 \Delta y_{t-1} + \Gamma_2 \Delta y_{t-2} + \cdots + \Gamma_{t-(k-1)} \Delta y_t + u_t \ldots\ldots\ldots\ldots\ldots 4.21$$

Where $\Pi = ((\sum_{i-1}^{k} \beta_i) - I_g$ and $\Gamma_i = (\sum_{j=1}^{i} \beta_j) - I_g$

From equation 4.21 y_t is an nxl vector of variables that are integrated of the 1st order I(1) and u_t is an nxl vector of constants. If the coefficient matrix Π has reduced rank $r < n$, then there exist nxr matrices $\propto$ and β each with rank r such that $\Pi = \alpha\beta'$ and $\beta' y_t$ is stationary, r is the number of cointegrating relationships, the elements of $\propto$ are known as

the adjustment parameters in the vector error correction model (VECM) and each column of β is a cointegrating vector. It can be shown that for a given r, the maximum likelihood estimator of β defines the combination of y_{t-1} that yields the r largest canonical correlations of Δy_t with y_{t-1} after correcting for lagged differences and deterministic variables when present (Hjalmarsson and Osterholm, 2007).

There are two test statistics proposed by the Johansen approach namely; trace and maximum eigenvalue test as shown below:

$$\lambda_{trace}(r) = -T \sum_{i-r+1}^{g} \ln\left(1 - \acute{\lambda}_{\iota}\right) \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots 4.22$$

And

$$\lambda_{max}(r, r+1) = -T\ln\left(1 - \hat{\lambda_{r-1}}\right) \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots 4.23$$

Where T is the sample size; r is the number of cointegrating vectors under the null hypothesis; $\acute{\lambda}_{\iota}$ is the estimated value for the *i*th ordered eigenvalue from the Π matrix. This means that the greater the λ is, the larger and more negative will be the $\ln\left(1 - \acute{\lambda}_{\iota}\right)$ and hence, the greater is the test statistic. Each eigenvalue is linked to a different cointegration vector which will be eigenvectors. A significant non-zero eigenvalue indicates a significant cointegrating vector (Brooks, 2014).

λ_{trace} is a joint test where the null means that the number of cointegrating vectors is less than or equal to r against an unspecified or general alternative that there are more than r . It starts with p eigenvalues, then successively the largest is removed. $\lambda_{trace} = 0$ when $\lambda_{\iota} \acute{=} 0$, for $i = 1, \dots, g$.

λ_{max} conducts separate tests on each eigenvalue and has its null hypothesis that the number cointegration vectors is r against the alternative of $r + 1$.

Johansen and Juselius (1990) provided these two test statistics with critical values which depend on the value of the $g - r$ (Brooks, 2014). From the Johansen's tables the null hypothesis that there are r cointegrating vectors is rejected if the test statistic is larger than the critical value. This is in favour of the alternative hypothesis that there are $r + 1$ for (λ_{trace}) or more than r for (λ_{max}). The Johansen test is conducted in a sequence

under the null of no cointegrating vectors which corresponds to Π having zero rank, $r = 0,1, \ldots, g-1$ so that the hypotheses for λ_{max} are

$$\begin{array}{c} H_0: r = 0 \text{ versus } H_1: 0 < r \leq g \\ H_0: r = 0 \text{ versus } H_1: 0 < r \leq g \\ H_0: r = 0 \text{ versus } H_1: 0 < r \leq g \\ \vdots \qquad\qquad \vdots \\ H_0: r = 0 \text{ versus } H_1: r = g \end{array}$$

Failure to reject the null hypothesis, would mean that there are no cointegrating vectors and the test would be completed. But, if the $H_0: r = 0$ is rejected that there is one cointegrating vector, $(H_0: r = 1)$ would be tested. The value of r will be increased repeatedly until the null is no longer rejected.

4.7.6. Step 6: Vector Error Correction Model (VECM)

If the variables are found to be cointegrated then it is proper to proceed to the next step which is the Vector Error Correction Model (VECM) likelihood of VAR. The first step in running a time series data is to determine if the data under review are stationary or not. If they are not, then the series needs to be differenced and the VAR needs modification so that there is consistency in the estimation, hence the VECM.

The vector error correction model (VECM) is simply a restricted VAR for variables that become stationary after differencing. The reason behind using this technique is that it allows for any cointegrating relationship in the variables, it explicitly includes the lagged error correction term (Brooks, 2014). It also, applies probability estimation to a vector error correction (VEC) model that simultaneously determine the long run and short run determinants of the dependent variable in the model.

In order to insert the concept of cointegration in the VAR framework, suppose that all individual variables are $I(1)$ or $I(0)$, the dimensional VAR (p) process without deterministic terms is therefore,

$$y_t = A_1 y_{t-1} + \cdots + A_1\, y_{t-p} + u_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ 4.24$$

Subtracting y_{t-1} on both sides of the equation and rearranging yields to the following VECM model

$$y_t = \Pi y_{t-1} + \Gamma 1\, \Delta y_{t-1} + \Gamma p - 1\, \Delta y_{t-p+1} + u_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ 4.25$$

Where: $\Pi = -(I_K - A_1 - \cdots - A_p$

and $\Gamma = -\left(A_{i+t} + - \cdots + A_p\right), i = 1, \ldots\ldots, p-1$

The only non-stationary model is y_{t-1}.

The Vector Error Correction Model can also be estimated as follows:

$$Y_t = \Pi y_{t-1} + \sum_{i-1}^{p-1} \Gamma \mathrm{i}\ \Delta y_{t-1} + B_{xt} + \varepsilon \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ 4.26$$

$$\Pi = \sum_{i-1}^{p} Ai - I, \Gamma \mathrm{i} = -\sum_{j=i+1}^{p} Aj \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ 4.27$$

Where: y_t is the key vector of non-stationarity $I(1)$ variables; x_t is the d-vector of the variables and ε is the vector innovation. From Granger's representation if the coefficient matrix Π has a reduced rank$r < k$, then there are $k * r$ matrices α and β each with rank r such that Π=$\alpha\beta'$ and βy_t is $I(0)$ and r is the number of cointegrating vectors. The elements of the α are known as the adjustment parameters in the VEC model.

4.7.7. Step 7: Impulse response function

The impulse response function is used to describe the effect of information impulse of a standard size of deviation from a random disturbance towards variables' current and future value (Li *et al,* 2017). It traces out the response of current and future values of each variable to a unit increase in the current value in one of the VAR errors (Brooks, 2014). As such, a unit shock is separately applied to the error of each variable in each equation and the effects upon VAR system over time are noted. For instance, if there are g variables in a system, a total of g^2 impulse responses could be generated. The impulse response function can show changes in the path of dynamic effects in the variables. The basic thoughts of the impulse response function can be analysed through VAR model (2) of two variables:

$$\left.\begin{matrix} x_t = 0_1 y_{t-1} + p_1 x_{t-1} + p_2 x_{t-2} + \varepsilon_{1t} \\ y_t = m_1 x_{t-1} + m_2 x_{t-2} + n_1 y_{t-1} + \varepsilon_{2t} \end{matrix}\right\} t = 1,2 \ldots T \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 4.28$$

The random term ε in equation 4.28 is called new innovation, implying that if ε changes it will influence both the variables of x and y in the future through the current value. Hence, the impulse response function attempts to describe the trajectory of these effects.

4.7.8. Step 8: Variance decomposition

Variance decomposition refer to the variations of each variable in the system that are decomposed into the sum of all the random shocks according to its origin Li *et al* (2017). They offer a slight different method for examining the VAR system dynamics (Brooks, 2014). Variance decomposition analysis provides separate deviations in the endogenous variable in the component shock in the VAR through the size of variance distribution; it can measure the significance of random disturbances towards the variable (Gujarati and Porter, 2010). They give the proportion of the movements in the dependent variables that are due to their own shocks as opposed to shocks of other variables. For instance, a shock of the *i*th variable will directly affect that variable, but it will also be transmitted to all of the other variables in the system through the dynamic structure of the VAR. Variance decomposition analysis can be expressed as follows:

$$y_{it} = \sum_{j=1}^{k} \left(\mu_{ij}\varepsilon_{jt} + \mu_{ij}\varepsilon_{jt} + \mu_{ij}\,\varepsilon_{t-2\,.} + \cdots .\right) i = 1,2, \ldots k; t = 1,2, \ldots T \ldots\ldots\ldots\ 4.29$$

From equation 4.29 the sum of the disturbance term ε_j from the infinite past to present moment is the effect of $\varepsilon_j$towards y_i.

4.7.9. Step 9: Diagnostic tests

After estimating the VECM it is important to test for the validity of the assumptions which underlie the model under study. This is done to test whether the multiple classical linear regression model assumptions hold and hence when one or more assumptions fail the inference might be misleading. This means that the model might need to be re-specified using a different method, depending on the exact nature of the misspecification (Karanasos, 2015). Model misspecification in regression analysis can create consequences that have detrimental impact on the sampling properties of both estimators and test. Econometric literature thus, puts emphasis on the procedures used for investigating the quality of the model's specification i.e. diagnostic checks (DeBenectis and Giles, 1996). The various diagnostic tests used in literature can be presented in the context of the classical multiple linear regression model as follows:

$$y_t = \beta' x_t + \varepsilon_t, t = 1 \ldots, T \ldots\ldots\ldots\ldots\ldots 4.30$$

or

$$y_t = \beta_1 + \beta_{2t}x_{2t} + \beta_{3t}x_{3t} + \cdots + \beta_{kt}x_{kt} + \varepsilon_t \ldots\ldots\ldots\ldots\ 4.31$$

It is important to note that when running diagnostic tests, the error term is assumed to follow the assumption of stationary processes. This means that the residuals are white noise (Kin, 2012). This study employs the normality test (Jarqua-Bera test), serial correlation tests, heteroscedasticity test and stability test as discussed in the next section.

4.7.9.1. Normality tests

The assumption of normality is expressed as;

$$\varepsilon_t \sim (0, \delta^2), or \left({}^{y_t}/_{x_t}\right) \sim N(\beta' x_t, \delta^2) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 4.32$$

If the above assumption does not hold during regression analysis, then the Ordinary Least Square estimator is said to be Best Linear Unbiased Estimator (BLUE). This implies that it remains consistent however, not to the maximum likelihood estimator which can only be defined if a particular distribution is specified for y_t. The study employs the Jarque Bara test.

4.7.9.1.1. Jarque-Bera (JB) Test of Normality

The Jarque-Bera test follows an asymmetrically chi-square distribution (Gujarati and Porter, 2010). It is based on OLS residuals and computes the skewness and kurtosis measures of OLS residuals. It is specified using the following test statistic:

$$JB = n\left[\frac{S^2}{6} + \frac{(K - 3^{2)}}{24}\right] \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 4.33$$

Where n = sample size, S = skewness coefficient, and K = kurtosis coefficient. For a normally distributed variable, $S = 0$ and $K = 3$. For normality test, the null hypothesis is specified as follows:

H_0: Normally distributed

H_1: Not normally distributed

The Jarque-Bera statistic will have a 0 statistic and if the computed *p* value of the JB statistic in an application is sufficiently low then the null hypothesis is rejected. This happens if the if the value of the statistic is very different from 0. However, if the *p* value is reasonably high, which happens if the value of the statistic is close to zero then the null hypothesis of normality is not rejected (Gujarati and Porter, 2010).

4.7.9.2. Serial correlation

Auto-correction occurs in time series studies where the errors associated with observation in a given time series period to carry over into future time periods (Gujarati and Porter, 2010). Serial correlation in residuals imply that they contain information which itself needs to be modelled and this is the consequence of having non-stationary variables or data manipulation (Makuria, 2013). The effects of such will result in an unreliable VAR model estimate. Therefore, it is imperative that the VAR models in the study are free from serial correlation.

The assumption of no serial correlation is presented as follows:

$$E(\varepsilon_t \varepsilon_\delta) = 0, t \neq \delta \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 4.34$$

Whereas, the presence of serial correlation can be expressed as follows:

$$E(\varepsilon_t \varepsilon_\delta) \neq 0, t \neq \delta \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 4.35$$

Hence the following hypothesis is formulated:

H_0: No serial correlation

H_0 : Series is correlated

If the $p-$ value is above 5% significance then it means there is not serial correlation and the null hypothesis of null hypothesis of no serial correlation is not rejected.

4.7.9.3. Heteroscedasticity

The classical linear regression assumes that the variance of the error terms is constant, i.e. the assumption of homoscedasticity symbolically is shown as;

$$E\ (u_i^2) = \sigma^2 \ \ i = 1,2 \ldots\ldots n \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 4.36$$

Heteroscedasticity occurs when the variance of the conditional regression error terms u_t are not constant, this implies that the error terms in the model are not homogenous (Brooks, 2014). It can arise due to the existence of outliers i.e. observations that are very different (either small or large) in relation to the observations in the sample; data manipulation by means of interpolation or extrapolation such as incorrect data transformation and incorrect functional form; as well as skewness in the distribution of one or more regressors included in the model (Gujarati and Porter, 2010). Heteroscedasticity is shown symbolically as follows;

$$E\ (u_i^2) = \sigma_i^2 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 4.37$$

4.7.9.3.1. White heteroscedasticity test

There are various tests for heteroscedasticity however, this study employs the most commonly used White heteroscedasticity test which tests for residuals where least squares exist. It is named in honour of its developer White (1980). The reason behind using the White heteroscedasticity test in this study is that it makes a few assumptions about the likely form of the heteroscedasticity (Brooks, 2014). The regression is run as follows; step 1 involves OLS estimation; step 2 run the supporting equations; step 3 obtaining the R^2 and; step 4 which is the last step rejects or accepts the null hypothesis.

The hypothesis for this test is formulated as follows;

H_0 No heteroscedasticity

H_1 Heteroscedasticity

If the p −value is above 5% significance the null hypothesis cannot be rejected, implying that the no heteroscedasticity.

4.7.10. Step 10 Stability tests

In regression modelling there is an assumption that the pattern of data on the dependent and independent variables remain the same throughout the entire period which the data is collected. However, with regression models involving time series data this assumption may not hold because the regressors and the regressand do not remain the same through the entire period (Gujarati and Porter, 2010). As such, in addition to the diagnostic residuals the study performs stability tests on VAR models. The reason stability tests are used in the study is to ensure that estimated parameters of all VAR models remain constant over time. There are two important types of stability tests namely, the cumulative sum CUSUM and the cumulative sum of squares CUSUMQ tests.

4.7.10.1. The Cumulative Sum of Recursive Residuals (CUSUM) test

The CUSUM statistic test is based on a normalised version of the cumulative sums of the residuals. It is tested on the null hypothesis of perfect parameter stability, implying that should the residuals fall outside the standard critical lines then the null hypothesis is rejected and the statistic is taken as evidence of parameter instability. It is also worth mentioning that many residuals are included in the sum because the expected value of the disturbance is always zero (Brooks 2014).

4.7.10.2. Cumulative Sum of Squared Recursive Residuals (CUSUMSQ) test

The CUSUMQ test is found on the normalised version of the cumulative sums of squared residuals based on the null hypothesis of parameter stability. As such, the null is rejected should the standard error bands lie outside the bands and will be considered as evidence of parameter instability (Brooks, 2014). The CUSUMSQ starts at 0 end the sample with a value of 1.

4.8. Conclusion

The purpose of the preceding chapter was to specify the procedures involved when investigating the determinants of energy intensity in the South African manufacturing industry. The Vector Error Correction Model (VECM) is the chosen technique to be used for estimation in the study reason being, it is easy to use, understand and it has ability to incorporate the residuals from past observations amongst its many advantages over other alternatives. Descriptive statistics as well as pairwise correlation among the variables under study were discussed. In order to avoid spurious regression, the variables in the study are tested for unit root using the Augmented Dickey Fuller and the Philip Peron tests. The Johansen likelihood estimation of the VAR system cointegration approach is used to test if a long run relationship amongst the variables exists. Based on the cointegration approach, the vector error correction model (VECM) which provides information on the long run and short run relationship between variables is estimated. Through the impulse response function and the decomposition analysis the model is tested for its ability to respond to shocks. Further, the estimated series undergo diagnostic checks such as the normality test, serial correlation, heteroscedasticity and stability tests.

Chapter Five

Empirical Results Presentation and Analysis

5.0 Introduction

This chapter presents empirical results obtained using the Vector Error Correction Model (VECM) estimation procedure on annual data for the period 1980 to 2017. Section 5.1 of the chapter reports on descriptive statistics results; section 5.2 reports on pairwise correlation results; section 5.3 presents unit root results obtained using informal graphical illustrations as well as the formal Augmented Dickey Fuller (ADF) and Philip Peron (PP) tests; section 5.4. presents cointegration results obtained using the Johansen test; section 5.5. presents VECM results; section 5.6. presents impulse response analysis; section 5.7. presents variance decomposition analysis; section 5.8. presents diagnostic tests results; section 5.9. presents the stability test results and section 5.10. presents the conclusion of the chapter.

5.1. Descriptive Statistics Results

The study first runs a descriptive statistic test. This is done in order to understand the way in which the data is distributed. Descriptive statistic tests are run on the natural values of the variables, not the logged values and the results are presented in Table 5.1.

Table 5.1 Descriptive Statistics

	EI	EP	FDI	TMVA	TO
Mean	0.384211	42.00605	0.904211	17.42053	52.62632
Median	0.390000	28.37500	0.510000	17.78000	51.54000
Maximum	0.430000	111.8000	5.980000	22.61000	72.87000
Minimum	0.300000	13.48000	-0.770000	11.60000	37.49000
Std. Dev.	0.029190	30.32126	1.263377	3.589110	8.328615
Skewness	-1.071577	1.194631	2.046863	-0.357350	0.112453
Kurtosis	4.566652	3.135925	8.175918	1.745976	2.499716
Jarque-Bera	11.15855	9.067821	68.95213	3.298672	0.476373
Probability	0.003775	0.010739	0.000000	0.192177	0.788056

Sum	14.60000	1596.230	34.36000	661.9800	1999.800
Sum Sq. Dev.	0.031526	34017.01	59.05653	476.6234	2566.536
Observations	38	38	38	38	38

From Table 5.1 the mean values for the different variables are as follows; for EI is 0.3842; for EP is 42.00605; for FDI is 0.904211 for TMVA is 31.99789 and for TOP is 52.62632. The median values for the variables are as follows; for EI is 0.39000; EP is 28.37500; FDI is 0.51000; TMVA is 29.62000; TOP is 51.54000.

The maximum in Table 5.1 indicates the highest value. For EI is 0.430000; EP is 111.8000; FDI is 5.98000; TMVA is 45.28000 and TOP is 72.87000. Whereas, the minimum in the Table indicates the lowest value. For EI is 0.30000; EP is 13.480000; FDI is -0.770000; TMVA is 26.03000; TOP is 37.49000. This means that the variables with the highest value is energy price, followed by manufacturing value added, trade openness, then foreign direct investment and energy intensity. The variables with the minimum value is foreign direct investment, followed by energy intensity, then energy price, manufacturing value added and trade openness.

Standard of deviation measures the deviation of the variables from the mean. A high standard deviation implies that the data points are spread over a large range of values; whereas, a low value indicates that the data points are spread closer to the mean. For EI the standard deviation is 0.029190; for EP is 30.32126; for FDI is 1.263377; for TMVA is 5.721883 and for TOP is 8.328615. This means that for the values of energy intensity, foreign direct investment, total manufacturing value added the data points are spread closer to the mean. Whilst for energy price and trade openness the data points are spread over a large range of values.

From Table 5.1 the variables present different values of skewness. The skewness value for EI is -1.071577; for EP is 1.194631; for FDI is 2.046863; for TMVA is 0.747745 and; for TOP is 0.112453. Based on these results, TMVA and TOP are moderately skewed because their values lie between 0.5 and 1; whilst EI, EP and FDI are highly skewed because their values are greater than -1 or 1. This implies that the distribution has a long left tail for EI and for EP and FDI the distribution has a long right tail.

For a normal distribution the Kurtosis value should not exceed the value of 3. In this case however, the Kurtosis value for EI is 4.566652; for EP is 3.135925; for FDI is 8.175918; for TMVA is 2.207118 and for TOP is 2.499716. From these results only the values for TMVA and TOP depict normal distribution since they are lower than 3. Whereas, for EI, FDI and EP the values are greater than 3 which indicates that distribution is peaked or leptokurtic.

The Jarque-Bera test results presented in Table 5.1 show that TMVA and TOP are normally distributed. The critical value for TMVA is 4.536494 with a p-value of 0.103493 and for TOP is 0.476373 with a p-value of 0.788056. With regards to the other variables, the probability values are significant indicating that they are not normally distributed. For EI the critical value is 11.15855 with a p-value of 0.003775; for EP the critical value is 9.067821 with a probability value of 0.010739; for FDI the critical value is 68.95213 with a probability value of 0.0000. The presence of normal distribution in TMVA and TOP implies that the null hypothesis of normal distribution is not rejected. Whereas, for the other variables the null hypothesis is rejected indicating that the variables are not normally distributed and the results simply show how the data is spread before their logged form.

5.2. Pairwise Correlation results

One way of determining the relationship for each of the variables is by conducting a pairwise correlation test. The pairwise test is used to determine the degree of association of the variables under study and the results are presented in Table 5.2.

Table 5.2. Pairwise correlation matrix

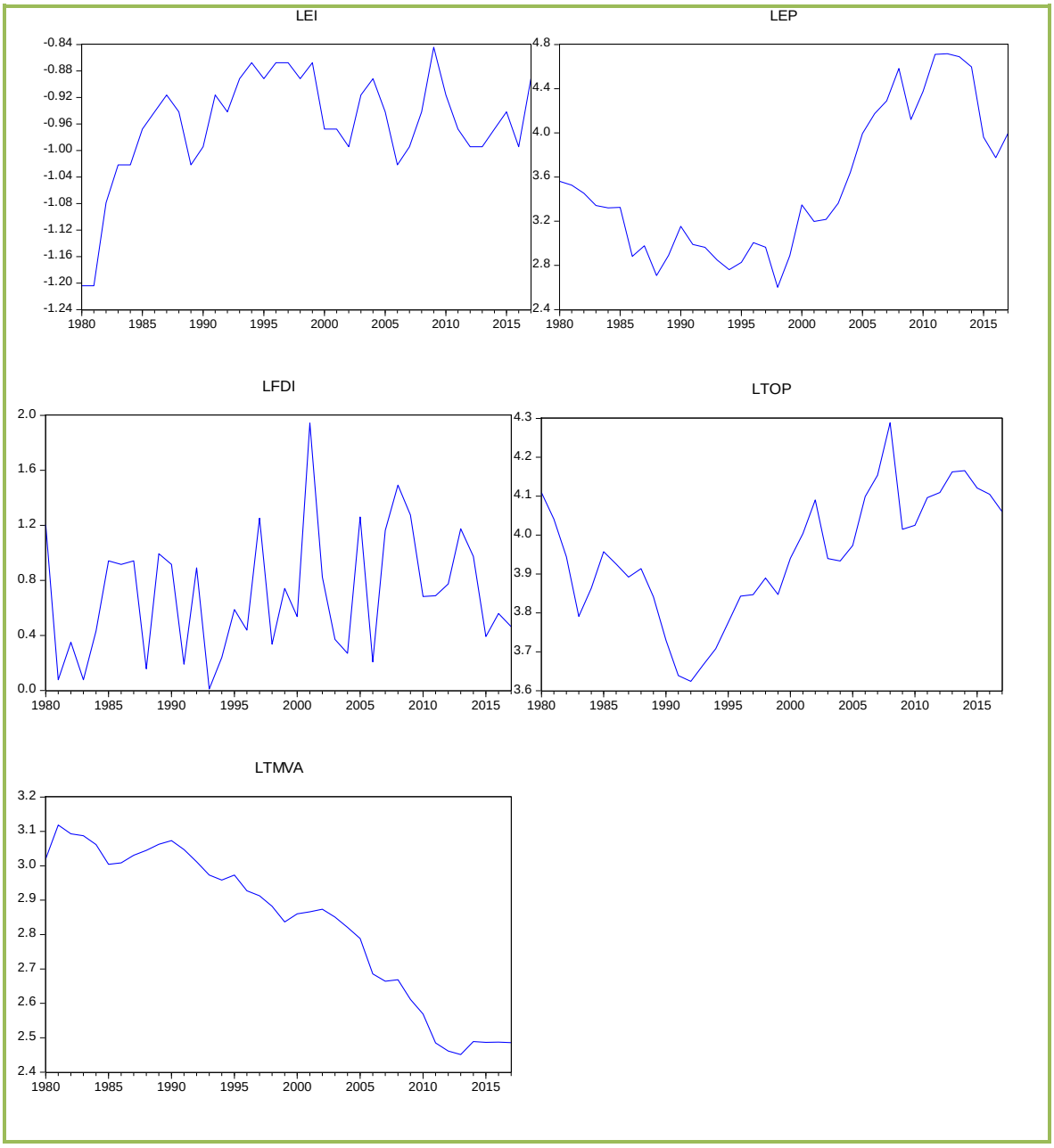
	LEI	LEP	LFDI	LTMVA	LTOP
LEI	1.000000	-0.078134	0.210709	-0.116119	-0.518283
LEP	-0.078134	1.000000	0.079887	-0.013300	0.256533
LFDI	0.210709	0.079887	1.000000	0.624625	-0.030870
LTMVA	-0.116119	-0.013300	0.624625	1.000000	0.341429
LTOP	-0.518283	0.256533	-0.030870	0.341429	1.000000

From the results presented in Table 5.2 all the variables except for LFDI are negatively correlated with energy intensity which is the ratio of energy used to produce a unit of manufacturing output. The positive and negative correlation of LFDI and TMVA with energy intensity is not in line with the theoretical assumptions made in the study. The other variables namely LEP and LTOP are negative and conform to the theoretical assumptions made in chapter 4. The implication is that a linear association or dependence between the variables and energy intensity exist. The variable of trade openness falls under the composition effect which covers changes in structural activities. With regards to energy prices, the assumption is that higher energy costs will inspire companies to raise of awareness through energy saving programs in order to manage costs. Therefore, a unit increase in energy prices will lead to a reduction in energy intensity and; a unit increase in trade openness will lead to a reduction in energy intensity. Furthermore, as discussed in the previous chapter, pairwise correlation is used to assess the presence of multicollinearity. The presence of multicollinearity is detected if the values of the explanatory variables are too high say close to 100. From the results presented in Table 5.2 the highest value is 51.83 % which is not too high. This suggests that the presence of multicollinearity is not detected and the variables are suitable for estimation. As such, we can proceed to check for the presence of unit root which is the next step.

5.3. Unit Root Tests

The first step in estimating the VECM is by testing whether the variables in the study are stationary or not. As discussed in the previous chapter, this is done to avoid spurious regression or illogical results. Before estimating the formal unit root tests informal graphical presentations of the variables are estimated at levels and difference forms as shown in Figure 5.1(a) and (b).

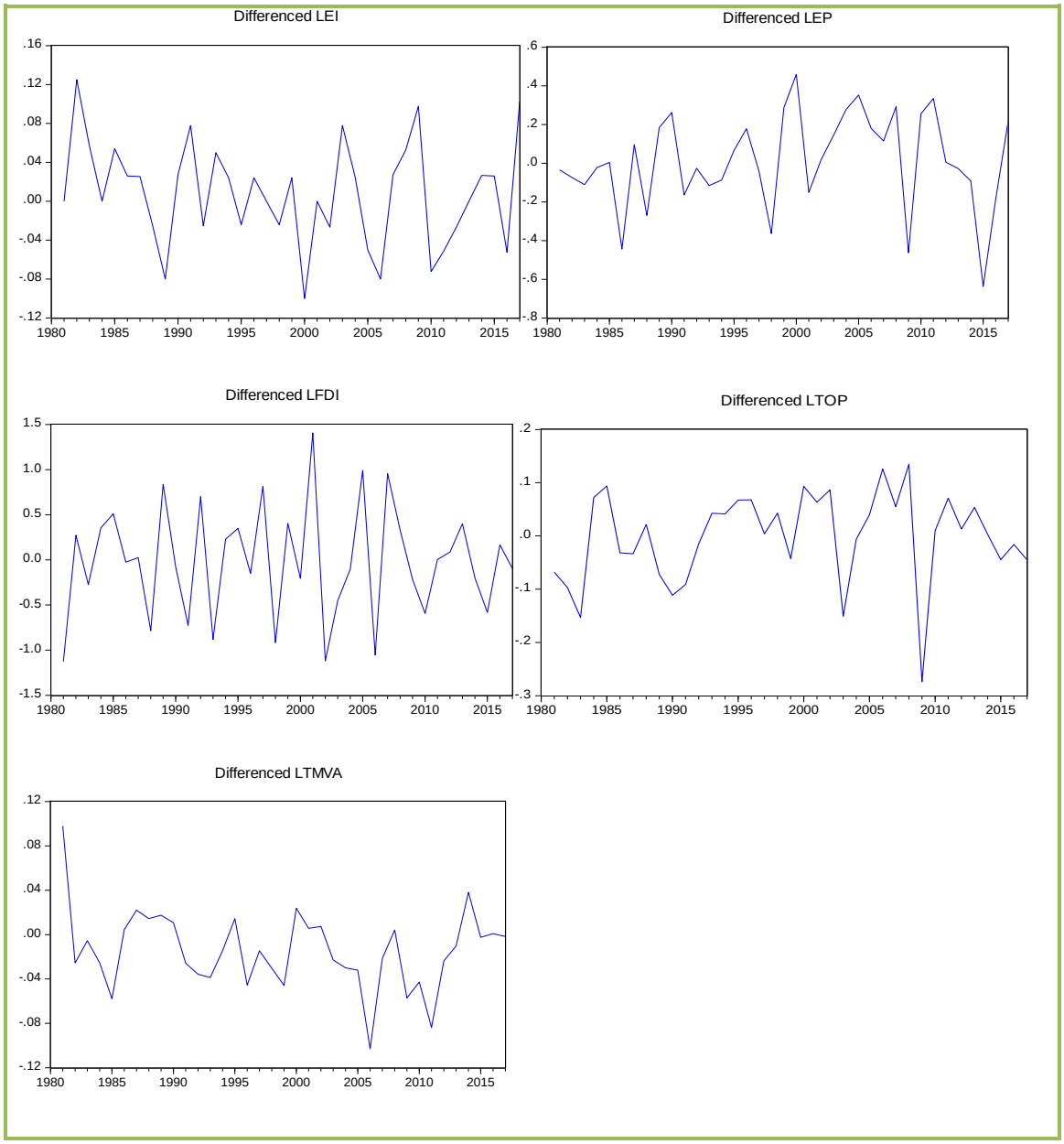
Figure 5.1(a) Informal unit root test at levels



Source: E-views output

Figure 5.1(a) shows that LEI, LEP LFDI, LTMVA and LTOP show a trend behaviour. This means that the variables have a growth trend, implying that the variance, mean and covariance are not constant over time. In other words, they are not stationary and as such they need to be differenced.

Figure 5.1(b) Informal unit root test at first difference



Source: E-views output

In order for one to determine if the data is stationary, the plots of the graphs are expected to fluctuate around a zero mean. Figure 5.1(b) indicates that the variables vary around a zero mean. In other words, the mean, variance and covariance are constant over time, implying that the data is stationary after first differencing. It is worth noting however, that conclusions on stationarity of the variables cannot be based on the informal presentations only. In light of this, formal tests such as the Augmented Dickey Fuller and the Philip Peron test are adopted and the results are presented in Tables 5.3 (a) and (b) respectively.

5.3.1. Augmented Dickey Fuller test (ADF)

Table 5.3(a) ADF Test

Variables	AFD-LEVELS			ADF1st Difference	
	Model	**t-stats**	**p-value**	**t-stats**	**p-value**
LEI	Intercept	-3.569957*	0.0114	-5.582096***	0.0001
	Trend and intercept	-3.348606*	0.0743	-5.566419***	0.0003
	None	-1.219927	0.2000	-5.422080***	0.0000
$LTMVA$	Intercept	-0.484933	0.9839	-5.776391***	0.0000
	Trend and intercept	-1.759464	0.7032	-5.568506***	0.0003
	None	-2.429467	0.1065	-4.697518***	0.0000
$LTOP$	Intercept	-1.716466	0.4149	-5.472288***	0.0001
	Trend and intercept	-2.914501	0.1698	-5.449078***	0.0004
	None	-0.161626	0.6211	-5.552126***	0.0000
$LFDI$	Intercept	-2.938596**	0.0025	-5.310333***	0.0000
	Trend and intercept	-3.345423**	0.0137	-6.060326***	0.0001
	None	-1.366705	0.1564	-10.46569***	0.0000
LEP	Intercept	-1.012994	0.7386	-5.473088***	0.0001
	Trend and intercept	-2.044136	0.5587	-5.440079***	0.0004
	None	0.102135	0.7090	-5.539853***	0.0000

10%(*), 5%(**), 1%(***) level of significance

The ADF unit root test results presented in Table 5.3 (a) using trend, trend and intercept and none show that most of the variables are not stationary at levels, except for EI and FDI. EI is stationary at 10% level of significance under trend, trend and intercept whereas, FDI is stationary at 5% level of significance under intercept as well as intercept and trend. This means that at levels the null hypothesis of unit root is not rejected for all the variables except for EI and FDI.

At first difference all the variables become stationary at 1% level of significance. Based on these results the null hypothesis of unit is rejected and it can be concluded that the variables are stationary at first difference.

5.3.2. Philip Peron (PP) Unit root test

Table 5.3 (b) PP Test results

Variables	**PP-LEVELS**			**PP 1st Difference**	
	Model	**t-stats**	**p-value**	**t-stats**	**p-value**
LEI	Intercept	-5.312845*	0.0613	-5.441801***	0.0001
	Trend and intercept	-3.859326	0.2420	-5.581473***	0.0003
	None	-1.450327	0.1350	-5.348015***	0.0000
$LTMVA$	Intercept	-0.489332	0.9839	-5.776391***	0.0000
	Trend and intercept	-2.769675	0.2168	-5.568506***	0.0003
	None	-2.233986*	0.0264	-4.808063***	0.0000
$LTOP$	Intercept	-1.794406	0.3774	-5.535514***	0.0001
	Trend and intercept	-2.870511	0.1832	-5.586016***	0.0003
	None	-0.166816	0.6192	-5.634200***	0.0000
$LFDI$	Intercept	-2.945906*	0.0766	-3.48335***	0.0001

	Trend and intercept	-3.487595*	0.0263	-3.73820***	0.0000
	None	-2.454672**	0.0015	-4.74949***	0.0000
LEP	Intercept	-1.035976	0.7301	-5.473088***	0.0001
	Trend and intercept	-2.087614	0.5355	-5.440079***	0.0004
	None	0.088942	0.7049	-5.539853***	0.0000

10%(*), 5%(**), 1%(***) level of significance

The PP results shown in Table 5.3. (b) derived from trend, trend and intercept and none indicate that most of the variables are not stationarity at levels expect for EI, TMVA and FDI which are stationary at 10% significant level under intercept and none. This implies that the rest of the variables contain unit root and thus the null hypothesis cannot be rejected. At first difference the results show that all the variables are stationary at 1% significant level and the null hypothesis of unit root is rejected respectively. The stationarity of the variables implies that the next step to test for cointegration using the Johansen test.

5.4. Johansen Cointegration Testing

5.4.1. Determining the order of integration

The cointegration test is conducted to determine if there is a long run or equilibrium relationship among the variables. The first step in running the Johansen test is by selecting the lag length.

5.4.2. Lag length selection criteria

For lag selection this study uses the lag length criteria and the results of the test are presented in Table 5.4(a).

Table 5.4(a) Lag length selection criteria

Lag	LogL	LR	FPE	AIC	SC

0	71.81140	NA	1.68e-08	-3.711745	-3.491811
1	183.4207	186.0156	1.39e-10	-8.523374	-7.203775*
2	211.8167	39.43890*	1.25e-10*	-8.712041*	-6.292776

From Table 5.4(a) the lag length chosen by most criterion is lag 2 and this lag was chosen based on the AIK, FPE and LR. After determining the lag length, the next step is to determine the trend assumption based on the Pantula Principle test.

5.4.3. Determining the trend assumption (The Pantula Principle Test)

As discussed in the previous chapter, E-views has five models from which the trend assumption can be made and from these only models 2 to 4 are of interest. Model 1 and 5 are however, not supported by theory. As such, the study employs models 2 to 4 starting with the most restrictive model to the least restrictive model as shown in Table 5.4(b) and (c).

Table 5.4 (b) Pantula Principle test based in the trace test

R	**n-r**	**Model 2**		**Model 3**		**Model 4**	
		Trace test statistic	**Critical values**	**Trace test statistic**	**Critical values**	**Trace test statistic**	**Critical values**
0	4	90.45973*	69.81889	96.55962*	76.97277	120.6289*	88.80380
1	3	52.95399*	47.85613	58.91043*	54.07904	81.03860*	63.87610
2	2	26.64698	29.79707	31.65691	35.19275	46.74552*	42.91525
3	1	13.10754	15.49471	17.95148	20.26184	20.93144	25.87211
4	0	5.371610*	3.841466	5.507873	9.164546	7.735352	12.51798

* denotes the first time the null hypothesis cannot be rejected

Table 5.4 (c) Pantula principle test based on the maximum eigenvalue test

R	**n-r**	**Model 2**		**Model 3**		**Model 4**	
		Max test statistic	**Critical values**	**Max test statistic**	**Critical values**	**Max test statistic**	**Critical values**

0	4	37.50574*	33.87687	37.64918*	34.80587	39.59025*	38.33101
1	3	26.30701	27.58434	27.25352	28.58808	34.29307*	32.11832
2	2	13.53944	21.13162	13.70543	22.29962	25.81408	25.82321
3	1	7.735930*	14.26460	12.44361	15.89210	13.19609	19.38704
4	0	5.371610	3.841466	5.507873	9.164546	7.735352	12.51798

*denotes the first time the null hypothesis cannot be rejected

The pantula principle test results presented in Tables 5.4 (b) and (c) show that option 2 which is the most restrictive one produced 3 cointegrating equations under the trace test and 2 cointegrating equation for the maximum eigenvalue test. Model 3 produced 2 cointegrating equations when taking into account the trace test and 1 cointegrating equation under the maximum eigenvalue test. Model 4 produced 3 cointegrating equations for the trace test whereas the maximum eigenvalue test produced 2 cointegrating equations. From the results it is noted that all three models produced at least 2 cointegrating equations when taking into account the trace test and as such the null hypothesis cannot be rejected. The researcher also noted that there too many cointegrating equations under the trace test for all 3 options which carries more weight. However, it is not possible to estimate so many equations as such more attention was placed on the maximum eigenvalue results and model 3 with lesser cointegrating equations was chosen.

5.4.4. Determining the number of cointegration vectors

The Trace and Max-Eigenvalue results of the cointegration test are presented in Tables 5.4 (d) and (e) respectively.

Table 5.4 (d) Trace Test

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.658938	96.55962	76.97277	0.0008
At most 1 *	0.540985	58.91043	54.07904	0.0174
At most 2	0.324014	31.65691	35.19275	0.1146
At most 3	0.299199	17.95148	20.26184	0.1008
At most 4	0.145610	5.507873	9.164546	0.2323

Trace test indicates 2 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level;
**MacKinnon-Haug-Michelis (1999) p-values

The trace results presented in Table 5.4 (d), indicate that there are at least 2 cointegrating equations at 0.05 level of significance. When paying attention to the first row the trace test of 96.55962 exceeds the critical value of 76.97277. Also, in row two the trace test of 58.91043 exceeds the critical value of 54.07904. Based on the results, the null hypothesis of no cointegration is rejected. This continues until the null hypothesis of at most 1 cointegrating vectors is not rejected.

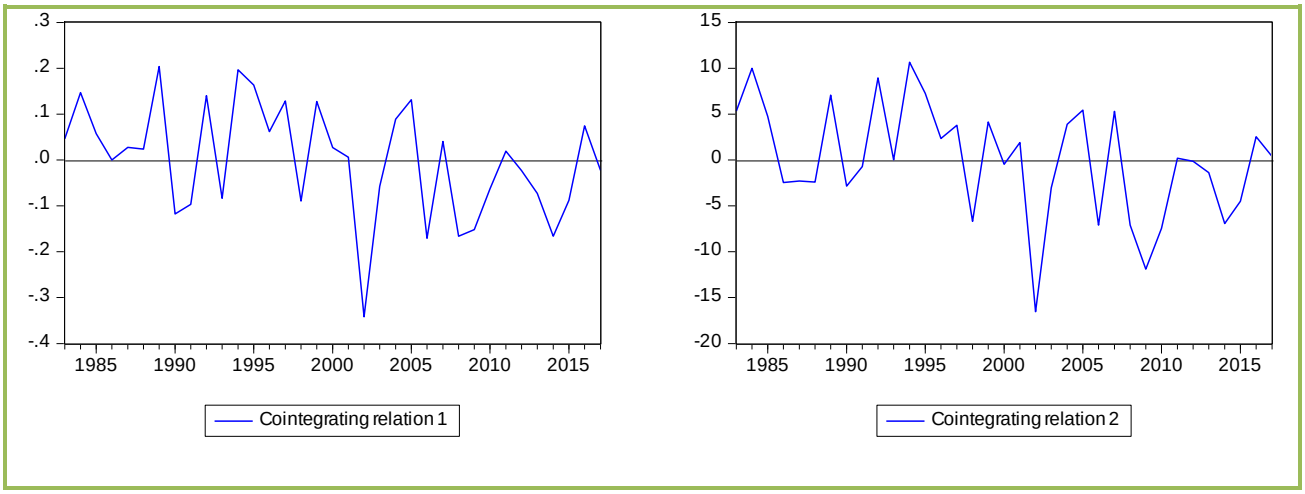
Table 5.4 (e) Max-Eigenvalue test

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.658938	37.64918	34.80587	0.0223
At most 1	0.540985	27.25352	28.58808	0.0732
At most 2	0.324014	13.70543	22.29962	0.4893
At most 3	0.299199	12.44361	15.89210	0.1617
At most 4	0.145610	5.507873	9.164546	0.2323

Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

The max-eigenvalue test results presented in Table 5.4 (e) indicate that there is 1 cointegrating equation at 0.05 level of significance. In the first row the max-eigen statistic of 37.64918 exceeds the critical value of 34.80587. Therefore, the null hypothesis of no cointegrating is rejected and it can be concluded that a long run relationship exist amongst the variables.

Figure 5.2 Cointegration Graphs



Source: E-views output

The cointegration graphs presented in Figure 5.2 show that from the period of 1980 to 2017 the deviations of energy intensity from equilibrium were stationary and this is critical for its use as an error correction model.

The existence of cointegration in the variables implies that it is appropriate to proceed to the next step which is estimating the vector error correction model (VECM) in order to disaggregate the relationship.

5.5. Vector Error Correction Model (VECM)

The use of VECM is necessary in the study as it is a suitable model for measuring the correction from disequilibrium previous periods.

Table 5.5(a) Error Correction model long run results

Cointegrating Eq:	CointEq1	CointEq2
LEI(-1)	1.000000	0.000000
LEP(-1)	0.000000	1.000000
LFDI(-1)	-0.260417	-12.67381
	(0.04840)	(2.90982)

	[-5.38086]	[-4.35553]
LTMVA(-1)	0.300743	2.963159
	(0.07703)	(4.63133)
	[3.90425]	[0.63981]
LTOP(-1)	0.211929	-8.122783
	(0.08281)	(4.97869)
	[2.55931]	[-1.63151]
C	-0.735231	27.37419

*Standard errors are indicated by ( ); t-statistic are indicated by [ ]

The long run effect of the independent variables on energy intensity presented in table 5.5(a) is illustrated using an equation as follows:

$$LEI = -0.735231 + 0.00000 - 0.260417LFDI + 0.300743LTMVA + 0.211929LTOP \ldots\ldots\ldots\ldots\ldots\ldots 5.1$$

$$LEI = 27.37419 + 1.00000LEP - 12.67381LFDI + 2.963159LTMVA - 8.122783LTOP \ldots\ldots\ldots\ldots\ldots\ldots 5.2$$

From the results presented in equation 5.1 the coefficient of LFDI and LTMVA have the correct sign and are statistically significant. Whereas, LEP and LTOP have the wrong signs and they are statistically insignificant. In equation 5.2 only the coefficient of LFDI has the correct sign and is statistically significant. On the other hand, the coefficients of LEP, LTMVA and LTOP either have a wrong sign or they are statistically insignificant. When taking into account the results of equation 5.1 and 5.2, the long run results will be

interpreted based on equation 5.1 with more statistically significant variables which is an indication of a true relationship.

LFDI is statistically significant in explaining manufacturing energy intensity since it has a t-value that is greater than 2. The coefficient of LFDI is -0.260417 with a t- value of -5.38086. This implies that a 1% increase in foreign direct investment will reduce manufacturing energy intensity by 2.60417. The results are in line with the findings of Li *et al* (2017) who found that the impact of FDI towards manufacturing energy intensity in China was significant in the long and medium term. The results also conform to the technique effect assumption that FDI introduces new advanced technologies and managerial skills to the host country and thus improving firm efficiency. The conclusion therefore is that when FDI rises, manufacturing energy intensity decreases. Suggesting that access to foreign technology is vital for the survival of the manufacturing industry.

The positive coefficient of LTMVA is statistically significant in explaining manufacturing energy intensity. The coefficient of LTMVA is 0.300743 with a t-statistic of 3.90425. This means that a 1% increase in LTMVA will result in 3.00743 increase in manufacturing energy intensity. In terms of the positive impact the results conform to the findings of Fisher-Vanden *et al* (2018) and Adom (2015) who found that industrial value added increased manufacturing energy intensity in China and in South Africa. The findings also conform to the theory that an increase in this variable indicates above-average growth on the production of manufacturing products, including energy intensive products, this is captured by the composition and technique effects discussed in chapter 4 of this study (Petrivic *et al,* 2017). The implication of the these results is that an increase in the variable indicates growth on the production of manufacturing products which includes energy intensive products. The conclusion thus, is that when total manufacturing value added is increased, energy intensity is likely to increase as well. This means that there is a need for policymakers to pay attention to the manufacturing industry.

Table 5.5(b) Error correction model short run results

Variable	Coefficient	Standard error	t-statistics
CointEq 1	-0.815997	0.21901	-3.72577
CointEq 2	0.015975	0.00406	3.93002

$D(LEI(-1))$	0.487648	0.17965	2.71439
$D(LEP(-2))$	-0.111152	0.00331	-3.35829
$D(LFDI(-2))$	-0.004723	0.02429	-0.19447
$DLTOP(-1))$	0.161365	0.13241	1.21866
$DLTMVA(-1))$	0.475750	0.16594	2.86692

In Table 5.5(b) the coefficient of CointEq1 is -0.815997 is significant with a t-statistic of -3.72577. Based on the coefficient of equation 1 the previous year's deviation from long run equilibrium is corrected in the current period at a speed of 81%. This is the speed with which energy intensity returns to its equilibrium after a shock in the independent variables. The coefficient of CointEq2 is 0.015975 is statistically insignificant with a t-statistic of 3.93002 and therefore cannot be interpreted.

LFDI is not statistically significant in explaining manufacturing energy intensity in the short run. The coefficient of LFDI from the first equation has the correct sign but is not statistically significant. Whereas, the coefficient of cointegrating equation 2 has the wrong sign and is statistically insignificant.

The coefficient of LMTVA is 0.475750 with a t statistic of 2.86692 in the first cointegrating equation. This means that manufacturing value added is significant in explaining energy intensity, since the t-value is greater than 2. Thus, a 1% increase in manufacturing value added will increase manufacturing energy intensity by 4.75750 in the short run. The results conform to the findings of Kwakwa and Adusah-Poku who found a positive link between manufacturing value added and energy intensity in South Africa. This implies that it is imperative that policy makers pay attention to the manufacturing sector.

LEP is significant in explaining manufacturing energy intensity in the second cointegrating equation. The coefficient of LEP is -0.111152 and the t-statistic is -3.35829. This means that a 1% increase in energy price will reduce manufacturing energy intensity by 1.11152. The results are supported by empirical and theoretical literature in the sense that the cost of energy is assumed to motivate industry players to implement more energy saving programs in an attempt to avoid high costs. Moreover, the findings correspond to those of Li *et a*l (2017).

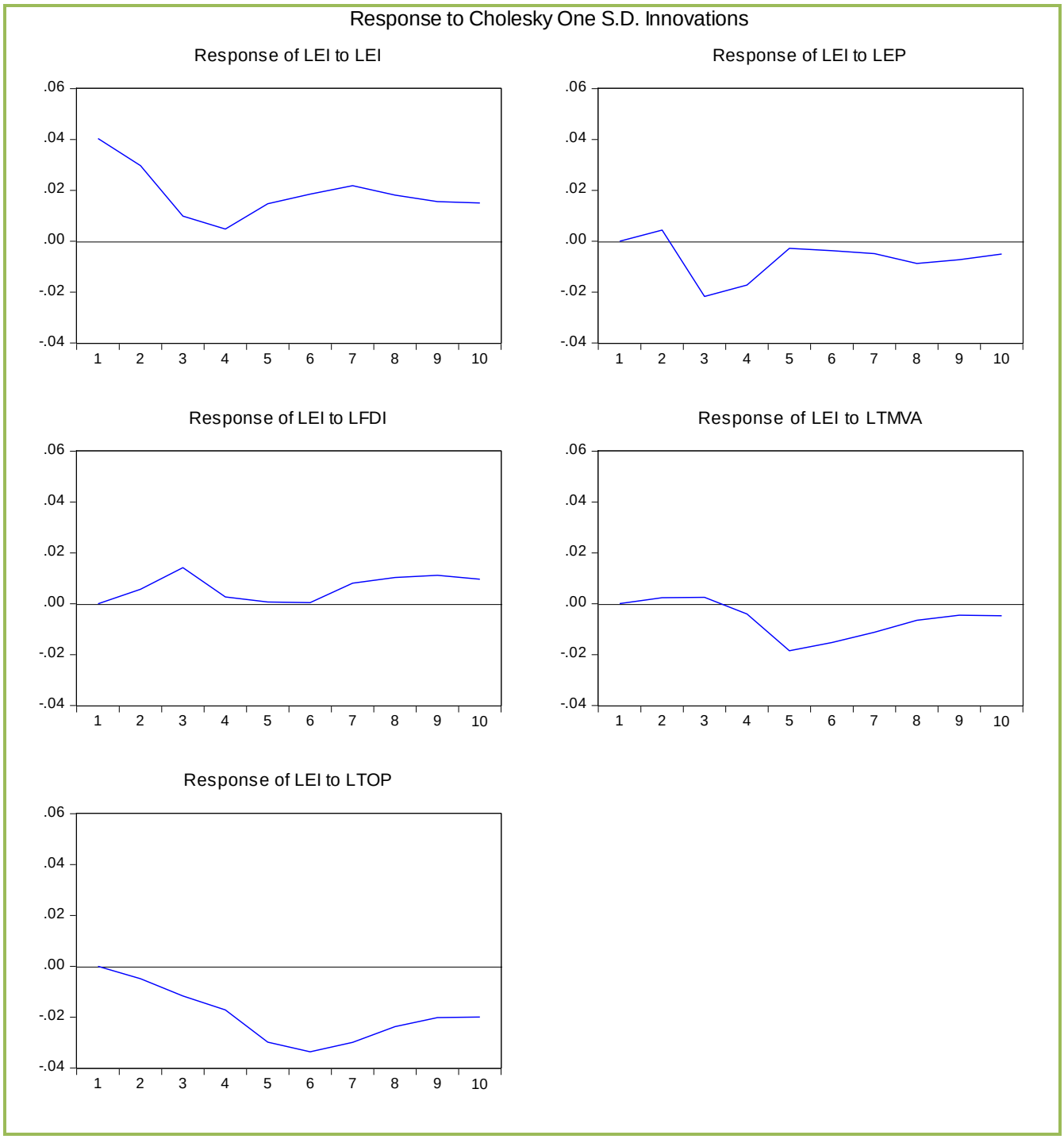
The coefficient of TOP is not significant in explaining manufacturing energy intensity both in the long run and the short run. This means that the null hypothesis that it is zero cannot be rejected. The conclusion therefore is that the effect of trade openness on manufacturing energy intensity does not exist when considering the findings of this study. These results are similar to the findings of Petrovic´ *et al* (2017) who found that the effect of trade openness on EU energy intensity was indeterminate.

From the long and short run results presented in Tables 5.5(a)and(b) total manufacturing value added is statistically significant in explaining manufacturing energy intensity both in the short and long run. Foreign direct investment is only able to explain energy intensity in the long run. Whereas, energy price is able to explain manufacturing energy intensity only in the short run. With regards to trade openness, the results could not find any association with manufacturing energy intensity. Having estimated the VECM the next step is to estimate the impulse response and variance decomposition analysis, which is the response of manufacturing energy intensity to shocks of the independent variables.

5.6. Impulse response analysis

The impulse response function is used to analyse the response of manufacturing energy intensity to impulse or shocks of a unit standard deviation of influencing factors for a 10-year period. Impulse response results are presented in Figure 5.3.

Figure 5.3 Impulse Response



Source: E-views output

Based on the results presented in Figure 5.3 the dependent variable, energy intensity responds positively to its own shocks, the graph starts off at an upward trend but begins to drop gradually at year 2 and 3, at year 4 it starts to rise up gradually then becomes steady in year 6 to year 10. The response of energy intensity to energy prices (LEP) is negative from year 2 up to year 10. One standard deviation shock of foreign direct

investment (FDI) to energy intensity is positive, in the 1st and 2nd year it rises sharply until year 3 where it becomes steady and rise gradually in year 4 until year 10. The shock of trade openness to energy intensity is negative, from year 1 it drops steadily until year 10. A standard deviation shock of manufacturing value added on energy intensity starts off positively in year 1 and 2 but drops negatively sharp in year 5, it rises gradually from year 6 until year 10. This means that the response of energy intensity to standard deviation of the variables is negative except for FDI.

5.7. Variance decomposition analysis

The variance decomposition results for a 10- year period, are presented in Table 5.6.

Table 5.6. Variance decomposition analysis

Period	S.E.	LEI	LEP	LFDI	LTMVA	LTOP
1	0.040363	100.0000	0.000000	0.000000	0.000000	0.000000
2	0.050920	96.91100	0.723120	1.244544	0.208070	0.913268
3	0.059212	74.44467	14.01812	6.620320	0.330858	4.586032
4	0.064379	63.51319	19.02091	5.770068	0.679820	11.01601
5	0.074857	50.84456	14.21441	4.276111	6.598142	24.06678
6	0.085561	43.57187	11.07346	3.276016	8.213187	33.86546
7	0.094383	41.15339	9.366359	3.418980	8.157193	37.90408
8	0.100131	39.83959	9.091840	4.104600	7.669005	39.29496
9	0.104283	38.94578	8.872209	4.932607	7.258560	39.99085
10	0.107888	38.32573	8.509802	5.404546	6.976188	40.78374

The variance decomposition output presented in Table 5.6 indicate that in the short run that is, year 1 to 5 the dependent variable energy intensity strongly influences itself. In period 5 the impulse or shock to energy intensity is 50.84%; the shock of energy prices is 14.21%, a unit shock of FDI is 4.27%, a unit shock of trade openness is 24.07%, an

impulse of manufacturing value added is 6.60%. In the long run which is period 6 to 10 the influence of energy intensity on energy intensity is 38.32. In the 10th year the shock of energy prices is 8.51%, a unit shock of FDI is 5.40 %, a unit shock of trade openness is 40.78%, an impulse of manufacturing value added is 6.98%. The conclusion therefore is that energy intensity is explained by its own innovations in the short run whereas in long run energy intensity is strongly explained by trade openness, while the other variables explain the remaining.

5.8. Diagnostic tests

It is important to test for the validity of the assumptions underlying the model under study, that is, the multiple classical linear regression model assumption. The diagnostic tests used in the study are serial correlation test based on the Langrage Multiplier, normality test based on the Jarque-Bara and heteroscedasticity based on the White test as presented in Table 5.7

Table 5.7 Diagnostic tests

Test	**Null hypothesis**	**t-statistic**	**Probability**
Serial correlation	No serial correlation	36.61891	0.0627
Normality test Jarque-Bera	Normally distributed	2.231412	0.3277
White Heteroscedasticity	No heteroscedasticity	371.2009	0.3307

N0: rejected if p value is less than 0.05% significant

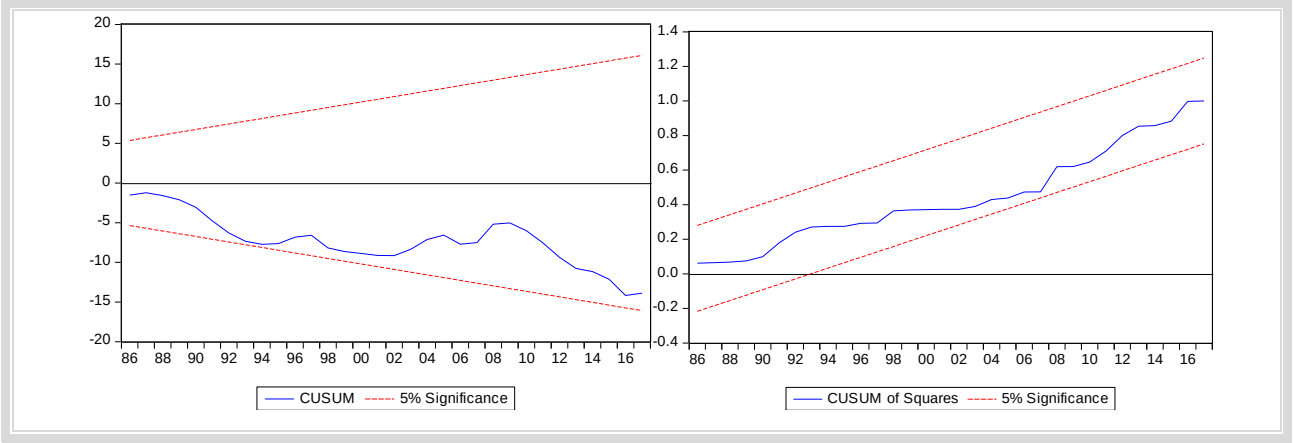
From Table 5.7 the serial correlation results derived from LM test show a t-statistic of 36.61891 and a probability value of 0.0627. Serial correlation as discussed in the previous chapter occurs when error terms from different time periods are correlated. Based on the results presented in Table 5.7, the probability value of 0.0627 is greater than 0.05 significant interval this implies that there is no serial correlation and as such the null hypothesis cannot be rejected. For the normality test the accepted *p*-value of the Jarque-Bera is expected to be between 0 and 3. The results presented in the table show a t-statistic of 2.231412 and a probability value of 0.3277 and based on these the study passes the normality test. Thus, the null hypothesis of normal distribution is not rejected. The heteroscedasticity results show a t-statistic of 371.2009 and a probability value of 0.3307. Based on the linear regression assumption the variance of the error terms is

constant, implying that it is homoscedastic. When testing for heteroscedasticity, the *p*-value is expected to be above 5% significance interval. Based on the results presented in the Table the variables used in the study pass the heteroscedasticity test. This means that the null hypothesis of no heteroscedasticity cannot be rejected. The diagnostic tests indicate that the model is suitable for estimation that is, there is no serial correlation, no misspecification and the errors are normally distributed.

5.9. Stability tests

Stability tests as discussed in the previous chapter are based in recursive estimates. The study employs the Cumulative Sum of Recursive Residuals (CUSUM) and the CUSUMQ test and the results are presented in Figure 5.4 below.

Figure 5.4. Stability tests



Source: E-views 9 output

The model is said to be stable if the CUSUM and CUSUMQ line in blue moves within the bounds of the 5% significant level. From figure 5.4 above the CUSUM and CUSUMQ line indicated in blue shows that the model is stable.

5.10. Conclusion

The purpose of the preceding chapter was to present and discuss empirical results obtained using the Vector Error Correction Model (VECM) estimation method. The descriptive test was run to understand the behaviour of the variables that is, the way they are distributed. Measures of tendency such as the mean and median were estimated. Also, measures of dispersion and normality test were estimated. From these tests the

variables were found to have different results, some were normally distributed and others were not normally distributed. The pairwise test was estimated to determine the degree of association of the variables used in the study. From the pairwise correlation results the presence of multicollinearity could not be detected implying that the model was good for estimation.

The unit root tests results indicated that the variables employed are stationary after first difference, implying that the variables are integrated of order 1. Based on the pantula principle test model 3 with lesser cointegrating equations was selected. The trace test showed 2 cointegrating equations at most 1 and the maximum eigen test showed 1 cointegration equation at none. This is an indication that there is a long run or equilibrium relationship among the variables hence, the VECM was estimated at lag 2. Based on the VECM results presented the coefficient of total manufacturing value added was more statistically significant in explaining manufacturing energy intensity both in the long run and short run. Foreign direct investment and energy prices were found to be statistically significant either in the long or short term. The coefficient of trade openness was found to be insignificant both in the short and long term. The variance decomposition and impulse response results indicated that energy intensity strongly influences its own innovations and the rest of the variables explain the remaining. The diagnostic test results showed that the model is good for estimation, that is, there is no misspecification, no serial correlation and the errors are normally distributed. The stability test results indicated that the model is stable, a confirmation that the model is good for estimation.

Chapter Six

Summary, Conclusions and Recommendations

6.0. Introduction

Chapter 5 presents a summary, conclusions and suggests recommendations for future policy formulation. The chapter is divided into different sections as follows; section 6.1 presents a summary on the background of the study together with the objectives of the study; section 6.2 presents a summary on the overview of the manufacturing industry, energy industry and determinants of energy intensity; section 6.3 presents a summary of the literature reviewed in the study; section 6.4 presents a summary of the methodology and technique employed in the study; section 6.5 presents a summary of findings; and section 6.6 concludes and makes policy recommendations, section 6.7 presents limitations of the study; and section 6.8 presents areas for further research.

6.1. Motivation and objectives of the study

The study sought to investigate the factors influencing manufacturing energy intensity in South Africa. The study was motivated by the increasing concern over energy security, climate change and the depletion of energy resources in the economy. Also, the manufacturing industry is considered as one of the most energy intensive industries, leading to increased levels of energy intensity. Although the industry, government and other scholars have made attempts at formulating policies and made recommendations aimed at reducing the use of energy in the industry. There is still a gap with regards to understanding the determinants of manufacturing energy intensity which is the main objective for the study.

The purpose of the study was also to contribute to already existing literature on energy intensity and the manufacturing industry. It also, sought to assist policy makers to review existing policies on energy efficiency and to bring to light the effects of some industry specific characteristics on energy intensity.

6.2. A Summary of the overview of the manufacturing industry and energy sector

This section of the study discussed the overview of the manufacturing industry, energy sector and analysed trends on the determinants of manufacturing energy intensity. During the analysis, the manufacturing industry was found to be one of the important industries in the economy of South Africa as it contributes to the overall GDP and employment.

The most dominant sectors of the industry are metals and machinery (22.1%), food and beverages (20.1%) and chemicals and petrochemicals (13.9%). These three (3) sub-sectors alone make up almost 60% of the total manufacturing industry of South Africa (statsSA, 2018). Despite this, the industry's contribution to GDP over the years has declined. For instance, the industry's contribution to GDP between 1994 and 2012 declined from 20.9% in 1994 to 12.4% in 2012, with the industry currently holding the 4th position in terms of its contribution to GDP contributing about 13.53% (Quantec, 2018). With regards to energy consumption patterns, the study found that the manufacturing industry consumes more energy when compared to the other sectors of the economy with coal and electricity as the most consumed energies (Energy Sector Report, 2019).

With regards to the energy sector the study took into account energy demand and supply, energy sector legislation as well as energy intensity in the world and in South Africa. The study found that the country's energy supply is dominated by coal which is uses as primary energy and for producing electricity. The study further discussed different legislation governing the energy sector under the National Energy Regulator (NERSA).

Furthermore, under energy intensity and efficiency different economies have implemented several policies with the aim of improving energy efficiency. With these policies the different economies have recorded a decline in overall energy intensity. When it comes to South Africa, the country's energy intensity has been fluctuating over the years and as at 2019 it stood at 8.50MJ per dollar of GDP measured at purchasing power parity basis (National Strategy Energy Efficiency Report, 2019).

When analysing the trends of the different determinants of manufacturing energy intensity, it was found that manufacturing value added was declining steadily over the reviewed period. Whereas, the other determinants such as energy prices, trade openness and foreign direct investment were fluctuating at different levels over the period under review.

6.3. A Summary of the literature reviewed in the study

The chapter on literature review discussed the theoretical and empirical literature. With regards to the theoretical literature the different theories discussed include the energy demand theory, decomposition theory and the new growth endogenous theory. The

energy demand theory by Beenstock and Dalziel (1989) is based on the assumption that the demand for energy arises for different reasons, for instance households demand energy to meet certain needs whilst industries demand energy as an input of production. It also, assumes that in the long and short run the demand for energy is decomposed by factors such as technological change, energy prices, efficiency and the utilization of deployed capital and the influence of policy. According to this theory, each of these factors influence energy intensity, which is the quantity of energy consumed per unit of economic output.

The decomposition theory was first introduced by Grossman and Krueger (1993) and Antwieler *et al* (2001). It is based on the assumption that changes in energy demand arises from a number of factors which include economic changes, structural changes and technological changes (Bhattacharyya, 2011). The decomposition model attempts to determine the contribution of these effects to changes in energy consumption i.e. to separate the effects of improvements in the use of energy from the structural shifts of the economy. It can distribute variables between industries in an aggregate indicator to predefined factors also known as decomposition results.

The new growth theory by Paul Romar (1986) and Robert Lucas (1998) is included in the study because it is believed that for manufacturing industries to be energy efficient they need to invest more in new technologies as well as research and development. It takes into account four (4) variables namely capital, labour, technology and output and is set in continuous time. Technology is viewed as an endogenous factor which could be related to energy (Odularu and Okonkwo, 2009). In this context, the technology referred to is plants and machinery.

The empirical literature discussed in the study is categorised as follows; (i) grouped countries; (ii) developed countries; (iii) developing countries; and (iv) literature on South Africa. Previous studies on energy intensity and the manufacturing industry have emphasised the significant relationship between structural effects of the industry, energy policies, technological advancements or improvements, capital intensity and energy intensity.

Literature from developed countries established that innovation or the introduction of newly improved technologies improved manufacturing energy intensity. Also, the structural and organizational shifts from industries that consume more energy to

industries that consume less energy helped to reduce energy intensity in the long term. The cost of energy was found to reduce energy intensity in the short term.

Literature from developing countries found that firms with high research and development, and capital embodied technical progress were more energy efficient. Also, the improvements in energy intensity in these countries were as a result of production and product mix. Further, certain obligations such as energy audits or energy management system reduced energy intensity in the manufacturing industry.

In South Africa, the studies reviewed advocated for new technologies to be adopted by the different manufacturing industries. The introduction of foreign technology through FDI was found to reduce manufacturing energy intensity. Also, continuous structural shifts in the economy reduced energy intensity in the long run.

6.4. A Summary of methodology employed in the study

This section presents a summary of the procedures involved when assessing the factors influencing energy intensity in the South African manufacturing industry. The chapter discussed the research philosophy followed in the study, i.e. the positivism paradigm. It then discussed the endogenous growth theory as a theoretical foundation for variable selection and model specification. The chosen variables were defined and their expected signs were discussed based on theory and empirical literature.

The Vector Error Correction Model (VECM) is the chosen technique used for estimation in the study reason being, it is easy to use, understand and it has ability to incorporate the residuals from past observations amongst its many advantages over other alternatives. Descriptive statistics as well as pairwise correlation among the variables under study were discussed. Informal graphical illustrations as well as the formal the Augmented Dickey Fuller and the Philip Peron unit root test were discussed.

In order to test for long run relationship amongst the variables, the Johansen likelihood estimation of the VAR system cointegration approach was discussed. The reason behind using the Johansen approach is because it has the ability to remove simultaneous equation bias and it gives estimates of all cointegrating relationships that may exist in a vector of non-stationary variables. Based on the cointegration approach, the vector error correction model which contains information on the long run and short run relationship between variables was discussed.

Further, the section of the study discussed the impulse response and the decomposition analysis in order to determine the dependent variable's ability to respond to external shocks. Also, the diagnostic checks and stability tests used in the study were discussed and these are serial correlation, normality test, and heteroscedasticity tests and the cumulative sum of recursive residuals.

6.5. A Summary of findings

In this section, a summary of the results from chapter 5 is presented. The determinants of manufacturing energy intensity were investigated using time series data from the period of 1980 to 2017. In order to reach the conclusions based on the VECM estimation method, different tests were estimated.

The descriptive test was run to understand the behavior of the variables that is, the way they are distributed. Measures of tendency such as the mean and median were estimated. Also, measures of dispersion and normality test we estimated. From these tests the variables were found to have different results, that is some were normally distributed and other were not normally distributed. The pairwise test was estimated to determine the degree of association of the variables used in the study. From the pairwise correlation results the presence of multicollinearity could not be detected implying that the model was good for estimation.

When taking in account the informal graphical illustrations and the formal ADF and PP unit root tests. The results from the formal tests indicated that the variables were stationary after first differencing at 1% significance interval. This implies that the variables are integrated of the 1^{st} order. The graphical illustrations also conquered with the formal tests in that the variables were stationary after first differencing.

The Johansen cointegration test was used to determine the order of integration, to determine the trend assumption based on the pantula principle test, and the number of cointegrating vectors. The first issue when running the cointegration test was choosing the appropriate lag length based on the lag length criteria and the selected lag was 2. Based on the pantula principle test model 3 with lesser cointegrating equations was selected. The trace test showed 2 cointegrating equations at most 1 and the maximum eigen test showed 1 cointegration equation at none. This is an indication that there is a long run or equilibrium relationship among the variables hence, the VECM was estimated at lag 2.

Based on the VECM results presented the coefficient of total manufacturing value added was more statistically significant in explaining manufacturing energy intensity both in the long run and short run. The results conform to the theory and the findings of Fisher-Vanden *et al* (2018) and Adom (2015) who found that industrial value added increased manufacturing energy intensity in China and in South Africa. Foreign direct investment was found to be statistically significant in explaining manufacturing energy intensity in the long run. The results are similar to those of Li *et al* (2017) who found that the impact of FDI towards manufacturing energy intensity in China was significant in the long and medium term. The coefficient of energy prices was found to be statistically significant in explaining manufacturing energy intensity in the short run. The results correspond with those of Li *et a*l (2017). The coefficient of trade openness was found to be insignificant both in the short and long term. Thus, the null hypothesis that it is zero could not be rejected.

The variance decomposition and impulse response results indicated that energy intensity strongly influences its own innovations and the rest of the variables explain the remaining. The variance decomposition tests results showed that on the 10^{th} year energy intensity(LEI) is explained strongly by trade openness(LTOP) with 40.78%, followed by itself with 38.32%, then energy prices (LEP) with 8.51%, then total manufacturing value added (LTMVA) with 6.98% and foreign direct investment (LFDI) with 5.40%.

The diagnostic test results based on the lagrange serial correlation test, Jarque-Bera normality and white heteroscedasticity tests showed that the model is good for estimation, that is, there is no misspecification, no serial correlation and the errors are normally distributed. The stability test results indicated that the model is stable, a confirmation that the model is good for estimation.

6.6. Synthesis of Empirical Evidence

When taking into account the results from chapter five it can be concluded that total manufacturing value added, foreign direct investment and energy price are important determinants that drive energy intensity in the South African manufacturing industry. Comparing the study with other empirical studies that employed panel data, it may be concluded that an individual country approach produces better results.

6.7. Conclusions and Policy Recommendation

The times series results presented in chapter five revealed that total manufacturing value added, foreign direct investment inflows and energy price are important determinants that explain manufacturing energy intensity. Total manufacturing value added is significant in both the long run and short run. Foreign direct investment and energy price are able to influence energy intensity either in the long run or short run. When taking into account the results on variance decomposition energy intensity responds to its own shocks and the response is strong in the short run whereas, in the long run trade openness strongly influences energy intensity. This implies that with increased total manufacturing value added, energy intensity in the manufacturing industry will be increased. With regards to foreign direct investment, a unit increase in the determinant will reduce energy intensity in the long run but not in the short run. A unit increase in energy prices will reduce energy intensity in the short run but not in the long run.

Based on the time series results of this study, manufacturing activity increases energy intensity in the industry over the reviewed period. The implication of this is that the industry needs to be closely monitored when it comes to its energy use. It is also recommended that traditional and old technology should be banned and innovation of new energy saving technologies should be encouraged. Government should subsidize energy efficient machinery that will enable the industry to consume less energy. Furthermore, government should also develop high-tech industries and reduce the number of energy intensive firms.

With regards to foreign direct investment, the time series results indicate that when FDI is increased manufacturing energy intensity is reduced in the long run. This is due to the introduction of foreign technology that comes with investing firms. The implication of this is that the FDI program should be viewed as an integrated approach not as a one size fit all. Another recommendation is that the foreign direct investment policy should be reviewed such that it attracts more foreign investment and technological progress through FDI be promoted in order to reduce manufacturing energy intensity

The findings of this study revealed that energy prices reduce manufacturing energy intensity in short run. It is therefore recommended that government should promote energy price reform. Also, government should use subsidies for manufacturing firms that purchase energy saving equipment as this will encourage them to be more energy efficient.

6.8. Limitations

There is limitation with regards to the use of secondary data as it cannot be controlled by the researcher and the quality cannot be ascertained. There is also limitation with regards to the time frame as the study employs data from the period of 1980 to 2017 which does not necessarily present the current state of the industry. Also, data on energy prices was not available in the local currency and hence, it was used in US dollars making it subject to mistakes. Furthermore, data on manufacturing energy intensity was not readily available hence, it was calculated based on energy use in the industry divided by total manufacturing value. However, this did not lead to loss of statistical significance.

6.9 Areas for further research

Despite the fact that the study was able to answer certain pertinent issues. There are still issues that did not receive much attention. From the analysis it was discovered that industry specifics were not captured as the focus was on the overall manufacturing industry not the detailed analysis of the different sectors of the industry. As such, for further research the study recommends the use of qualitative data through surveys as this will give a clear picture of the industry characteristics. Also, a comparative study through the use of panel data would also help address the problem of energy intensity in the different sectors of the industry.

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List of Appendices

Appendix 1: Data on variables

Year	EI	EP	FDI	TOP	TMVA
1980	0,30	35,19	- 0,01	60,89	20,50
1981	0,30	34,02	0,08	56,89	22,61
1982	0,34	31,59	0,42	51,64	22,04
1983	0,36	28,29	0,08	44,30	21,92
1984	0,36	27,68	0,54	47,62	21,37
1985	0,38	27,80	- 0,77	52,31	20,17
1986	0,39	17,84	- 0,07	50,68	20,26
1987	0,40	19,65	- 0,22	49,01	20,71
1988	0,39	15,00	0,17	50,09	21,01
1989	0,36	18,03	- 0,20	46,59	21,38
1990	0,37	23,43	- 0,07	41,68	21,61
1991	0,40	19,89	0,21	38,05	21,06
1992	0,39	19,37	0,00	37,49	20,32
1993	0,41	17,26	0,01	39,12	19,55
1994	0,42	15,82	0,27	40,77	19,27
1995	0,41	16,91	0,80	43,61	19,55
1996	0,42	20,22	0,55	46,67	18,68
1997	0,42	19,39	2,50	46,85	18,41
1998	0,41	13,48	0,40	48,90	17,86
1999	0,42	17,97	1,10	46,86	17,06
2000	0,38	28,46	0,71	51,44	17,47
2001	0,38	24,47	5,98	54,80	17,57
2002	0,37	24,95	1,28	59,76	17,70
2003	0,40	28,89	0,45	51,40	17,30
2004	0,41	38,16	0,31	51,08	16,79
2005	0,39	54,28	2,53	53,15	16,26
2006	0,36	64,99	0,23	60,28	14,67
2007	0,37	72,95	2,20	63,68	14,36
2008	0,39	97,77	3,45	72,87	14,42
2009	0,43	61,59	2,58	55,42	13,62
2010	0,40	79,54	0,98	55,99	13,05
2011	0,38	111,19	0,99	60,11	12,00
2012	0,37	111,80	1,17	60,90	11,72
2013	0,37	108,79	2,24	64,24	11,60
2014	0,38	99,24	1,65	64,43	12,05
2015	0,39	52,50	0,48	61,62	12,02
2016	0,37	43,58	0,75	60,64	12,03
2017	0,41	54,25	0,59	57,97	12,01

Appendix 2: Pantula Principle test

Option 2

Date: 11/13/20 Time: 13:30
Sample (adjusted): 1983 2017
Included observations: 35 after adjustments
Trend assumption: Linear deterministic trend
Series: LEI LEP LFDI LTMVA LTOP
Lags interval (in first differences): 1 to 2

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.657537	90.45973	69.81889	0.0005
At most 1 *	0.528402	52.95399	47.85613	0.0154
At most 2	0.320801	26.64698	29.79707	0.1106
At most 3	0.198305	13.10754	15.49471	0.1109
At most 4 *	0.142277	5.371610	3.841466	0.0205

Trace test indicates 2 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.657537	37.50574	33.87687	0.0176
At most 1	0.528402	26.30701	27.58434	0.0721
At most 2	0.320801	13.53944	21.13162	0.4039
At most 3	0.198305	7.735930	14.26460	0.4062
At most 4 *	0.142277	5.371610	3.841466	0.0205

Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Option 3

Date: 11/13/20 Time: 13:31
Sample (adjusted): 1983 2017
Included observations: 35 after adjustments
Trend assumption: No deterministic trend (restricted constant)
Series: LEI LEP LFDI LTMVA LTOP
Lags interval (in first differences): 1 to 2

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.658938	96.55962	76.97277	0.0008
At most 1 *	0.540985	58.91043	54.07904	0.0174
At most 2	0.324014	31.65691	35.19275	0.1146
At most 3	0.299199	17.95148	20.26184	0.1008
At most 4	0.145610	5.507873	9.164546	0.2323

Trace test indicates 2 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.658938	37.64918	34.80587	0.0223
At most 1	0.540985	27.25352	28.58808	0.0732
At most 2	0.324014	13.70543	22.29962	0.4893
At most 3	0.299199	12.44361	15.89210	0.1617
At most 4	0.145610	5.507873	9.164546	0.2323

Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Option 4

Date: 11/13/20 Time: 13:32
Sample (adjusted): 1983 2017
Included observations: 35 after adjustments
Trend assumption: Linear deterministic trend (restricted)
Series: LEI LEP LFDI LTMVA LTOP
Lags interval (in first differences): 1 to 2

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.677338	120.6289	88.80380	0.0000
At most 1 *	0.624615	81.03860	63.87610	0.0009
At most 2 *	0.521713	46.74552	42.91525	0.0197
At most 3	0.314105	20.93144	25.87211	0.1824
At most 4	0.198291	7.735352	12.51798	0.2740

Trace test indicates 3 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.677338	39.59025	38.33101	0.0357
At most 1 *	0.624615	34.29307	32.11832	0.0267
At most 2	0.521713	25.81408	25.82321	0.0501
At most 3	0.314105	13.19609	19.38704	0.3125
At most 4	0.198291	7.735352	12.51798	0.2740

Max-eigenvalue test indicates 2 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Appendix 3 Lag length selection criteria

VAR Lag Order Selection Criteria
Endogenous variables: LEI LEP LFDI LTMVA LTOP
Exogenous variables: C
Date: 11/13/20 Time: 10:28
Sample: 1980 2017
Included observations: 36

Lag	LogL	LR	FPE	AIC	SC
0	71.81140	NA	1.68e-08	-3.711745	-3.491811
1	183.4207	186.0156	1.39e-10	-8.523374	-7.203775*
2	211.8167	39.43890*	1.25e-10*	-8.712041*	-6.292776

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Appendix 4 Cointegration test

Date: 11/13/20 Time: 13:31
Sample (adjusted): 1983 2017
Included observations: 35 after adjustments
Trend assumption: No deterministic trend (restricted constant)
Series: LEI LEP LFDI LTMVA LTOP
Lags interval (in first differences): 1 to 2

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.658938	96.55962	76.97277	0.0008
At most 1 *	0.540985	58.91043	54.07904	0.0174
At most 2	0.324014	31.65691	35.19275	0.1146
At most 3	0.299199	17.95148	20.26184	0.1008
At most 4	0.145610	5.507873	9.164546	0.2323

Trace test indicates 2 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.658938	37.64918	34.80587	0.0223
At most 1	0.540985	27.25352	28.58808	0.0732
At most 2	0.324014	13.70543	22.29962	0.4893
At most 3	0.299199	12.44361	15.89210	0.1617
At most 4	0.145610	5.507873	9.164546	0.2323

Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level

* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Appendix 5: diagnostic tests

Included observations: 35

Lags	LM-Stat	Prob
1	36.61891	0.0627
2	40.66959	0.0549

Probs from chi-square with 25 df.

Joint test:

Chi-sq	df	Prob.
371.2009	360	0.3307

Component	Jarque-Bera	df	Prob.
1	2.231412	2	0.3277
2	1.157869	2	0.5605
Joint	9.465989	10	0.4885