Investigating the Factors Influencing Energy Intensity in the South African Manufacturing Industry

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The study investigates the determinants of energy intensity in the South African 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 Government should subsidize energy efficient machinery and equipment and the use of old outdated technology should be banned.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: South Africa, Energy Intensity, Manufacturing industry, Manufacturing Value Added, Foreign Direct Investment, Energy Prices, Trade Openness, Vector Error Correction Model

INTRODUCTION

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 comes as a special focus because it is closely linked to energy inefficiency and higher carbon dioxide emissions (Kwakwa and Adusah-Poku, 2019). It also relates to issues on energy security and economic competitiveness.
In South Africa primary energy intensity currently stands at 8.5MJ/$ with manufacturing energy intensity currently standing at 4 MJ/$, a figure which is still high when compared to other BRICS member states (National Strategy Efficiency 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 revealed 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 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).

These programs and 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, such as Thiel (2016); Cargill (2015); Kohler (2012); Olanrewaju (2017; Adom (2014); and Kan et al, (2020) 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. 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%.

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 seek to assist industry players, academics and policy makers to make informed decisions when it comes to energy use in the industry. The study proceeds as follows: Section 2 presents literature review; Section 3 presents methodology; Section 4 presents results and interpretation and; Section 5 draws conclusions and makes policy recommendations.

LITERATURE REVIEW

This section discusses the literature review taking into account theoretical and empirical literature relating to energy intensity and the manufacturing industry.
Theoretical Framework

The different theories that are discussed in this section include the energy demand theory, decomposition theory and the endogenous growth theory. The section begins with discussions of the energy demand theory developed by Beenstock and Dalziel (1989), which 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:

\[ Q = K, E \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (1) \]

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 long and short run the demand for energy is decomposed by many factors (Evans and Hunt, 2009). These factors include economic structure, technological change, 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 the decline in energy intensity. Technological development assumes that the more energy efficient capital deployed, the more the decline in energy requirement for a particular level of output, thus allowing the expansion of 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 \((A, I, \text{and} \, S)\) 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

\[ \frac{E}{Y} = \frac{E_A}{Y_A} + \frac{E_I}{Y_I} + \frac{E_S}{Y_S} \ldots \ldots \ldots \ldots (2) \]

\[ = \frac{E_A}{Y_A} \cdot \theta_A + \frac{E_I}{Y_I} \cdot \theta_I + \frac{E_S}{Y_S} \cdot \theta_S \ldots \ldots \ldots \ldots \ldots (3) \]

Where

\( \theta_i \) 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:

\[ \frac{E_A}{Y_A} < \frac{E_S}{Y_S} < \frac{E_I}{Y_I} \ldots \ldots \ldots \ldots (5) \]
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

$$\frac{d(E/Y)}{d\theta_I} = -\left(\frac{d\theta_A}{Y_A} \cdot \frac{E_A}{Y_A} + \frac{d\theta_S}{Y_S} \cdot \frac{E_S}{Y_S} \cdot \frac{d\theta_I}{Y_I}\right) + \frac{E_I}{Y_I} > 0 \quad \ldots \ldots \quad (6)$$

Equation 6 is positive because

$$\left|\frac{E_A}{Y_A} \cdot \frac{d\theta_A}{Y_A} + \frac{E_S}{Y_S} \cdot \frac{d\theta_S}{Y_S} \cdot \frac{d\theta_I}{Y_I}\right| < \frac{E_I}{Y_I} \quad \ldots \ldots \quad (7)$$

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,

$$\frac{E}{Y} = \frac{u_A}{\varepsilon_A} \cdot K_A \cdot \theta_A + \frac{u_I}{\varepsilon_I} \cdot K_I \cdot \theta_I + \frac{u_S}{\varepsilon_S} \cdot K_S \cdot \theta_S \quad \ldots \ldots \quad (8)$$

Equation 8 show 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 8 with respect to energy efficiency in sector $i$.

$$\frac{d(E/Y)}{d\varepsilon_I} = -\frac{u_A}{\varepsilon_A} \cdot K_I \cdot \theta_I < 0 \quad \ldots \ldots \quad (9)$$

In this case, the impact of technological change will have a great impact if it occurs in the sector with the largest total output. Also, the negative impact on energy intensity will increase with innovation. Thus, any innovation in the industrial sectors that occur in a country can result in substantial impact on energy intensity in countries that develop later in times if the technology is transferable.

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:

\[ D_{\text{tot}} = D_{\text{str}} \times D_{\text{int}} = \frac{I_t}{I_0} \]

\[ D_{\text{str}} = \exp \sum_{i}^{n} \left[ \frac{L[w_{i,t}, w_{i,0}]}{\sum_{i}^{n} L[w_{i,t}, w_{i,0}]} \ln \frac{S_{i,t}}{S_{i,0}} \right] \]

\[ D_{\text{int}} = \exp \sum_{i}^{n} \left[ \frac{L[w_{i,t}, w_{i,0}]}{\sum_{i}^{n} L[w_{i,t}, w_{i,0}]} \ln \frac{I_{i,t}}{I_{i,0}} \right] \]

\[ L[w_{i,t}, w_{i,0}] = \ln \frac{w_{i,0}}{w_{i,t}} = \frac{E_{i,0}}{E_{t}} - \frac{E_{i,t}}{E_{t}} \]

\[ S_{i} = \frac{y_{i}}{y} \]

Where:

- \( D_{\text{tot}} \) = total change of energy intensity in year \( t \) relative to the reference year
- \( D_{\text{str}} \) = change of total energy intensity due to structural change effect
- \( D_{\text{int}} \) = 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

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:

\[ Y(t) = \left[ (1 - a_k)K(t) \right] \propto [A(t)(1 - a_L)L(t)] \propto -1, \quad 0 < \alpha < 1 \]
Equation 11 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.

**Empirical**

Empirical literature in the study is categorised as follows; (i) grouped countries; (ii) developed countries; (iii) developing countries; and (iv) literature on South Africa.

From grouped countries 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. They found that energy intensities in the most industrialised countries of the world have decreased over the years. This was as a result of a decline in the consumption of energy and an increase in value add which were influenced by technological advancements with some economic gains. Also, in leading developing economies such as China, India and Brazil industrial growth were not achieved in an energy efficient manner, was rather due to increasing energy intensities.

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.

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 tightly 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.
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).

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.

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.

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Similar thoughts were shared by Chontanawat et al, (2014) who 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.

In the developing countries Sahu & Narayanan (2010; 2011) found that a positive link between industry performance and energy intensity exist. 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) have 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 23 434 firms from 2005 to 2013. The sample was divided into three categories based on the primary energy demand namely natural gas, petroleum and coal.

Correspondingly, 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 was 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.

Differently, Locmelis et al, (2018) used the decomposition analysis for 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.

In South Africa, there is plenty of literature advocating for new technologies to be adopted by the different manufacturing sectors. 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.

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.

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.

**METHODOLOGY**

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:

\[ Y_t = AK^x E^{1-x}, 0 < A < 1 \]  \quad (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 return 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).

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:

$$LEI_t = \beta_0 + \beta_1 LTMVA_t + \beta_2 LTOP_t + \beta_3 LFDI_t + \beta_4 LEP_t + \mu \ldots \ldots (2)$$

Where:

- $LEI$ – Logarithm of Energy intensity
- $LTMVA$ - 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
- $\mu$ - Captures the error term

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). 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 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). Energy is assumed to be one of the basic input elements 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). 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.

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.

Estimation procedure includes descriptive statistics which is used to summarise data in a more meaningful way; pairwise correlation test is used to determine the degree of association and to detect the presence of multicollinearity; unit root is tested using informal graphical illustrations and the ADF and PP formal tests, the null hypothesis is rejected if the p-value is below 5% an indication that there is no unit root in the variables; the lag length selection criteria is chosen based on the Akaike Information Criterion, Schwarz Information Criterion (SIC) and the Hannan-Quinn information criterion (HQIC); in order to determine an equilibrium relationship among the variables a cointegration test is conducted using the Johansen test and the principle pantula test is conducted in order to determine the trends components; the presence of cointegration in the variables implies that the VECM technique can be estimated in order to disaggregate the relationship; variance decomposition and impulse response analysis is employed in order to determine the response of the dependent variables to shocks of the independent variables; diagnostics tests used to test for the validity of the assumptions underlying the study include the normality test based on the Jaque-Bera, the serial correlation based on Langrage Multiplier and heteroscedasticity based on the White heteroscedasticity test if the p-value of the diagnostic tests is above 5% significant level then the null hypothesis is not rejected implying that there is no serial correlation, the model is not mis-specified and it is normally distributed; lastly stability tests are conducted using the Cumulative Sum of Recursive Residuals (CUSUM) test and the Cumulative Sum of Squared Recursive Residuals (CUSUMSQ) test.

PRESENTATION AND INTERPRETATION OF FINDINGS

Descriptive Statistics

Descriptive statistic tests are run on the natural values of the variables, not the logged values and the results are presented in Table 1.

Table 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         |
Pairwise Correlation

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 2.

**Table 2. Pairwise correlation matrix**

|       | LEI  | LEP  | LFDI | LTMVA | LTOP  |
|-------|------|------|------|-------|-------|
| LEI   | 1.00 | -0.08| 0.21 | -0.12 | -0.52 |
| LEP   | -0.08| 1.00 | 0.08 | -0.01 | 0.26  |
| LFDI  | 0.21 | 0.08 | 1.00 | 0.62  | -0.03 |
| LTMVA | -0.12| -0.01| 0.62 | 1.00  | 0.34  |
| LTOP  | -0.52| 0.26 | -0.03| 0.34  | 1.00  |

From the results presented in Table 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 the study. 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 2 the highest value is 51.83 % which is not too high.

Unit Root Tests

The first step in estimating the VECM is by testing whether the variables in the study are stationary or not. Before estimating the formal unit root tests informal graphical presentations of the variables are estimated at levels and difference forms as shown in Figure 1(a) and (b).

Figure 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.
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 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.

**Figure 1(a). Informal unit root test at levels**
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 3 (a) and (b) respectively.

**Augmented Dickey Fuller test (ADF)**

The ADF unit root test results presented in Table 4.3 (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.

**Table 3(a). ADF Test**

| Variables | AFD-LEVELS | ADF1st Difference |
|-----------|------------|--------------------|
| Model     | t-stats    | p-value            | t-stats     | p-value     |
| 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      |
Variables | AFD-LEVELS | ADF1st Difference | t-stats | p-value | t-stats | p-value
---|---|---|---|---|---|---
Model | | | | | | |
**LEI** | 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 | -1.032845* | 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 | 

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

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.

**Philip Peron (PP) Unit root test**

**Table 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 | -2.33986* | 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 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.
**Johansen cointegration test**

The steps involved when testing for cointegration test are shown and discussed in the next sections.

**Lag length selection.**

When running the Johansen test, there is a need to determine the lag length and the results are presented in Table 4(a).

| 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 4(a) the lag length chosen by most criterion is lag 2 and this lag was chosen based on the AIC, FPE and LR. After determining the lag length, the next step is to determine the trend assumption based on the Pantula Principle test.

**Principle Pantula test**

The principle pantula test results are shown in Table 4 (b).

| R   | n-r | Model 2 Trace test statistic | Critical values | Model 3 Trace test statistic | Critical values | Model 4 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 4 (c). Pantula principle test based on the maximum eigenvalue test**

| R   | n-r | Model 2 Max test statistic | Critical values | Model 3 Max test statistic | Critical values | Model 4 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 4.4 (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.

Determining the number of cointegration vectors

The Trace and Max-Eigenvalue results of the cointegration test are presented in Tables 4.4 (d) and (e) respectively.

**Table 4 (d). Trace Test**

| 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 4.4 (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 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 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 exists amongst the variables.

Figure 2. Cointegration Graphs

The cointegration graphs presented in Figure 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.

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(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(a) is illustrated using an equation as follows:

\[
LEI = -0.735231 + 0.00000 - 0.260417LFDI + 0.300743LTMVA + 0.211929LTOP \ldots \tag{1}
\]

\[
LEI = 27.37419 + 1.00000LEP - 12.67381LFDI + 2.963159LTMVA - 8.122783LTOP. \tag{2}
\]

From the results presented in equation 4.1 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 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 1 and 2, the long run results will be interpreted based on equation 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 theoretical assumptions made in chapter 4 of this study. This implies that the trade liberalization post-apartheid 1994 was able to boost the economy of South Africa through foreign direct investment. 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 theoretical assumptions made in chapter 4 of the study. Implying 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.

| 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 4.5(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 al (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.

**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 3.
Based on the results presented in Figure 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.

**Variance decomposition analysis**

The variance decomposition results for a 10-year period, are presented in Table 6.

| 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 6.4 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.

**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 Lagrange Multiplier, normality test based on the Jarque-Bera and heteroscedasticity based on the White test as presented in Table 7.

| 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 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 7,
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.

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 4 below.

![CUSUM and CUSUMQ](image)

Figure 4. Stability tests

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 4 above the CUSUM and CUSUMQ line indicated in blue
shows that the model is stable.

CONCLUSIONS AND POLICY RECOMMENDATION

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. 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
Findings 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.

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.

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.

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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